UNIVERSITY OF PORTSMOUTH
Systems Engineering Research Group
Department of Mechanical and Design Engineering

INTELLIGENT SOFTWARE SYSTEMS TO ASSIST IN USING THE INTERNET

by

Jorge Bergasa – Suso
BSc, MIEEE

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DECLARATION OF CONFORMITY

I hereby declare that the research documented in this Thesis has been undertaken by the author and that any work included that was not undertaken by the author has been appropriately attributed.

J. Bergasa – Suso.

ABSTRACT

This dissertation describes the creation of new Web-Based Teaching (WBT) systems to assist in the use of the Internet, as well as the creation of new intelligent agent systems to monitor user behaviour while browsing the World Wide Web (WWW). A key contribution to knowledge is the creation of a method to infer user learning style from user behaviour while browsing the WWW and the inference rules resulting from the application of this method.

Existing commercial WBT systems provided useful tools to facilitate the use of the Internet. However, most of these systems were designed for distance learning, and not for using the Internet within classrooms, so students could lose concentration and navigate to unrelated Web sites. Existing commercial WBT systems did not provide intelligent advice on potential sites, consider student activity or provide content-specific filtering of Web pages.

A system called CITA was designed to overcome these limitations. A prototype was created using a standard proxy server as a platform for testing the effectiveness of filtering methods. The knowledge gained from testing the prototype suggested a need for another type of software tool that provided structured, focused and controlled access to the Internet in an intuitive and non-intrusive way, relying on a minimal network infrastructure. A novel set of tools called iLessons was created to achieve these goals. iLessons enabled teachers to: gather resources from the Internet; create lesson Web pages; define student access to the Internet; and load lessons into student computers. iLessons also provided students with tools to create resource collections and to create coursework. Users considered iLessons to be intuitive and easy to use because it was embedded into a standard Web browser.

The research moved on to create a model of a new collaborative agent system that filtered and recommended Web pages to students based on three different dimensions: page relevance; student learning style; and student activity. In order to automatically determine the learning style of students and recommend suitable Web pages, patterns were sought in the way students interacted with a standard Web browser and in the structure of Web pages that were preferred by each learning style group. Two new intelligent agent systems were created to record user activity and Web page structure while using Web browsers: Solstice and BUCAgent. Solstice was a first prototype created to test the methodology. BUCAgent was then created to record UI activity information and Web page structure features. The same technology as iLessons was used so that they could be fully integrated with it.

BUCAgent was utilised in a controlled environment while volunteers completed a research task. Collected data was analysed using a data mining engine to find rules to predict user dimensions of learning style. Rules to predict the Active/Reflective, Sensing/Intuitive and Visual/Verbal dimensions of learning style were found. It was also proved that parameters in the way that users interacted with the Internet could be measured to classify users in a number of behavioural groups, such as different learning style models or larger scale psychological models. Systems could then adapt their behaviour to suit the behavioural traits of the user.

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GLOSSARY AND ACRONYMS

AI	Artificial Intelligence
AR	Active/Reflective
BUCAgent	Browser, User and Content Agent
CAI	Computer Aided Instruction
CBT	Computer Based Teaching
ce	Classification Efficiency
CITA	Caught In The Act
COM	Component Object Model
cp	Classification Probability
DCOM	Distributed COM
DF	Document Frequency
DHTML	Dynamic HTML
Dm	Mouse distance
d_s	Scroll distance in the Y axis
d_x	Mouse distance in the X axis
d_y	Mouse distance in the Y axis
GUI	Graphical User Interface
HCI	Human-Computer Interaction
HTML	HyperText Modelling Language
HTTP	HyperText Transfer Protocol
ICT	Information and Communication Technologies
IE	Microsoft Internet Explorer
IG	Information Gain
ILS	Index of Learning Styles
IP	Internet Protocol
MAC	Media Access Control Layer
MHTML	MIME embedded HTML file format
MI	Mutual Information
MSPS	Microsoft Proxy Server 2
OLE	Object Linking and Embedding
OOP	Object-Oriented Programming
OS	Operating System
PC	Personal Computer
PVal	P-Value
R-Sq	R-Squared
SG	Sequential/Global
SI	Sensing/Intuitive
s_{im}	Average instant mouse speed
SIn	Significance Index
s_{is}	Average instant scroll speed
s_m	Average mouse speed
Stderr	Standard Error
TCP	Transfer Control Protocol

TS	Term Strength
UI	User Interface
UID	Unique Identifier
UML	Unified Modelling Language
URL	Uniform Resource Locator
VV	Visual/Verbal
WBT	Web-Based Teaching
WWW	World Wide Web

CHAPTER ONE
INTRODUCTION

The vision of the United Kingdom (UK) government in 2003 for the use of Information and Communication Technology (ICT) in educational institutions was that:

"ICT could make a significant contribution to teaching and learning by providing opportunities to engage and motivate pupils and meet their individual learning needs" [Department for Education and Skills (2003)].

ICT was seen as a key, integral element of the school reform agenda. The UK government encouraged the use of ICT in schools through a number of programmes such as the "National Grid for Learning" (NGfL) and "ICT in schools". The ultimate aim was to integrate the effective use of ICT in teaching and learning and to promote high levels of ICT competence amongst teachers and students.

The "Curriculum On-Line" programme, part of the NGfL programme, gave schools access to a wide range of educational materials available from the Internet. A number of tools were available to create and deliver Web-based educational materials, but there was a need for easy to use and flexible tools to make effective use of educational materials made available by the Curriculum On Line programme.

A study conducted at the beginning of this research suggested that teachers found the Internet difficult to use in a classroom environment due to a lack of control over the pages that students accessed during a lesson [Bergasa *et al.* (2003, 2005), Owston (1997), Wiesenmayer & Ravinder (1997), Wiesenmayer & Meadows (1998)]. Filtering systems provided general restriction settings that did not adapt to teaching aims and objectives. Moreover, teachers were rarely IT specialists and available tools were difficult to manage. Software tools that allowed students to interact with the Internet did not take into account student learning styles or motivation, and did not present information in a way that was suitable for each student and the subject being taught.

New easy-to-use software tools were required to enable teachers to create and reuse Web-based educational materials and to define criteria to focus student attention in Web resources that matched the aims of a lesson. It might also be possible to assist students by selecting information depending on their learning styles.

1.1. Research Aim and Objectives

The thesis set out and described in this dissertation is that:

New intelligent software tools and methods could be created to assist teachers and students in using the Internet

The aim of this research was to identify the limitations of current Web-Based Teaching (WBT) systems and to investigate the needs of teachers and students and then to create new software systems to assist teachers and students in using the Internet more effectively. Specific objectives were to:

- Investigate existing WBT systems.
- Create new User Interfaces to assist teachers.
- Create a novel WBT system.
- Investigate filtering methods and intelligent document classification
- Create new models for intelligent document filtering.
- Investigate learning style models.
- Define user behaviour and document parameters to determine user learning style.
- Design and implement a new and intelligent student agent.
- Find ways to infer student learning style from student behaviour

1.2. Methodology

Current WBT systems were investigated. Feedback from teachers was recorded and compared to the features of current systems in order to identify limitations This suggested a need for a new type of software tool to create Web-based lessons and define areas of the Internet that could be accessed by students during a lesson. A client/server system called "Caught In The Act" (CITA) was designed to overcome the identified limitations.

1.2.1. The first prototype filter

The goals of CITA were to provide tools that enabled teachers to: Create lesson Web pages; Define student access to zones of the Internet depending on the lesson being taught; and receive real time notifications of attempts to view blocked pages.

A first prototype implementation consisted of a proxy server plug-in that filtered student requests made from Web browsers and a client application that received student activity notifications from the proxy server plug-in and displayed them to teachers.

After testing the prototype and receiving feedback from teachers and testers in the collaborating company, it was found that using CITA involved the need to establish and maintain a network infrastructure that was not available in many schools and colleges. Also, redeveloping existing technology in a proprietary software package was an ineffective way of developing the CITA client. These limitations suggested a need for another type of software tool that provided structured, focused and controlled access to the Internet in an intuitive and non-intrusive way while relying on minimal network infrastructure. The research therefore progressed to create a system with these characteristics, called iLessons.

1.2.2. iLessons

iLessons was created to overcome the limitations of CITA after gathering information from the marketing department at the collaborating company and receiving feedback from teachers. iLessons gave teachers the ability to structure the use of the Internet by reusing materials readily available on the Internet, create a set of lesson Web pages; restrict Internet access to keep students focused, and to control the user of the Internet by selecting lessons and restrictions per classroom.

The iLessons UI was integrated in a standard Web browser, so that existing technology was reused and users did not have to learn to use a new software application. Unlike CITA, iLessons did not rely on any server to provide lesson implementation. Lessons were copied to network folders named after each classroom, where they could be accessed by student computers.

Drag and drop technology was available to collect Internet resources such as plain text; images; hyperlinks; and HTML fragments and reuse them in lesson Web pages. Students were also able to collect resources and to use them to create Microsoft Word coursework files from within IE.

Teachers could define default permissions for a lesson as well as to set permissions for individual Web pages, page elements, directories, and domains. A filter monitored IE and granted access to pages or page elements as specified in the navigation zone.

1.2.3. New intelligent agent systems

Allowing and denying specific areas of the Internet was an effective way of controlling the misuse of the Internet during a lesson and focusing students attention, however students were not able to use the Internet to carry out their own research. Devedžić (2003) stated that:

"Next-generation Web-based educational applications should exhibit more theory and content-oriented intelligence and adaptability, pay more attention to interoperability, reusability, and knowledge sharing issues, and look more closely to general trends in Web development".

To achieve this aspiration, the research moved on to investigate intelligent document classification algorithms that were considered to filter Web pages more liberally by granting student access to documents classified as relevant to a subject rather than granting access to lists of documents specified by teachers. Other research concerning similar applications for document classification algorithms were reviewed and five document classification algorithms were investigated and enhanced to create new intelligent filtering models to assist users in researching using the Internet.

Subject-specific filtering using document categorisation was flexible enough to enable students to use the Internet as a research tool while keeping them focused on a subject, but the system lacked adaptability to meet student learning styles and did not provide any collaboration facilities. Research work in the literature did not provide Internet access control based on the relevance of page contents to a subject; use Web pages readily available on the Internet; or infer students' learning styles without the need of questionnaires or other tests.

A model of a new collaborative agent system was created to overcome these limitations. The system filtered and recommended Web pages from the Internet to students based on three different dimensions: page relevancy, based on contents, page layout based on student learning style; and user activity.

In order to automatically determine the learning style of a student and recommend suitable Web pages, it was necessary to find patterns in the way users with different learning styles interacted with a standard Web browser, as well as patterns in the layout and elements of Web pages that were easier to understand by students depending on their learning style. Two new intelligent agent systems (Solstice and BUCAgent) were created to record user activity while using Web browsers as well as document ratings and features.

1.2.4. Experiment and results

Data collected by the new intelligent agent systems from the way students with different learning styles interacted with standard Web browsers was analysed to find rules to automatically determine the learning style of students. Rules were also sought to identify student preferences for the layout and elements of Web pages, so that suitable Web pages could be recommended to students based on their learning style.

An experiment was implemented in three stages to find rules: Volunteers were first requested to complete the Index of Learning Styles (ILS) questionnaire [Felder & Spurlin (2005)] so that their dimensions of learning style were known. Volunteers then investigated a subject using IE and BUCAgent embedded within it. Finally, data from volunteers was cleaned and imported into a data mining engine to search for rules.

Sixty seven volunteers completed the ILS questionnaire and at first, twenty of these volunteers took part in further stages. Data from volunteers was cleaned and imported into a data mining engine. Accurate and significant rules were successfully found by the data mining engine for the Active/Reflective, Sensing/Intuitive and Visual/Verbal dimensions of learning style. It was also found that probabilistic rules could be generated by observing the maximum and minimum value of recorded user attributes for each dimension of learning style. The most significant parameters for each dimension were used to create rules that could predict the probability of users belonging to a dimension of learning style. A significant and accurate rule was found for one of the dimensions of learning style using this approach.

A second round of experiments took place to improve the statistical significance and accuracy of the rules. Data from fifty volunteers was used to find rules to predict user learning style. Although accurate rules were found, they were not always statistically significant. However, several user attributes appeared repeatedly across most rule searches, which implied that these attributes may be indicative of the dimension of learning style of the volunteers as they continued to appear even when the number of volunteers grew.

1.3. Research claims

Research into WBT; Human-Computer Interaction (HCI); document classification and filtering; and learning styles has been undertaken. New intelligent agent systems were created. The research work brought the following successes

Main systems created:

- Caught In The Act (CITA) prototype.
- iLessons.
- Solstice Agent.
- Browser and User Activity Agent (BUCAgent).

New methods:

- Resource collection from Web browser.
- Web page editing from Web browser.
- Web page filtering from Web browser.
- New Web page filtering models.
- Model of a new collaborative agent system.
- Methods to capture user behaviour and relate it to learning styles.
- Rules to infer student learning style from student behaviour.

A key contribution to knowledge was the creation of a method to infer user learning style from user behaviour while browsing the Internet, and the rules resulting from the application of this method.

1.4. Overview of the dissertation

Chapter 2 illustrates the policy for the use of ICT in education in the UK and describes current Computer Aided Instruction (CAI) and WBT systems. The Chapter then describes hardware, software and computer programming methodologies as well as learning style models related to the research.

Chapter 3 describes the design of CITA and a first prototype filter created using a proxy server and a proprietary client. It then describes the feedback received from users and illustrates the limitations of the system.

Chapter 4 describes a new system called iLessons, intended to overcome the limitations found in the systems described in Chapters 2 and 3.

Chapter 5 describes the software and usability tests carried out on the systems described in Chapters 3 and 4, the feedback received from users and the actions taken to improve the systems.

Chapter 6 describes the creation of a model of a new collaborative agent system. It also introduces two new intelligent agent systems used to record user activity and page structure information from users while navigating the Internet.

Chapter 7 describes the software and usability tests carried out on the systems described in Chapter 6, the test results and the actions taken to improve the systems.

Chapter 8 describes an experiment to retrieve data from volunteers using the student agent system described in Chapter 6, how the data was cleaned and analysed, and what the results of the analysis were.

Finally, Chapter 9 describes the research findings and discusses the successes and failures of the research, as well as providing recommendations for future research.

CHAPTER TWO

LITERATURE SEARCH

This Chapter reviews the government strategy on the use of Information and Communication Technologies in education in the United Kingdom (UK). It then describes existing Computer Aided Instruction (CAI) systems and revises the hardware and software technologies related to the creation of the new systems described in Chapters 3, 4 and 6, including computers, computer networks, Operating Systems (OS), Web browsers and software development techniques

2.1. The National Grid for Learning programme

Education in the UK was regulated by the Department for Education and Skills (DfES). The DfES worked to create learning opportunities for people of all ages in England. It was responsible for setting national standards and legislating to improve the quality of teaching. [Holt *et al.* (2002)].

The Scottish Executive Education Department (SEED) was responsible for administering policy on pre-school and school education, children and young people in Scotland [Paterson (2002)]. Public education in Northern Ireland, other than University education, was administered by the Department of Education for Northern Ireland (DENI).

The National Grid for Learning (NGfL) strategy for Information and Communications Technology (ICT) in education and lifelong learning was a national strategy that aimed to provide a gateway to educational content on the Internet; to develop an infrastructure in educational establishments. workplaces and homes to support access to the Internet; and to provide training to develop good practice in ICT [Selwyn & Fitz (2001)].

The document established various targets to be met by 2002, which included the connection of educational establishments and community centres to the Internet, to ensure that teachers were competent users of ICT; to provide ICT training for librarians;to ensure that school leavers had a good understanding of ICT; to ensure that administrative communications ceased to be paper-based; and to make Britain a centre for excellence in the development of networked software content and a world leader in the export of learning services.

From 1998 to 2002, the NGfL programme achieved the following results in England:

- All schools were connected to the Internet, of which over a quarter had a fast broadband connection.
- A portal of indexed educational content was developed.
- The average number of computers in schools for teaching and learning was doubled.
- Over 100.000 teachers received a computer through centrally-funded initiatives.
- 'Curriculum Online' was launched.
- Over 6000 UK centres were established to provide access to ICT in the community.

[DfES (2003)]

Following responses from individuals, educational institutions and industry, the Curriculum Online programme was officially launched in December 2001 as part of the NGfL programme. The Curriculum Online portal gave access to a wide range of digital materials for teaching and learning. Products could be purchased using e-learning credits [Curriculum Online-About us (n.d)].

All maintained Nursery, Primary and Secondary Education in England, up to and including Key Stage 4 received government funding for teaching and learning material in the form of e-learning credits. E-learning credits could be used by schools to purchase approved digital teaching and learning material. For the 2003 / 2004 year, each eligible school was entitled to £1000 plus £9.85 for each pupil.

2.1.1. The ICT in Schools programme

In January 2002 the Government set out a new vision for the future of ICT in schools. The next phase of the NGfL strategy, called the ICT in Schools programme, was developed from 2003 to 2006. The aim of this programme was to ensure that using and applying ICT as an integral part of the learning process became a natural process for all schools, becoming "e-confident schools". The National College for School Leadership developed an initial framework that identified ten key features of the e-confident school:

- High levels of staff confidence, competence and leadership.
- Re-engineered teaching, learning and assessment.
- Leading and managing distributed and concurrent learning.
- Effective application within organisational and management processes
- Coherent personal learning development, support and access.
- Appropriate resource allocation to ensure sustainable development
- Availability, access and technical support.
- Students with high ICT capability.
- School as the lead community learning and information hub.

[The e-confident school (n.d.)]

2.1.2. Discussion

This Section described the context of this research within the government strategy for the use of ICT in UK education. The efforts of the UK government to integrate Internet resources within educational establishments uncovered a need for new software tools to assist teachers and students in using these resources effectively

2.2. Computer Aided Instruction

Computer Aided Instruction (CAI) or Computer-Based Teaching (CBT) was defined as "the use of computer programs as teaching tools". [Phelps *et al.* (1995)]. The use of integrated tutorials to assist users in learning how to use an application was also considered to be CAI. Daniel (1999) described three generations of CAI:

- Mainframes were used for CAI during the 1960s and 1970s, but its cost effectiveness and value added were questioned. It was found that "*CAI appears to generate no more (or no less) cognitive achievement but probably costs more than conventional methods*" [Siegfried & Fels (1979)]

- Microcomputers were used for CAI during the 1980s and early 1990s, with the expectation that they would reduce development costs and overcome earlier limitations.

- Network computing and the World Wide Web (WWW) were used for CAI from the late 1990s. The WWW could sustain a level of experimentation, innovation, and collaboration necessary to produce significant advances in CAI.

Web-Based Teaching (WBT) was defined by Horton (2000) as "*Any purposeful, considered application of Web technologies to the task of educating a fellow human being*". Instruction could be led by trainers or self-directed by the trainees. Four different types of WBT were observed:

- Individual learning that featured drill and practice, simulations, reading, questioning and answering.

- Just-in-time teaching focused on problem-solving, scientific method, experiential method and project method.

- Non-real-time group learning that employed experiential tasks, discussions and team projects.

- Real-time collaborative group learning that used discussions, problem solving and reflection.

[Driscoll (1998)]

WBT enhanced teaching and learning experiences within classrooms. In joint research between the UK's Royal Air Force and Oxford Aviation Training, it was demonstrated that instructor-led WBT was more cost-effective than fully-interactive WBT [Computer Aided Instruction (n.d.)]. Greater teaching effectiveness reduced the classroom teaching content and improved exam pass rates; and new instructors became operational more rapidly than with traditional teaching methods.

A number of pedagogical benefits were also identified in the use of instructor-led WBT: Difficult concepts were made easier to understand; it was used for private study and enhanced retention of knowledge; it delivered effective English-language based teaching to non-native speakers; it transmitted difficult concepts in an easy to understand way; and provided greater standardisation of instruction.

2.2.1. Existing WBT systems

A number of commercial WBT systems were investigated. Existing WBT systems were separated into distance learning systems and instructor-led systems.

Distance learning systems

The following distance learning systems were reviewed:

a) WebCT

b) Lotus Learning Space

c) LearnPoint Suite

a) WebCT

WebCT Campus Edition, by WebCT Inc. was a course management system that enabled the delivery of high quality online education [WebCT (2001)]. It provided tools for course development, course delivery, and course management. It was scalable and was built on standards-based technology, such as HTTP and HTML, integrating with existing campus infrastructure.

b) *Lotus Learning Space*

Lotus Learning Space 5, by IBM Inc. provided a cost-effective, self-paced learning solution that integrated various contents that were deployed and delivered depending on instruction objectives and budget. [IBM Solutions directory (n.d.)].

c) *LearnPoint Suite*

LearnPoint Suite by LeanForward Inc. was an e-Learning platform to implement and maintain teaching and certification programs. LearnPoint Suite consisted of two products:

- LearnPoint Creator enabled learners and content managers to create contents and authorise lessons, courses, and curriculums.

- LearnPoint Server provided the ability to manage and serve tests, track user access data and produce advanced reports.

[LearnPoint (n.d.)]

None of these systems filtered access to the Internet so students could get distracted by navigating to other Internet pages while using the system within the educational institution premises. They did not provide intelligent advice on potential sites or consider student activity and learning style to enhance student learning. Also, functionality available from the clients was limited as most functions were server based.

Instructor-led systems

The following instructor-led systems were reviewed:

a) Lotus Learning Space Virtual Classroom

b) I-Gear

a) *Lotus LearningSpace Virtual Classroom*

Lotus LearningSpace Virtual Classroom, by IBM Inc. enabled live interactive e-learning sessions over the Internet . It provided tools required for real-time teaching: course outline tools, application sharing, whiteboard, audio/video and chat capabilities for interactivity, as well as assessments to gauge teaching effectiveness [IBM Solutions directory (n.d.)]. Lotus LearningSpace Virtual Classroom did not filter access to the Internet so students could get distracted by navigating to other Internet pages during lessons.

b) I-Gear

I-Gear, by Symantec Corp. was a comprehensive content management application. Its key features were content filtering, access scheduling and reporting [I-Gear for education (n.d.)]. I-Gear filtered Web pages by using an index available from a Web server. The index was created by a Web crawler which blocked pages containing certain keywords and word patterns. Many Web sites that were appropriate to education were often added to the blocking list without human supervision.

None of these systems tracked user activity, provided intelligent advice on potential sites or considered student activity and learning style to enhance student learning. Proprietary client applications were also needed to run the systems.

WebQuests

WebQuests were inquiry-oriented activities in which information that learners interacted with came from resources on the Internet, optionally supplemented with videoconferencing [Dodge (1997)]. There were two levels of WebQuests:

Short Term WebQuests were designed to be completed in one to three class periods. The instructional goals of short term WebQuests were knowledge acquisition and integration. At the end of a short term WebQuest, learners tackled a significant amount of new information and made sense of it.

Longer Term WebQuests lasted between one week and a month in a classroom setting. The instructional goals of longer term WebQuests were extending and refining knowledge. Learners analysed a body of knowledge deeply, transformed it and demonstrated an understanding of the material by creating something that others could respond to.

If WebQuests were not carefully designed they could lead to poor learning experiences. Students could easily search for information on the Internet and copy already existing material to complete WebQuests if they were created as fact-finding exercises that did not engage students in problem solving, role taking or learning to view problems from multiple perspectives [Gibson (2004)].

2.2.2. Discussion

This Section described existing commercial WBT systems available at the time of writing as well as WebQuests, a framework for the creation of educational Internet resources. The described systems provided limited functionality to clients or required expensive proprietary applications. They did not provide intelligent advice on potential sites, consider student activity or provide content-specific filtering of Web pages. Some existing experimental systems that included intelligent document classification are described in Chapter 6, Section 6.1.4 Experimental systems that included learning styles are described in Chapter 6, Section 6.2.1.

2.3. Hardware

Hardware technologies related to Computer Assisted instruction are reviewed in this section.

An example of a first generation computer was the "Electronic Numerical Integrator and Computer" (ENIAC), created in 1946. It contained 17468 electronic valves and was capable of 5000 10-digit additions per second [Akera (2002)] Transistors were invented in 1948 and were smaller and more reliable components which replaced inefficient vacuum valves [Williams (1997)]. The first computer that used transistors was developed in 1958. Integrated circuits (IC) or microchips were electronic circuits whose components were etched on a single slice of semiconductor material [Phelps (1995)]. Computers using them appeared from 1963. Called "minicomputers", they were affordable by smaller businesses From the 1970s, computers were developed using microprocessors Microprocessors were ICs that contained the entire Central Processing Unit (CPU) of a computer in a single microchip [Phelps (1995)]. Microprocessors allowed computers to be smaller and faster than previous models and enabled the development of Personal Computers (PC). PCs first appeared in the late 1970s The Apple II (Figure 2.1) was introduced in 1977 by Apple Computers During the late 1970s and early 1980s, many new models and competing Operating Systems

(OS) appeared. In 1981, IBM released a personal computer known as the IBM PC (Figure 2.2) [Campbell-Kelly & Aspray (1996)]. IBM PCs became a standard and other companies created cheaper IBM PC compatible computers that used the same microprocessors as IBM PCs and were capable of running the same software.

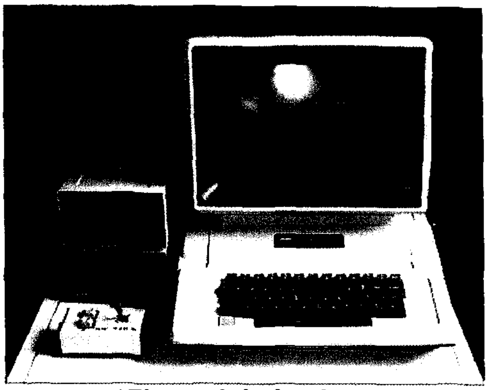


Figure 2.1: Apple II [Computer History Online (n.d.)]

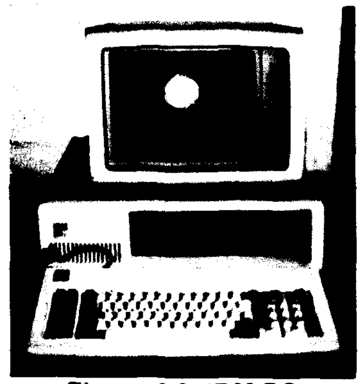


Figure 2.2: IBM PC [IBM PC (n.d.)]

2.3.1. Computer networks

Computer networks were systems of computers and peripherals linked together [Phelps (1995)]. Computers on networks were called nodes or hosts. The smallest networks were Local-Area Networks (LAN) where computers were connected by cables within small geographic areas. Larger networks, called Wide-Area Networks (WANs) used telephone lines or radio waves to link computers that were far from each other. The geometric arrangement of computer networks was called 'network topology'. Common topologies were bus, star, and ring (Figure 2.3).

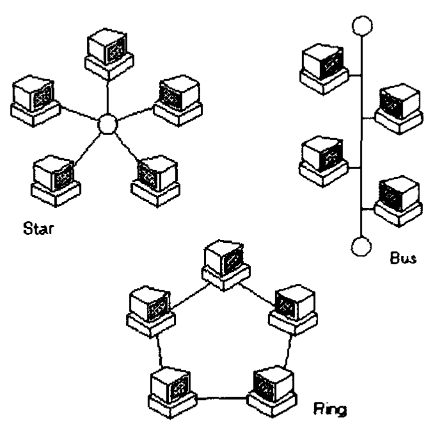


Figure 2.3: Network topologies [Network (n.d.)]

Computer network architectures

The most common types of network architectures were peer-to-peer architecture and client/server architecture. In peer-to-peer architecture each node acted both as client and server [Phelps (1995)]. In client/server network architecture, computers were differentiated into clients and servers:

- Servers provided access to network resources such as files or peripherals.
- Clients were computers that requested services provided by servers.

Computer network infrastructure

In addition to servers and clients, computer networks included other electronic devices concerned with moving data through the network, such as hubs, switches, bridges and routers.

- Hubs were electronic devices that accepted data from sending computers and delivered it to the appropriate destination.
- Switches were devices that transmitted information between computers by determining which computer should receive the frame from the destination address.
- Bridges connected two LANs and copied information from one network to another
- Routers attached two or more networks and forwarded data between networks according to a routing table.

[Comer (2004)]

Other devices such as Domain Name Servers (DNS) and Dynamic Host Configuration Protocol Servers (DHCP) maintained dedicated databases of network information and provided information to clients and servers so that they could communicate [Huitema (2000)]. Network names were preferred by users because they were easier to remember than numeric network addresses. DNS servers translated network names into network addresses.

DHCP servers assigned network addresses to devices on a network so that new computers could be added to networks without manually assigning unique addresses.

Computer network protocols

Network protocols were "*an agreement between the communicating parties on how communication is to proceed*" [Tanenbaum (2003)]. They were a common set of rules that computers used to communicate. Most network protocols were based on the International Standards Office (ISO) standard 'Open System Interconnection' (OSI). OSI defined a framework for implementing protocols in a stack of seven layers (see Figure 2.4). Control was passed from one layer to the next, starting at the top layer in one station until it reached the bottom layer. Data was then transmitted over networks to the recipient station and processed upwards in the receiving station OSI layers [Marsden (1991)].

Application	**Top layer**
Presentation	
Session	
Transport	
Network	
Data Link	
Physical	**Bottom layer**

Figure 2.4: The OSI stack

- The application layer supported application and end-user processes such as file transfer and e-mail.

- The presentation layer provided independence from differences in data representation such as encryption by translating from application to network format, and vice versa.

- The session layer established, managed and terminated connections between applications.

- The transport layer provided transparent transfer of data between end nodes. It was responsible for end-to-end error recovery and flow control, ensuring complete data transfer.

- The network layer provided switching and routing technologies, creating circuits for transmitting data from node to node.

- The data link layer encoded and decoded data packets into bits. It was divided into two sub layers: the Media Access Control (MAC) sub layer controlled how computers gained access to data and permission to transmit it; the Logical Link Control (LLC) layer controlled synchronization, flow control and error checking.

- The physical layer converted the bit stream from the data link layer into a physical signal, like electrical impulses, light or radio waves and sends it through the network.

2.3.2. The Internet

In 1973, the United States Defense Advanced Research Projects Agency (DARPA) initiated a research program to investigate techniques and technologies for interlinking packet networks of various kinds [Naughton (1999)]. A packet network transmitted data by dividing and encapsulating it into packets. Packets were then transmitted individually and could follow different routes to their destination. When all the packets forming a message arrived at a destination, they were recompiled into the original message [Tanenbaum (2003)]. The objective was to develop communication protocols which would allow networked computers to communicate transparently across multiple, linked packet networks. This was called the 'Internetting project' and the system of networks which emerged from the research was known as the 'Internet'. A system of protocols developed over the course of this research effort became known as the TCP/IP Protocol Suite, after the two initial protocols developed: Transmission Control Protocol (TCP) and Internet Protocol (IP). TCP enabled hosts to establish connections and exchange streams of data, guaranteeing the correct delivery of data. IP specified the format of packets and the addressing scheme [Stevens (1994)].

In 1972, the first e-mail program was created by Ray Tomlinson [Naughton (1999)]. Simple Mail Transfer Protocol (SMTP) servers moved e-mail messages across networks, while Post Office Protocol (POP) servers stored e-mail messages and served them to recipient users.

The World Wide Web, URLs and HTTP

The World Wide Web (WWW) evolved from a project at the European Centre for Nuclear Research (CERN) that began in 1989, when Tim Berners-Lee and Robert Cailliau built a prototype system that became the core the WWW [Wolinsky (1999)]. The intent of the system was to make sharing research papers among colleagues easier by creating links to other documents within the contents of documents, called hyperlinks, which could be followed by clicking on them.

The WWW was a system of Internet servers, called Web servers, that supported documents formatted using Hypertext Mark-up Language (HTML). Documents were identified by Uniform Resource Locators (URL), transmitted using Hypertext Transfer Protocol (HTTP) and viewed using Web browsers. URLs were the unique global addresses of documents and other resources on the WWW (Figure 2.5). They indicated what application protocols to use and the IP address or network name of the server where resources were located, and the full path to the resource within the server [Comer (2000)].

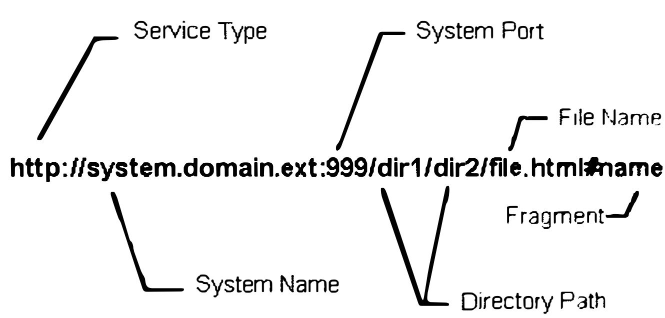


Figure 2.5: Uniform Resource Locator (URL) [Thompson (1996)]

HTML was an authoring language used to create documents on the WWW, called Web pages [Comer (2000)]. HTML defined the structure and layout of Web pages by using tags and attributes. Web pages supported graphics, audio, and video files as well as hyperlinks to other documents, which enabled users to navigate from one Web page to another by selecting hyperlinks.

HTTP was the underlying application protocol used by the WWW [Comer (2000)]. HTTP defined how messages were formatted and transmitted, and what actions Web servers and browsers took in response to commands. HTTP was a stateless protocol because each command was executed independently, without any knowledge of previous commands. This was the main reason that it was difficult to implement Web sites that reacted intelligently to user input.

Client applications used to retrieve and display documents from the WWW were called 'Web browsers'. Graphical Web browsers displayed multimedia information such as graphics, sound and video [Wolinsky (1999)].

2.3.3. Discussion

This Section described the hardware technologies related to the research: computers, computer networks and the Internet. The systems described in Chapters 3, 4 and 6 were created during this research to run on PCs connected to the Internet.

2.4. Software

Software technologies related to CAI are reviewed in this section.

2.4.1. Operating Systems

Operating Systems (OS) performed tasks such as recognizing user input; sending output to devices such as display screens; keeping track of files; and controlling peripheral devices such as printers (see Figure 2.6). General purpose computers had an OS to run other programs [Stallings (2001)]. For large systems, the OS managed users and programs running simultaneously.

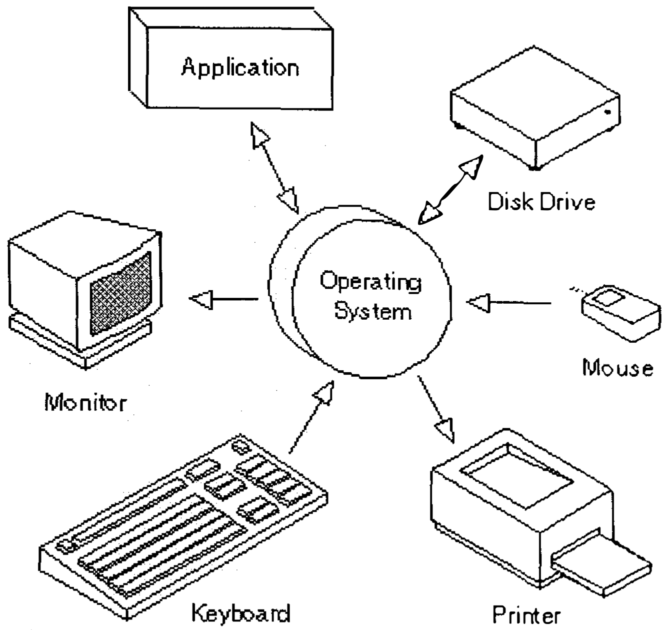


Figure 2.6: OS functions [Operating system (n.d.)]

OSs provided a software platform on which application programs ran. Computer programs were written to run on a particular OS and this determined the applications that computers could run. An exception were computer programs created using programming languages such as .NET or Java: they were written using an intermediate language so that they could be executed in any OS, provided that the OS contained the software necessary to translate the intermediate language to a language specific to the OS. The most popular OSs for personal computers were: Microsoft Windows for IBM PC-compatible computers; Apple Mac OS for Apple Power-PC compatible computers; and Linux, that ran in both platforms. All three operating systems supported computer programs written in Java. At the moment of writing, only Microsoft Windows supported programs written in .NET.

Microsoft Windows

Windows 1.0, released in 1985, featured an easy to use graphical interface, device-independent graphics and allowed several programs to run concurrently [Windows history (n.d.)].

Windows 2.0, introduced in 1987, provided usability improvements to Windows. With the addition of icons and overlapping windows, Windows became a viable environment for development of major applications.

Windows 3.0 (see Figure 2.7), released in 1990, provided the capability to address memory beyond 640K and a more powerful User Interface (UI).

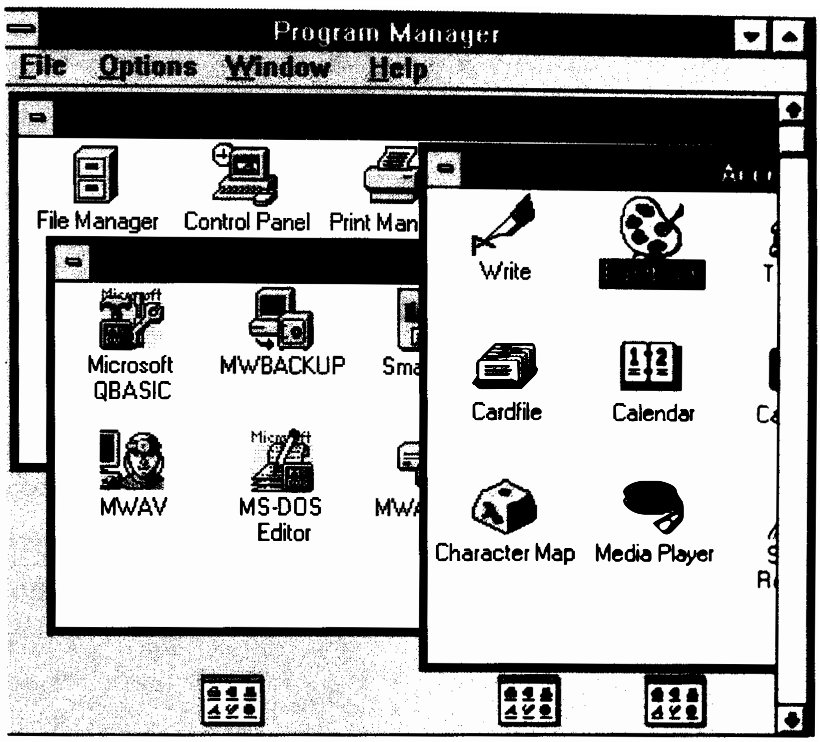


Figure 2.7: Windows 3.1 screenshot [Windows history (n.d.)]

Windows for Workgroups 3.1, released in October 1992, was the first integrated windows and networking package. It provided peer-to-peer file and printer sharing capabilities.

Windows NT 3.1, released in 1994, was intended for use in network servers, workstations and software development machines; While the Windows NT UI was similar to Windows 3.1, it was based on a new core.

Windows 95, released in August 1995, provided full pre-emptive multitasking, advanced file systems, threading and networking. Windows 98, released in June 1998, integrated a Web browser and made navigation through the file system similar to navigating in the WWW. It also supported larger hard drives and hardware support for technology such as DVDs.

Windows NT 5.0 was released in 1998. Like Windows 98, it integrated Web browsing facilities. A distributed file system provided a location-independent way to organise and navigate big volumes of information stored on servers. In November 1998, NT 5.0 became known as Windows 2000. Windows XP (see Figure 2.8) was released in October 2001. It used the same core as Windows 2000 but also provided enhanced multimedia and networking capabilities.

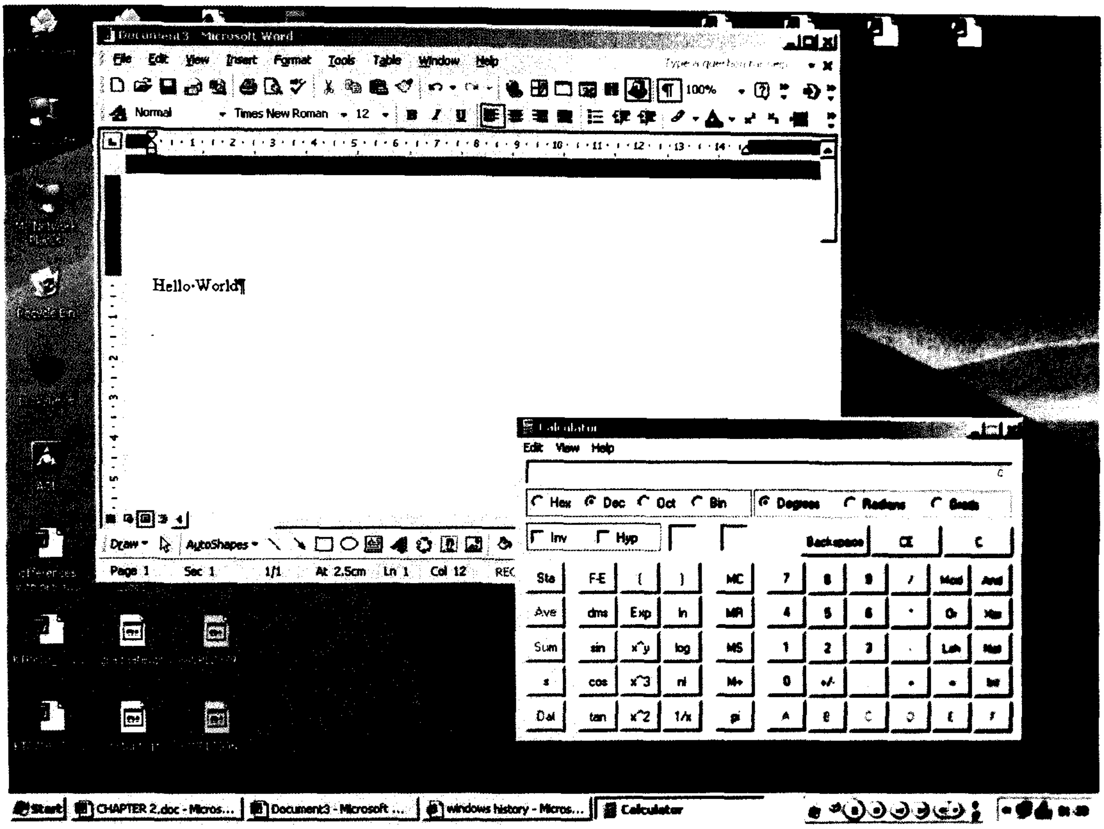


Figure 2.8: Microsoft Windows XP screenshot

Apple System / Mac OS

System 1.0, released in 1984, was designed by Apple to run in Macintosh personal computers [Mesa (n.d.)]. It featured a simple and easy to use graphical UI (GUI), and also included a separate tutorial disk, which was one of the first applications of CAI in PCs. System 3.0, launched in 1986, featured a more efficient and fast GUI due to a disk cache, which stored frequently used data in memory. It also introduced a fully hierarchical file system that physically divided storage space in folders and files.

System 7 (see Figure 2.9), released in 1990, could run multiple applications at the same time [Knight (n.d.)]. It included colour icons, file sharing, virtual memory and 32-bit addressing.

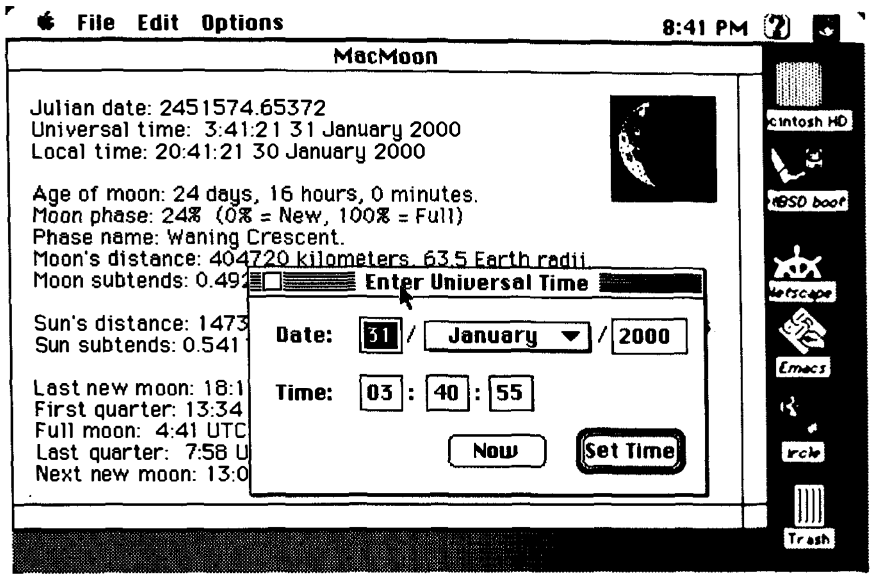


Figure 2.9: System 7 screenshot [Mesander (n.d.)]

Apple Computer purchased NeXT and its OS in 1996. A combination of the NeXT OS and Macintosh UI developed into the Mac OS X OS [Glaser (1991)]. A screenshot of Mac OS X can be seen in Figure 2.10.

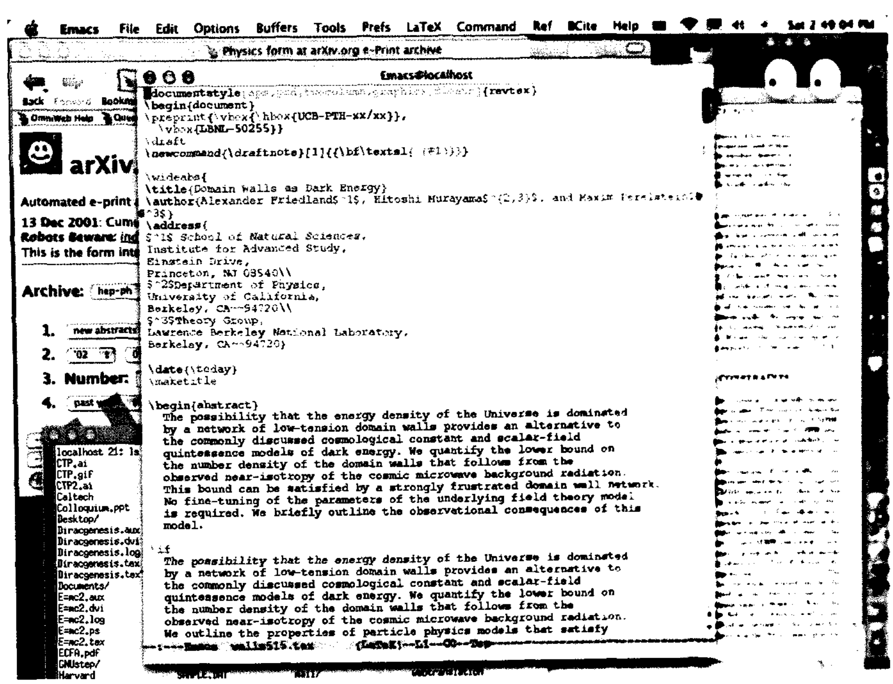


Figure 2.10: Mac OS X screenshot [Murayama (n.d.)]

Linux

UNIX was created by programmers at Bell Laboratories in the early 1960s and proved to be a reliable OS [Cooper (2001)]. It became a de facto standard OS before the development of the PC, and prevailed as the OS for more powerful computers.

Linux was created by Finnish computer scientist Linus Torvalds in 1991 as a UNIX-compatible OS that could run in PCs. The ability to run on PCs and the fact that the Linux source code was free inspired many programmers to improve it, eventually becoming better than some commercial UNIX packages.

Companies such as RedHat, SuSE and Mandrake provided packaged Linux distributions. They integrated GUIs to ease management of programs and services (see Figure 2.11). Developments included 3D acceleration support, support for USB devices and single-click updates of system and packages.

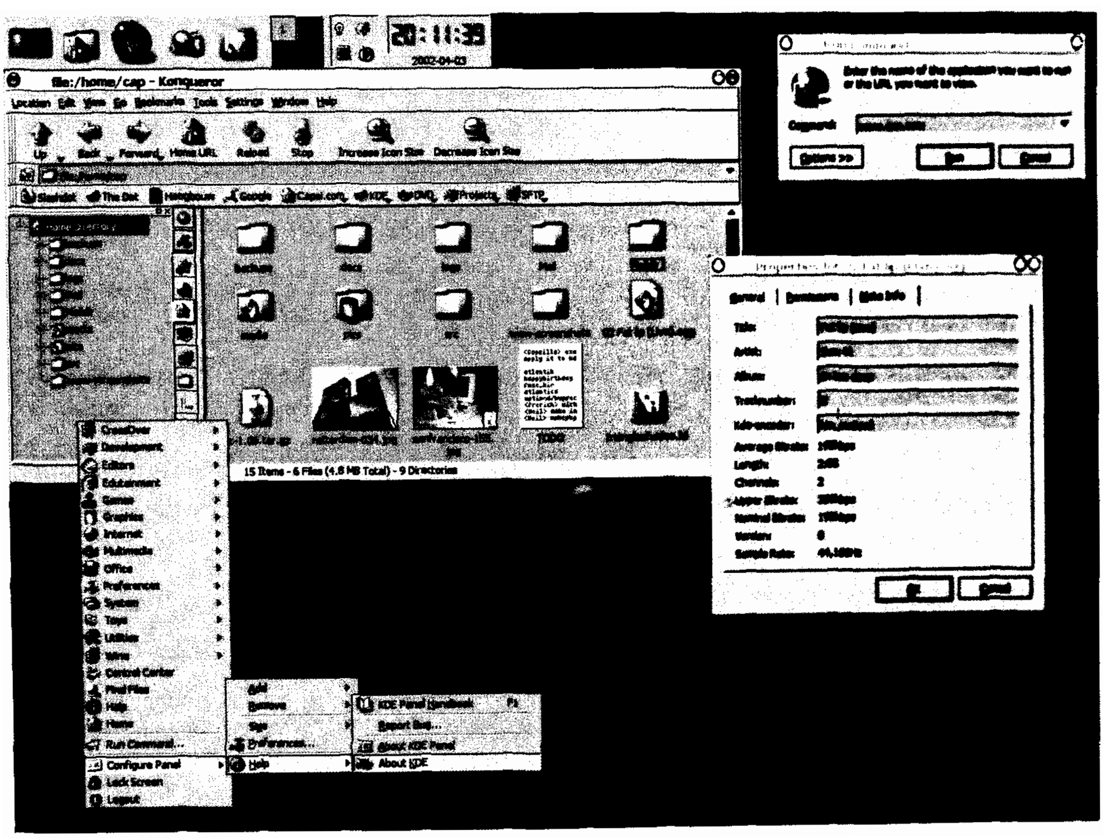


Figure 2.11: KDE Linux screenshot [KDE screenshots (n.d.)]

2.4.2. Web browsers

NCSA Mosaic

Mosaic was a Web browser developed by the National Centre for Supercomputing Applications (NCSA) at the University of Illinois. Mosaic was available for Linux, Apple Macintosh and Microsoft windows. Its main features were:

- "Autosurf" enabled users to automatically download documents linked to Web pages and store them to disk.
- "Collaborate" enabled users to link Mosaic sessions with other Mosaic users, send files, and exchange data with collaborators.
- "Site map" allowed users to scan Web pages and create local HTML files outlining a list of links to those pages.

[Rivera *et al.* (1994)]

Netscape Navigator

Netscape Navigator 6.1 by Netscape Corporation was a software suite for Windows, Mac OS and Linux that included a Web browser, email, instant messaging, address book, and a Web page editor. The most relevant features of Netscape 6.1 were:

- "Search" initiated searches of Web pages by entering keywords in an address field.
- "Bookmarks" enabled the saving of links to pages in a hierarchical menu
- "History" enabled the display of a list of previously visited Web pages in the order that they had been accessed.
- "Form Manager" filled forms automatically.
- "Password manager" automatically filled in user names and passwords.

[Shelly *et al.* (2001)]

Microsoft Internet Explorer

Microsoft Internet Explorer 6.0 (IE) was available to users of Windows OSs. It integrated a Web browser and an external email client. Its main features were:

- "Image Toolbar" saved, e-mailed, and printed pictures from a Web page, as well as view saved pictures in the My Pictures folder.
- "Media Bar" provided a UI for locating and playing media within the browser window.
- "Auto Image Resize" resized pictures so they fitted within the dimensions of the browser window.
- Support for advanced authoring standards such as DHTML, XML, CSS1, DOM1 and others.
- A powerful programming model including support for standards based on Internet technologies to write Web-based applications.

[Shelly *et al.* (2004)]

2.4.3. Software development

Software development technologies related to the research are described in this Section.

Computer programming

Computer programs were organised lists of instructions that caused computers to behave in a predetermined manner [Ben-Ari (1996)]. Computer programs were written using programming languages, standardised communication techniques for expressing instructions to a computer. They enabled programmers to precisely specify what kinds of data a computer will act upon, and precisely what actions to take under various circumstances. Four programming methodologies could be differentiated depending on the way that programs are written:

a) Sequential programming

b) Procedural programming

c) Structured programming

d) Object-oriented programming.

a) Sequential programming

Sequential programming was a method of writing computer programs as a list of instructions that were executed sequentially by the computer. A subset of the instructions were dedicated to control the flow of the instruction sequence, making possible the use of loops, conditional branches and jumps to other locations within the program [Marcotty & Ledgard (1987)].

b) Procedural programming

Procedural programming was a method of computer programming based upon procedures, also called functions, routines or subroutines depending on programming language [Marcotty & Ledgard (1987)]. It was possible for a procedural program to have multiple levels or scopes, with procedures defined inside other procedures. Each scope could contain variables which could not be used in outer scopes. Procedural programming code was easier to read and more maintainable and flexible than sequential programming code.

c) Structured programming

Structured programming was a subset of procedural programming that enforced a logical structure on the program being written to make it more efficient and easier to understand and modify [MacLennan (1987)]. Structured programming employed a top-down design model, in which developers split the overall program structure into separate subsections. Sets of similar functions were coded in separate modules so that code could be loaded into memory more efficiently Modules could be reused in other programs.

d) Object-Oriented Programming (OOP)

Object-Oriented Programming (OOP) was a programming methodology in which programmers defined data types within data structures and also the types of functions that could be applied to data structures [Coad & Nicola (1993)]. Data structures became objects that included both data and functions. Programmers could also create relationships between objects. For example, objects could inherit characteristics from other objects.

Component technologies

Software components encapsulated software functionality, often in the form of objects, so that components could exist autonomously from other components in a computer [Szyperski (1998)]. Other programs or components used functionality encapsulated in other components by retrieving interfaces (Figure 2.12). Interfaces were lists of definitions of methods and properties implemented by a component, which could be called from other programs or components.

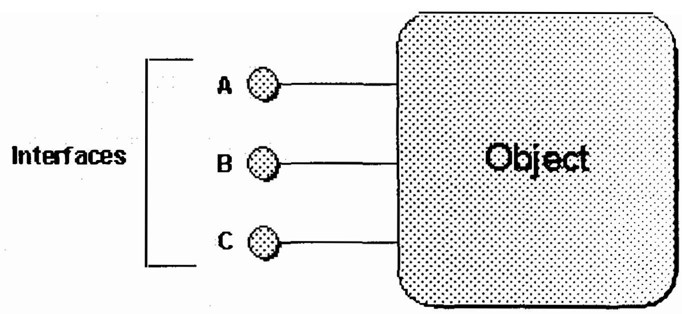


Figure 2.12: Representation of a software component [Williams & Kindel (1994)]

Software was developed by connecting prefabricated components together by their interfaces (see Figure 2.13), much like in the field of electronics or mechanics.

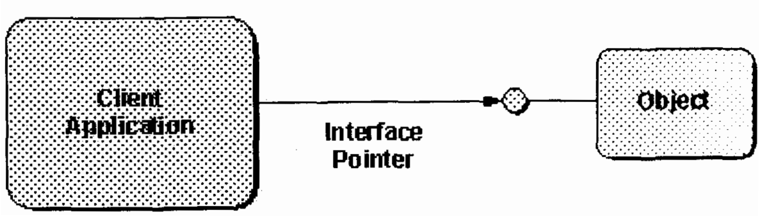


Figure 2.13: Usage of software components [Williams & Kindel (1994)]

Component Object Model (COM) was a technology for software components developed by Microsoft. The first version of COM was called Object Linking and Embedding (OLE) technology. It was initially used for copying and data transfer between different applications as well as the creation and management of compound documents. OLE controls were a special kind of component that included their own UI so that they could be embedded into other applications' UI

The entire component framework was later renamed as COM. Distributable COM technology (DCOM) provided a means to execute components located on remote computers. Components could be reused by new calls to their initialising routine without unloading them from memory. The COM technology was strategically replaced by the Microsoft .NET initiative in 2002. The .NET initiative was a Microsoft project to create a new software development platform focused on network transparency, platform independence, and rapid application development [Davis (2003)].

Unified Modelling Language (UML)

Unified Modelling Language (UML) was an industry standard language for specifying, visualizing, constructing, and documenting the artefacts of software systems. It simplified the complex process of software design, making a "blueprint" for construction [Bruegge & Dutoit (2004)]. UML could be used to analyse the requirements of a software system and design a solution to meet them, representing the results using UML standard diagram types. Each diagram type in UML could be grouped to represent views of the system [Larman (1998)]

- The user view showed what users require from the system, including use cases diagrams.
- The structural view showed the relationship between classes in class diagrams (see Figure 2.14).
- The behavioural view showed the system logic, including sequence, collaboration, activity and state chart diagrams.
- The implementation plan modelled the realisation of the plan and the source code: Dependencies and location for distributed systems.
- The environmental view included the realisation in the real world and the application of the system. This included configuration, communication, and support between different system nodes.

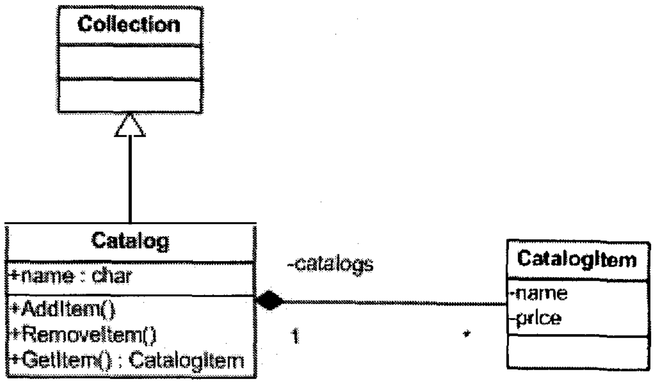


Figure 2.14: Example of UML class diagram.

Human-Computer Interaction and GUIs

Human-Computer Interaction (HCI) was the set of processes, dialogues and actions through which human users employed and interacted with a computer [Baecken & Burton (1987)]. The purpose of the discipline of HCI was to apply systematically knowledge about human purposes, human capabilities and limitations, and machine capabilities and limitations so as to extend the reach of users. Another goal was to enhance the quality of interaction between human and machine.

The capabilities and disciplines required to meet those goals included graphic and industrial design, an understanding of organisational dynamics and processes, and understanding of human cognitive, perceptual and motor skills, a knowledge of display technologies, input devices, interaction techniques and design methodologies, and an aptitude for elegance in system design [Baecken & Burton (1987)]. Effective interface design was a multidisciplinary process requiring a holistic view of any design problem.

Computer systems had a UI through which human users and computers interacted. GUIs used computers' graphics capabilities to make programs easier to use [Preece *et al.* (1997)]. GUIs featured the following basic components:

- Pointer: A symbol that appeared on the display screen and that users moved with a pointing device such as a mouse or trackball to select objects and commands.

- Windows: Different areas into which screens were divided. Users could run different programs or display different files, move windows around the display screen, and change their shape and size.

- Menus: Lists of options that users could select to execute commands.

- Icons: Small pictures that represent commands, files, or windows. By moving a pointer to an icon and pressing a mouse button, users could execute commands or convert icons into windows. Users could also move icons around the display screen.

- Desktop: The background area on the display screen where icons were grouped was referred to as "desktop" because icons were intended to represent real objects on a real desktop.

Software Testing

Tan (2006) cited Mantere & Alander (2005) defining software testing as *"The process of analysing a software item to detect the difference between existing and required conditions and evaluate the features of the software items"*. Testing was first regarded as "debugging" or fixing a known error in early days of software development. From 1957 it was differentiated from debugging and became identified as detecting the bugs in the software. Bugs were defined as unwanted and unintended properties or behaviour of a program or piece of hardware. especially ones that caused it to malfunction. Software testing was critical as the cost of fixing bugs increased tenfold with time [Patton (2001)]. Greif (2005) classified software testing into two categories: dynamic and static tests, as shown in Figure 2.15.

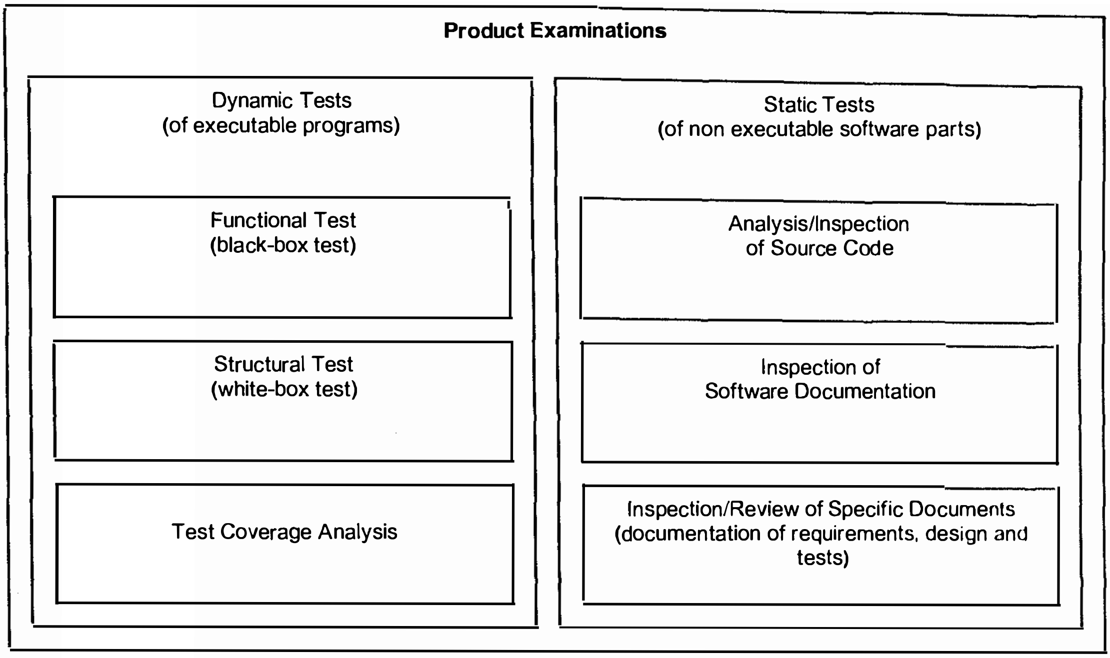


Figure 2.15 Techniques of Software Product Evaluation [Greif (2005)]

Static tests referred to the analysis and inspection of source code and software documentation such as requirements, design and tests. Dynamic testing was described as tests conducted on a program while it was running. Figure 2.16 shows the difference between the two main dynamic testing methods: black-box testing and white-box testing. In black-box testing, testing was conducted by seeing if the output result was as expected from the inputs given, without knowing how the program operated [Patton (2001)]. In white-box testing, sometimes called clear-box testing, the software's code was shown to testers so that testing could be performed in more detail.

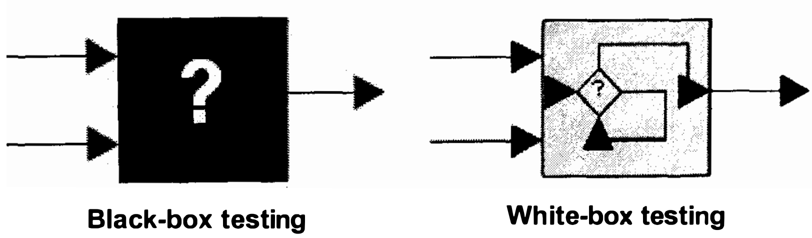


Figure 2.16: Black-Box and White-Box Testing [Zeilinger (n.d.)]

There were two fundamental approaches to testing software within black-box testing and white-box testing: test-to-pass and test-to-fail. With the test-to-pass approach, software was tested with the simplest and most straightforward test cases and it was not pushed to its maximum capabilities. After software was tested and passed the test-to-pass testing, the test-to-fail approach was then carried out with the intention to break the software by testing it with every possible test case.

Proxy Servers

Proxy servers mediated between client applications, such as Web browsers, and other servers. They intercepted requests sent by clients to real servers and fulfilled the requests themselves if possible. Otherwise, they forwarded the request to the real servers and recorded the response. Proxy servers had two main purposes [Luotonen (1997)]:

- Improve Performance: Proxy servers could improve performance for groups of users because they saved results of requests for a certain amount of time. For example, if many users accessed the Internet through a proxy server and a first user requested a certain Web page then later another user requested the same page, then instead of forwarding the request to the Internet (a time-consuming operation), the proxy servers would return the page that was fetched for the first user. Since proxy servers were often on the same network as users, this was a faster operation.

- Filter Requests: Proxy servers could also filter requests. For example, companies used proxy servers to prevent their employees from accessing a specific set of Web sites.

Proxy servers such as Internet Junkbuster could be installed on single computers. Internet Junkbuster filtered HTTP transactions between Web servers and Web browsers [Internet junkbuster (2000)]. Internet Junkbuster used a configuration file, that determined which sites would be blocked and how requests would be filtered.

Larger proxy servers such as Microsoft Proxy Server 2.0 provided a larger range of features, such as intelligent content caching based on how often a document was retrieved or the possibility of chaining several servers in an array for use in large networks. A key feature was the ability to use COM components called plug-ins to enhance server functionality. Plug-ins for Microsoft Proxy Server such as RBAProxy allowed network administrators to assign lists of allowed Websites to different groups of users [Richard (n.d.)]. Users access was restricted to a well defined set of Web pages servers without requiring full Internet access. Microsoft Proxy Server plug-ins were classified into "Internet Services Application Programming Interface" (ISAPI) filters or ISAPI extensions [Clements *et al.* (1997)].

a) ISAPI filters

ISAPI filters captured and processed specific events. ISAPI filters were called for every request, regardless of such details as the identity of the resource requested in the URL. Thus, ISAPI filters could monitor, log, modify, redirect, or authenticate requests sent to the Web server. For example, a customised log for every Web request could be developed, or an authentication system against a legacy database.

a) ISAPI extensions.

ISAPI extensions exposed functions that could be called from Web browsers by requesting URLs of ISAPI extensions. ISAPI code was executed in the server and response was given in the form of Web pages.

Explorer extensions

Explorer Bars (Figure 2.17) were introduced with IE 4.0 to provide a display area adjacent to the browser pane [Seely (2000)]. They were windows within the main IE window, and they could be used to display information and to interact with users. Explorer Bars were displayed as a vertical pane on the left side of the browser pane or horizontally, below the browser pane.

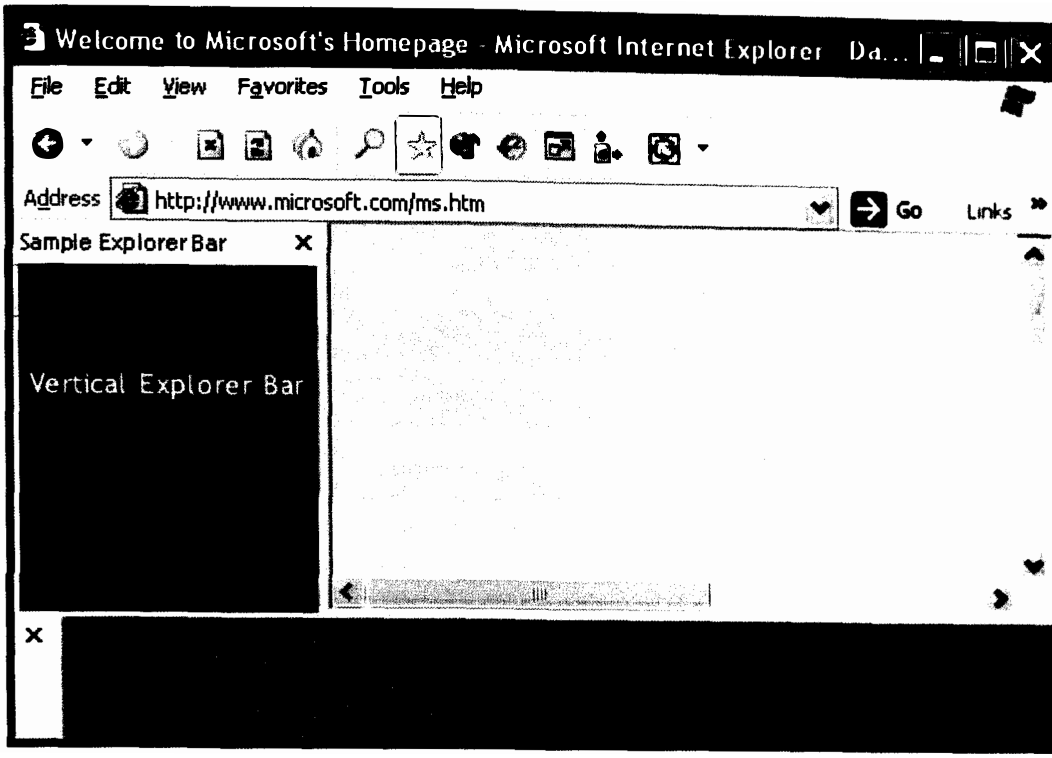


Figure 2.17: Vertical and horizontal explorer bars [Creating Custom Explorer Bars (2001)]

Tool bands, also called toolbars (Figure 2.18) were band objects that were introduced with IE 5.0 to support the Microsoft Windows radio toolbar feature. However, like Explorer bands, tool bands were general-purpose windows.

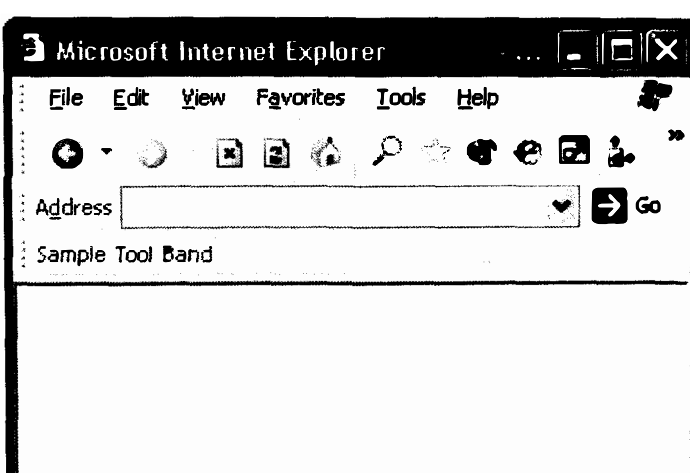


Figure 2.18: Sample tool band [Creating Custom Explorer Bars (2001)]

Band objects were also used to create desk bands (Figure 2.19). While their basic implementation was similar to Explorer Bars, desk bands were unrelated to IE Desk bands were dockable windows on the desktop.

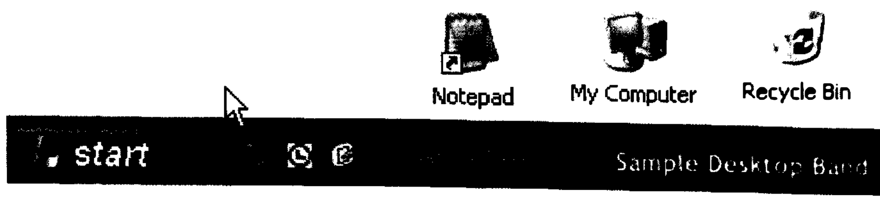


Figure 2.19: Sample desk band [Creating Custom Explorer Bars (2001)]

2.4.4. Artificial Intelligence

The term 'Artificial Intelligence' (AI) was coined in 1956 by John McCarthy at the Massachusetts Institute of Technology as the branch of computer science concerned with making computers behave like humans [Russell & Norvig (2003)]. Rusell & Norvig (2003) also described AI as "*the capability of a device to perform functions that are normally associated with human intelligence, such as reasoning and optimization through experience*" and "*the branch of computer science that attempts to approximate the results of human reasoning by organizing and manipulating factual and heuristic knowledge*".

Machine learning

Machine learning was an area of AI involving the development of techniques to allow computers to adapt to new circumstances and to detect and extrapolate patterns [Russell & Norvig (2003)]. Common algorithm types were supervised learning and unsupervised learning.

In unsupervised learning, a data set of input objects was gathered and typically treated as a set of random variables. A model was then built for the data set.

Supervised learning created functions from training data. Training data consisted of pairs of input objects and desired outputs. The task of the supervised learner was to predict the value of the function for any valid input object after observing a small number of training pairs. To achieve this, learner algorithms generalised from the presented data to unseen situations. In order to solve problems using supervised learning, various steps were taken:

- A set of input objects and the corresponding outputs characteristics of the real world, called corpus, was gathered either from human experts or from measurements.

- Input objects were transformed into feature vectors, which contained a number of features that were descriptive of the object.

- The learning algorithm was executed on the gathered training set. Parameters of the learning algorithm could be adjusted by optimising performance on a subset (called a validation set) of the training set, or via cross-validation.

- Performance was measured on a test set that was separate from the training set.

Examples of application of supervised learning were present in document classification, information retrieval, object recognition in computer vision, optical character recognition, and speech recognition.

Intelligent agents

Agents were anything that could be viewed as perceiving its environment through sensors and acting upon that environment through actuators [Russell & Norvig (2003)]. Software agents were programs that operated in a software environment such as the Internet. Intelligent or rational agents were those which for each possible situation selected an action that was expected to maximise their performance in achieving their goals. Intelligent software agents were autonomous and operated without the direct intervention of humans. Agents could communicate with other agents or human users.

Data mining and knowledge discovery

Data mining was the use of AI techniques to discover hidden knowledge, unexpected patterns and new rules from large databases [Adriaans & Zantinge (1996)]. Data Mining was regarded as the key element of a more elaborate process called Knowledge Discovery in Databases (KDD). The knowledge discovery process consisted of six iterative stages:

- Selection of relevant data.

- Data cleaning: Removal of duplicates and inconsistencies in the data.

- Enrichment of data using external information related to the data.

- Data transformation to meet the input requirements of the data mining algorithm
- Data mining: The use of a data mining algorithm to discover hidden patterns and rules in the data.
- Translation of results to a human-readable form so that discovered knowledge can be used.

At every stage in the process it was possible to step back one or more stages in order to solve errors found in later stages or optimise the process using information found in previous iterations.

2.4.5. Document classification and filtering

[Goller *et. al* (2000)] defined document classification as "content-based assignment of predefined categories to documents". Document classification algorithms were based on the cluster hypothesis, which stated that "closely associated documents tend to be relevant to the same requests" [Van Rijsbergen (1979)].

Document classification algorithms were utilised to filter documents and route them to humans. Document classification algorithms were supervised machine learning algorithms that required a document training set to infer patterns to predict the category of new documents. Documents were represented as a vector of features, such as terms contained in text documents. Manual feature extraction was tedious and time consuming and prevented the categorisation of large amounts of documents. Feature extraction algorithms were used as part of the document classification process to extract relevant terms to classify documents effectively and accurately.

Feature extraction algorithms

Irrelevant or redundant features could have negative effects on classification algorithms [Liu & Motoda (1998)]: More training documents were needed to ensure statistical variability between patterns from different categories; irrelevant or redundant features could cause document classification algorithms to overfit the data; and resulting classification patterns were more complex, tending to be less accurate than simpler patterns. Yang & Pedersen (1997) evaluated five feature selection algorithms to reduce the amount of terms used by text categorisation algorithms: Document Frequency; Information Gain; Mutual information; Chi-Square Statistic; and Term Strength.

a) Document Frequency

The Document Frequency (DF) of a term was the number of documents in which a term occurred. It was assumed that rare terms with low DF were not informative or influential. Terms whose DF was below a threshold were discarded.

b) Information Gain

Information Gain (IG) measured how influential the presence of a term was to classify a document where the term was found. When a term appeared only in documents of a certain category, its IG was high. When a term appeared in all documents across categories, its IG was low. Terms whose IG was below a threshold were discarded.

c) Mutual Information

Mutual information (MI) measured a dependence between terms and categories in a set of document categories. MI was zero if a term and a category were independent. MI was not normalised, so MI values could not be compared across terms for the same category.

d) Chi square statistic

As well as MI, chi-square statistic (χ^2) measured dependence between terms and categories and could be compared to the χ^2 distribution. As MI, χ^2 was zero if a term and a category were independent. A difference between χ^2 and MI was that χ^2 was normalised. Also, χ^2 values could be compared across terms for the same category. χ^2 was known to be unreliable for low-frequency terms.

e) Term Strength

Term Strength (TS) was based on the assumption that documents with shared words were related. TS was computed based on the estimated conditional probability that a term occurred in the second half of a pair of related documents given that it occurred in the first half.

Document classification algorithms

Once terms were extracted from documents, they could be used to represent documents and processed by document classification algorithms. Yang & Liu (1999) evaluated five document classification algorithms: Support Vector Machines, k-Nearest Neighbour, Linear Least Squares Fit, Artificial Neural Networks and Naïve Bayes Classifier.

a) *Support Vector Machines (SVM)*

SVM was introduced to classify documents in two categories. Documents were represented by term vectors in a vector space. SVM found a decision surface that divided the documents into two categories. The decision surface was defined by the most similar documents to the surface, called support vectors. Support vectors were the only effective elements in the training set; the algorithm would learn the same decision surface if all other documents were discarded.

Figure 2.20 illustrates SVM in a two-dimensional vector space. Black and white data points represent documents of two categories. The decision surface is represented by a line separating the data points into two categories. Dashed lines represent the support vectors.

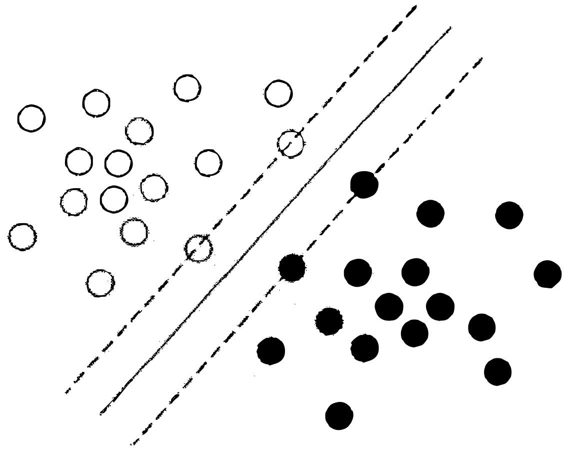


Figure 2.20: Decision surface splitting data points in two categories

b) *k-Nearest Neighbours (kNN)*

kNN was a well known statistical approach in text classification. kNN classified new documents by finding the k most similar documents, called "nearest neighbours", within the training documents. New documents were classified by weighing the categories of the k nearest neighbours according to the similarity (or "distance") to each neighbour. If more than one neighbour belonged to the same category, the category weights were added together. This provided a likelihood score for each category with respect to the new document.

Figure 2.21 illustrates kNN in a two-dimensional vector space. In this example, k=5. Black and white data points represent documents of two categories. Document A was classified as "white" because its four of its five closest neighbours were white. Document B was classified as "black".

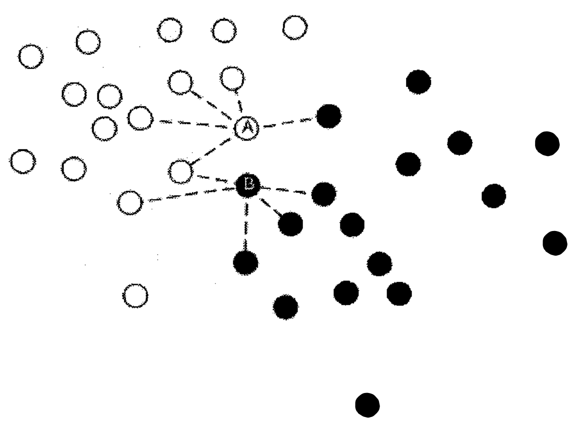


Figure 2.21: k-Nearest Neighbour document classification for k=5.

c) *Linear Least Squares Fit (LLSF)*

A multivariate regression model was created from a training set of documents and their categories. Training data was represented by pairs of input and an output vectors. Input vectors were document features weighed using feature extraction algorithms; output vectors were the weighted categories of each document. LLSF was utilised to find a term-category regression coefficients matrix that enabled the weighing of the categories to which new documents belonged by the terms contained in them.

d) Artificial Neural Networks (ANN)

ANN could be used to classify documents by using a different ANN for each category. The ANN input was a vector of terms contained in the document, and the output was the category to which documents belonged. The learning curve of ANN in document classification was longer than other methods.

e) Naïve Bayes Classifier (NB)

NB used the joint probabilities of terms and categories to estimate the probability that new documents belonged to each category based on the terms found in the new documents. NB was called naïve because it assumed that words were independent. This assumption made the computation more efficient than the exponential complexity of a non-naïve Bayes classifier because it did not use word combinations as predictors.

CAI systems using document classification

Other research work utilised content-based document filtering methods to assess the suitability and relevance of Web pages and to recommend new pages to users. The studied systems were: InLinx, WebMate, Syskill & Webert and WebACE.

a) InLinx

InLinx [Bighini *et al.* (2003)] was a Web-based system created for research at the University of Bologna that helped students to classify information that had been found on the Internet and saved as bookmarks; to recommend documents to students with similar interests; and to periodically notify of new potentially interesting documents. When students registered interesting pages, InLinx suggested a classification and recommended the pages to other users with similar interests. User interest was modelled from the contents of bookmarked pages.

b) WebMate

WebMate [Chen & Sycara (1998)] was a research system created at the Carnegie Mellon University comprised of a standalone proxy server and an applet controller WebMate monitored user interests in different domains from page ratings; extracted keywords from interesting pages to refine document search; and compiled and sent personal reports by automatically analysing news sources and compiling relevant headlines, sorting them by relevance.

WebMate's standalone proxy server monitored user actions; learned user interests from their page ratings, filtered news sources and compiled personal reports. WebMate's applet was a User Interface (UI) to provide relevance feedback for pages found in searches, rank interesting pages while browsing and receive keywords that WebMate extracted from interesting pages to refine searches.

c) Syskill & Webert

Syskill & Webert [Pazzani & Billsus (1997)] was designed in the University of California as a research system to help users distinguish interesting Web pages from uninteresting ones using a NB classifier. Syskill & Webert created a relevance pattern from user feedback by inserting controls in each Web page to enable users to rate a page as "interesting" or "uninteresting". When a Web page was retrieved, its relevance ranking (a value from 0 to 1) was displayed. Also, hyperlinks were explored and signs indicating whether links were interesting or not were added to the page.

d) WebACE

WebACE [Han *et al.* (1998)] was a proxy-based agent and a java application created in the University of Minnesota for research purposes that automatically classified a set of documents and generated new queries used to search for new related documents. The new set of documents was filtered to extract the set of documents most closely related to the training set. Feedback was not required from users. Interest profiles were generated by recording the number of times that users visited a document and the time spent browsing each document.

2.4.6. Discussion

This Section described the software technologies related to the research: Operating Systems, software development techniques, proxy servers, Web browsers, Web browser extensions, Artificial Intelligence and document classification. The system described in Chapters 3 was created to integrate within a proxy server. The systems described in Chapters 4 and 6 were created to interact with Web browsers using Web browser extensions and were designed to assist Teachers and Students in the use of the Internet. Finally, the systems described in Chapter 6 were created using artificial intelligence techniques.

2.5. Learning styles

The literature did not contain a unique definition of "learning style". Heineman (1995) cites a number of definitions: Kocinski (1984) defined learning style as the preferred way to learn and the way a person learns best; Zarghani (1988) noted that learning styles are "the cognitive, affective, and psychological traits that serve as relatively stable indicators of how learners perceive, interact with and respond to the learning environment".

Confusion appears in the literature concerning the terms *Cognitive Style* and *learning style* [Heineman (1995)]. Numerous authors use the terms interchangeably. McFadden (1986) stated that most definitions of learning style as well as Cognitive Style illustrate variations in individual information processing and no single definition for learning style or Cognitive Style was identified. Four models of learning style were considered.

Field dependency

Messick (1976) considered Cognitive Styles as means of problem solving, thinking, perceiving, and remembering. Field dependency was a dimension of Cognitive Style that described individual's propensity to discern and to isolate elements embedded in complex contexts [Calcaterra *et al.* (2005)]. Messick (1976) identified a number of connections between field dependency and learning:

a) Field dependent

Field dependent individuals were information processors and relied on external reference. They preferred situations where structure was provided for them and tended to solve problems through intuition and trial-and-error.

b) Field independent

Field independent individuals were analytic and relied on internal references They tended to actively structure their own learning by perceiving objects as a whole and by finding the underlying relationships of problems.

Felder and Silverman

Felder & Silverman (1988) modelled student learning style as four independent dimensions:

a) *Active / reflective*

Active learners retained and understood information best by doing something active with it: discussing or applying it or explaining it to others. Reflective learners preferred to think about it quietly first.

b) *Sensing / intuitive*

Sensing learners liked learning facts; intuitive learners preferred discovering possibilities and relationships.

c) *Visual / verbal*

Visual learners remembered best what they saw: pictures, diagrams, flow charts, time lines, films and demonstrations. Verbal learners got more out of words: written and spoken explanations. Most people were visual learners.

d) *Sequential / global*

Sequential learners gained understanding in linear steps. Global learners learnt in jumps, absorbing material almost randomly and then suddenly "getting it".

A measure of the affinity of individuals to each component of the dimensions of learning style could be obtained by completing the Index of Learning Styles (ILS) questionnaire [Felder & Spurlin (2005)] reproduced in Appendix E. The questionnaire consisted of 44 questions with two possible answer options each. If individuals found that both answers applied to them, they were asked to select the answer that applied most frequently. Once that all questions were completed, a measure in a scale of odd numbers from 1 to 11 was obtained for each dimension of learning style. A score of 9-11 indicated a strong affinity to one of the components of the dimension and a score of 1-3 indicated that the individual was comfortable learning with any of the two components of the dimension of learning style.

The core idea of the model was that students should not be taught exclusively according to their preferences, but rather to strive for a balance of instructional methods. To achieve this balance students should be taught mainly in a manner they prefer, which leads to an increased comfort level and willingness to learn, but also taught partly in a less preferred manner, which included relevant content and provided practice and feedback in ways of thinking and solving problems which they did not have to use to be fully effective professionals.

The Felder-Silverman model of learning style was widely used and the reliability and validity of the ILS questionnaire was confirmed by a number of independent studies [Constant (1997); Paterson (1999); Bruxeda & Moore (1999); De Vita (2001)].

Honey and Mumford

Honey & Mumford (1986) identified four learning styles:

a) Activist

Activists involved themselves fully and without bias in new experiences. They acted first and considered the consequences afterwards. They tackled problems by brainstorming. They thrived on the challenge of new experiences but were bored with implementation and longer term consolidation.

b) Theorist

Theorists liked to analyse and synthesize. They adapted and integrated observations into complex but logically sound theories. They thought problems through in a vertical, step-by-step logical way. Their approach to problems was consistently logical.

c) *Pragmatist*

Pragmatists tried out ideas, theories and techniques to see if they worked in practice. They liked to get on with things and act quickly and confidently on ideas that attracted them. They responded to problems and opportunities as a challenges.

d) Reflector

Reflectors liked to stand back to ponder experiences and observe them from different perspectives. They collected data and preferred to think about it thoroughly before coming to a conclusion.

Contrary to the Felder and Silverman dimensions of learning style model, Honey and Mumford recommended that to maximise personal learning learners had to understand their learning style and seek opportunities to learn using their preferred style.

Dunn and Dunn

The Dunn and Dunn learning style model [Dunn (2000)] described five groups of factors that affected learning:

a) Environmental

Lighting, sound, temperature, and seating arrangement.

b) Emotionality

Motivation, persistence, responsibility, and structure.

c) Sociological.

How individuals learn in association with other people: Alone or with peers; authoritative adult or with a collegial colleague; and learning in a variety of ways or routine patterns.

d) Physiological

Perceptual (auditory, visual, tactual and kinaesthetic), time-of-day energy levels. intake (eating or not while studying) and mobility (sitting still or moving around).

e) Psychological

Hemispheric, impulsive or reflective, and global or analytic.

2.5.1. WBT systems using learning styles

Intelligent technologies for WBT could be used to provide adaptive sequencing of educational materials, navigation support and adaptive presentation. A number of research systems that provided adaptation were described by Brusilovsky (1999) but most of them did not take learning styles into account. Other researchers examined and developed adaptive computer-based educational environments that utilised learning styles to model users and adapted educational content to match user learning style. The most common systems were: INSPIRE, AES-CS, CS388, TANGOW, LSAS, iWeaver, MANIC and CITS.

INSPIRE

INSPIRE (Intelligent System for Personalized Instruction in a Remote Environment) [Papanikolaou *et al.* (2003)] was a Web-based adaptive educational hypermedia system that provided adaptive curriculum sequencing, navigation support and presentation based on learning styles. The adaptive behaviour of INSPIRE was guided by the learner model which provided information such as knowledge level on the domain concepts and learning style based on the Honey and Mumford model of learning styles. User learning styles were assessed initially using the Honey and Mumford learning styles questionnaire. Users could update their learning style, but this was not automatically performed by INSPIRE.

AES-CS

The Adaptive Educational System – Cognitive Style (AES-CS) [Triantafillou *et al.* (2002)] was a hypermedia system that adapted content presentation depending on the previous knowledge and Cognitive Style of students based on the field dependent / field independent dimensions of Cognitive Style. Adaptation was achieved using conditional text and alternative pages for each dimension. Adaptive navigation was provided by selecting links depending on user knowledge and learning style. User Cognitive Style was assessed initially using the Group Figures Embedded Test (GEFT) [Witkin *et al.* (1971)]. AES-CS updated the domain knowledge in the user model by analysing student feedback, but it did not update student learning style.

CS383

Computer Systems (CS383) [Carver *et al.* (1999)] was a Web-based adaptive hypermedia course composed by educational material classified in categories such as audio files; graphic files; digital movies; slideshows; lesson objectives. note-taking guides; student papers and slideshows from previous semesters, course hypertext; and searchable terms definitions. The Index of Learning Styles (ILS) questionnaire [Felder & Spurlin (2005)] was used to determine each student learning style. Students could explore course material freely or according to their learning style. The suitability of each educational material category was ranked by teachers for each dimension of learning style, and the system presented students links to materials ordered by suitability ranking. Student learning style or content suitability rankings were not updated.

TANGOW

Task-based Adaptive learNer Guidance On the Web (TANGOW) [Paredes & Rodriguez (2002)] was a tool to create adaptive Web-based courses. The order in which course materials were displayed was adapted depending on the user's sequential/global and sensing/intuitive dimensions of the Felder-Silverman dimensions of learning style. The user model was initially assessed using the ILS questionnaire and updated automatically by analysing user navigation behaviour.

LSAS

The Learning Styles Adaptive System (LSAS) [LSAS (n.d.)] was a Web-based course designed to adapt to users based on the global/sequential dimension of the Felder-Silverman dimensions of learning style model. It assessed user learning style using ILS. The system did not provide automatic content adaptation but provided different presentations that users could choose depending on their learning style.

iWeaver

iWeaver [Wolf (2002)] was a Web-based adaptive learning environment that accommodated the physiological-perceptual factors of the Dunn & Dunn learning styles model. Different media representation and conditional text was allocated to each learning style. Users' learning styles were assessed initially using the Building Excellence Survey [Rundle & Dunn (2000)], but media style allocation was flexible and it could change dynamically according to learner ratings of previously presented media, using a Bayesian network to predict and recommend the most likely preferred options for media representations.

MANIC

MANIC [Stern & Woolf (2000)] was a Web-based instructional system that provided adaptive contents based on slides and audio organised in a semantic network of topics depending on the domain knowledge and learning style of users. MANIC did not apply a learning style model but modelled users learning style by their preferences for graphic or textual information, so it could be compared to the Visual/Verbal dimension in the Felder and Silverman learning styles model. A Naïve Bayes classifier was utilised to determine which contents will be presented to students based on past student feedback.

CITS

The Confidence Intelligent Tutoring System (CITS) was used for building self-adaptive courses on the Internet, assist students in on-line discussions and automatically search Web pages containing the keywords being discussed [Razek *et al.* (2003)]. CITS employed a test to determine student learning style consisting of selecting eight colours [Razek *et al.* (2002)]. A machine learning algorithm was then utilised to infer the user learning style from the colours selected.

2.6. Chapter discussion

This Chapter reviewed the background of this research:

Section 2.1 described the context of this research within the government strategy for the use of ICT in UK education. Section 2.2 described existing commercial WBT systems available at the time of writing and identified their limitations. Section 2.3 described the hardware technologies and Section 2.4 described the software technologies related to the research. Section 3.5 describes the learning style models related to the research. The systems described in Chapters 3, 4 and 6 were created during this research to run on PCs connected to the Internet.

CHAPTER THREE
THE FIRST PROTOTYPE FILTER

Existing CAI systems described in Chapter 2 (Section 2.2.1) provided tools to develop Web-based courses; deliver them on the Internet; test user knowledge; track user activity; and filter access to the Internet. They also provided tools to facilitate collaborative learning, such as application sharing, white board, and chat rooms. These systems provided limited functionality to clients, as most tools were Web-based. They did not provide intelligent advice on potential sites, consider student activity or provide content-specific filtering of Web pages. Students could be distracted and navigate to unrelated Web sites - an activity which these systems could not detect or react to. Most of these systems were designed for distance learning and not to use the Internet as an education tool within classrooms.

These limitations suggested a need for another type of software tool to create Web-based lessons and define areas of the Internet that could or could not be accessed by students during a lesson. This Chapter describes the design of a system to overcome these limitations called “Caught In The Act” (CITA) and the implementation of a first prototype to test the methodology. CITA was divided between a server and a client. The server side, called CITA server, consisted of a Web server that stored and delivered Web lessons to clients and a proxy server that filtered client requests depending on the lesson being taught at the client location. It used standard protocols such as HTML, HTTP and FTP, which allowed users to use a standard browser or FTP client when proprietary functions were not required. The client side was a proprietary application called CITA client that enabled teachers to edit lesson Web pages, grant access to areas of the Internet, publish lessons on a Web server and monitor student activity. Lessons could be accessed using a standard Web browser and filtering was done by the server depending on the computer location.

Microsoft Proxy Server 2.0 (MSPS) and Microsoft Internet Information Server (IIS) were selected as a platform for CITA server because they allowed the creation of "Internet Services Application Programming Interface" (ISAPI) filters and extensions to enhance and customise their functionality by using COM components as described in Chapter 2. This also enabled the reuse of standard functionality so that proxy and Web server code did not have to be written. MSPS and IIS ran in the Microsoft Windows operating system, which was widely used in educational institutions.

ISAPI filters and extensions were COM components and could be developed only using an object oriented programming language. Microsoft Visual C++ 6.0 was selected to create CITA because it was an object oriented programming language widely used for the development of COM components. Technical guides on ISAPI filters and extensions were written for Microsoft Visual C++ and technical support was available for the research.

3.1. Specifications

Specifications for CITA were defined after researching the systems described in Chapter 2 and gathering information from teachers and the marketing department at the collaborating company.

3.1.1. User model

A user model could be divided into three categories [Monzat (1999)]:

- *User Computer Experience*: user experience or familiarity in working within a certain environment.
- *User Technical Skill*: user's education, working environment, interest in the technology and outlook on the hardware and software.
- *User Specific Software Experience*: familiarity with specific and complex professional software and the ability to adapt to the interface.

Three different kinds of users were identified in this work based on these categories:

Teachers might have experience in the use of common computer applications such as word processors and spreadsheets; Internet applications such as e-mail or Web browsers; and education-specific tools such as assessment assistants or Internet-based educational material. They used computer applications on a day-to-day basis but might be reluctant about using them to assist in delivering lessons as they perceived the use of ICT as difficult to focus and control.

Students might have experience in the use of common computer applications, Internet applications and education-specific tools. They could potentially be more knowledgeable than teachers in the use of ICT. They might use ICT during lessons to access educational material and produce coursework, but they might get distracted and even misuse computer applications without guidance and control from teachers.

Administrators had a broad experience in the installation, usage and maintenance of ICT within educational institutions Their main concern was that applications and hardware were used according to the institution's policy, while keeping maintenance costs low.

Only teachers were expected to use the system. Administrators installed and maintained the system by using the management tools provided with it. Students were included in the model because they used the system indirectly by using standard Web browsers. In the following narrative, "users" mean teacher users.

3.1.2. System goals

The goal of CITA was to provide tools that enabled teachers to: create lesson Web pages; define student access to zones of the Internet; and receive real time notifications of attempts to view blocked pages.

3.1.3. System attributes

The following attributes were required in CITA:

Ease of use

As described in the user model (Section 3.1.1) teachers might have experience in the use of common computer applications and Internet applications. CITA was required to be intuitive and easy to use.

Interface metaphor

The CITA client user interface was required to be a single window application where Web pages could be displayed as in standard Web browsers. The user interface was also required to enable teachers to modify lesson Web pages in the browsing area and provide functionality by using toolbars within the main window. Additional user interfaces were required to be displayed in locally stored Web pages from the browser window.

Data access

Areas of the Internet allowed during lessons were required to be stored in the server as a Microsoft Access database. Lesson Web pages in the server were required to be stored in a directory where they could be accessed by the system and served to students using a standard Web browser.

3.1.4. System functions

There were four groups of functions that CITA featured to accomplish the stated goal.

Lesson design functions

Lesson management: Functions were required to create, save and load lessons using a single file, including lesson Web pages and Internet access granted to students.

Navigation zone: Functions were required to define the default Internet access permission and grant access to zones of the Internet.

Lesson page design: Functions were required to edit the contents of lesson Web pages.

Lesson implementation functions

Lesson implementation: Functions were required to assign lesson Web pages and proxy configuration to computers grouped by classrooms, so that Internet access in each classroom was restricted as specified in the assigned lesson.

Activity notification: Functions were also required to notify teachers when navigation attempts to blocked pages were detected.

Security functions

User login: Functions were required to identify teachers and administrators and provide only the functionality available to each type of user.

Administration functions

Classroom management: Functions were required to add or delete computer classrooms; and to specify the computers that form each classroom.

User administration: Functions were required to add, modify and delete teacher log in information.

3.1.5. CITA architecture

The CITA architecture was created from the specifications described in previous Sections and can be seen in Figure 3.1. Teachers created lessons and defined allowed areas of the Internet using the CITA client. Teachers also selected the active lesson for each classroom. Students did not use the CITA system directly but through a standard Web browser. Lesson Web pages were available from a Microsoft Web Server that was enhanced using ISAPI extensions to provide the right lesson to each student depending on their classroom. Student Internet requests were monitored by Microsoft Proxy Server 2 enhanced by an ISAPI filter that enforced the restrictions set for each lesson and notified teachers when students attempted to access denied content.

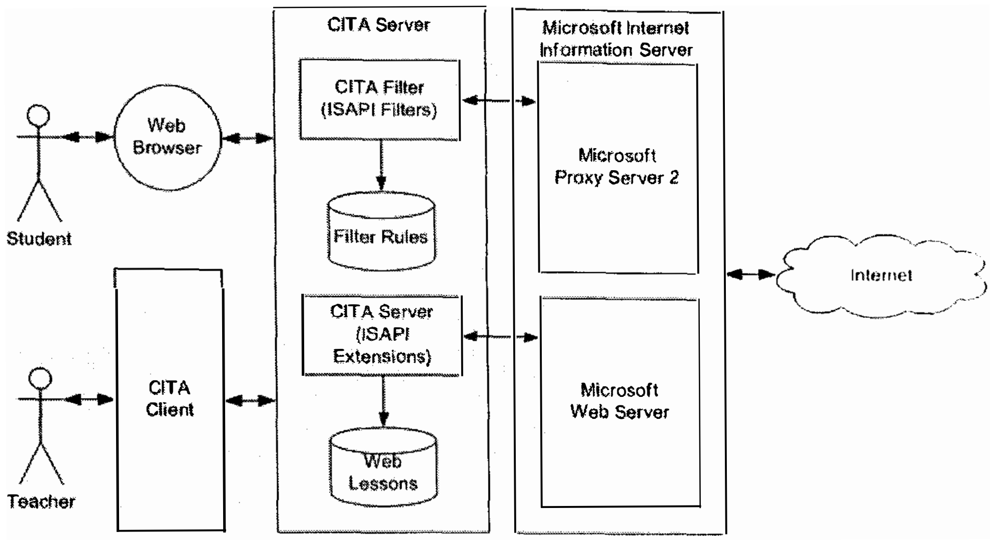


Figure 3.1: CITA architecture

3.2. Prototype implementation

A first prototype implementation which consisted of a client request filter and a client application that received student activity notifications from the client request filter was created using the technologies described in this Chapter.

3.2.1. Filtering methods

Four filtering methods were considered for the CITA request filter: URL filtering; full text filtering; feature-based filtering; and URL filtering combined with full text filtering.

URL filtering

URL filtering consisted of allowing access to Web pages depending on their URL and the directories and domains where pages were contained. During the creation of a lesson teachers specified documents, directories and domains that were either allowed or denied to the URL filter (see Figure 3.2). A database of allowed and denied URLs, directories and domains was populated by the filter using a database engine integrated within the system.

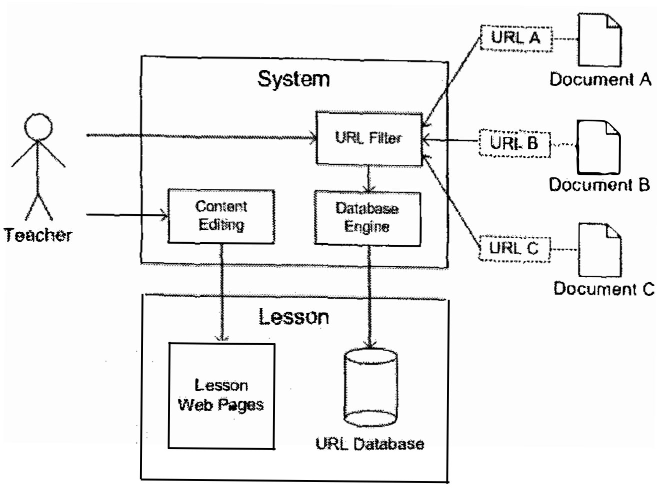


Figure 3.2: List of documents, directories and domains created by teachers

When page requests from students were received during a lesson, the URL filter attempted to identify the document permission using a database engine (see Figure 3.3). If permission for a document's URL was not found, permission for the directories and domains where the document was located was searched. If permission was granted then access to the page was granted accordingly. Otherwise, the default permission was applied.

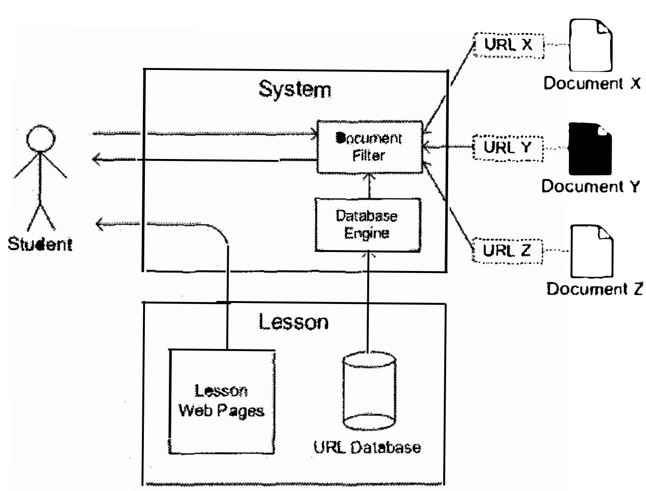


Figure 3.3: URL filtering system being used by students

Full text filtering

Full text filtering consisted of searching each page for a set of keywords. Teachers specified a set of subject-related keywords that must appear in the pages requested by students, and a set of keywords which prevented pages from being displayed. These were specified to the keyword filter during the creation of lessons and a keyword database was populated using a database engine integrated within the system (see Figure 3.4).

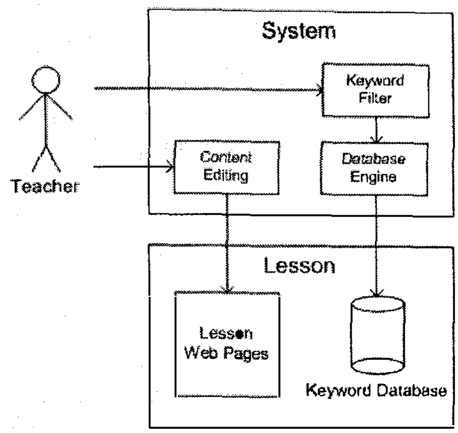


Figure 3.4: List of allowed and denied keywords being populated by teachers

When page requests from students were received during a lesson (Figure 3.5), pages were downloaded and analysed by the keyword filter. The keyword database was searched for each word in the page using the database engine. Access to Web pages was determined by the presence of keywords in the page.

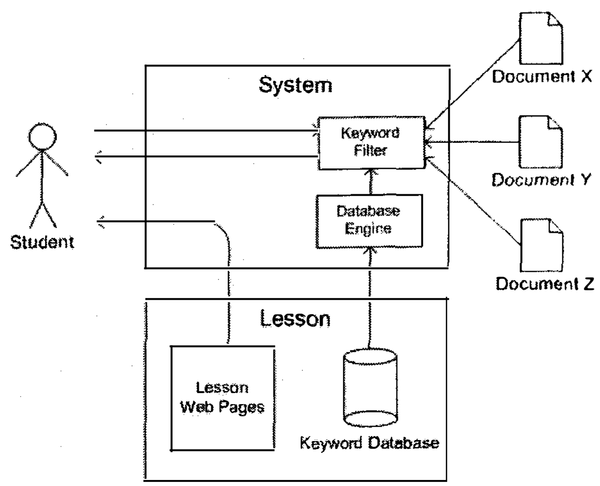


Figure 3.5: Keyword filtering system being used by students

Feature-based filtering

When using feature-based filtering, documents were represented by a group of semantic features such as keywords defining the contents of Web pages. Semantic features could be determined either by human users or by using feature extraction algorithms. When preparing lessons, teachers specified the features of pages related to a subject using a feature filter. This populated a feature database using a database engine integrated within the system (see Figure 3.6).

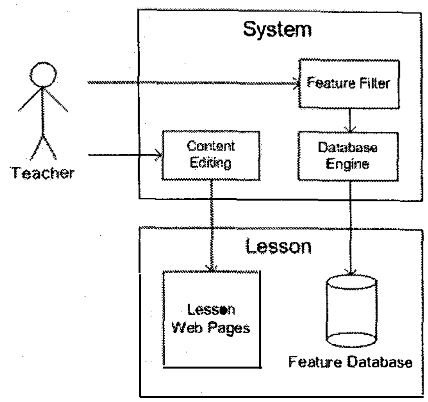


Figure 3.6: List of allowed and denied features being populated by teachers

When page requests from students were received by the feature filter (Figure 3.7), pages were downloaded and their features extracted. Feature database entries were searched in the page's semantic features by the feature filter using a database engine. Access to Web pages was determined by the presence of features in the page's semantic feature representation.

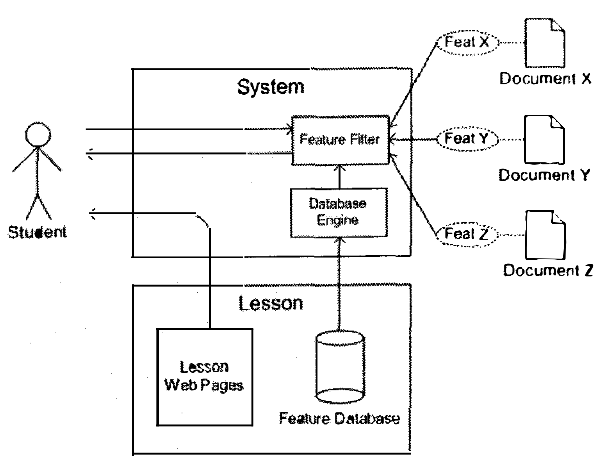


Figure 3.7: Feature filtering system being used by students

URL and full text filtering

URL filtering and full text filtering could be combined to make a more flexible filter. Teachers specified documents, directories and domains that were allowed and denied using a URL filter, as well as keywords that were allowed and denied using a keyword filter. A URL database and a keyword database were populated by the filters, using a database engine integrated within the system (see Figure 3.8).

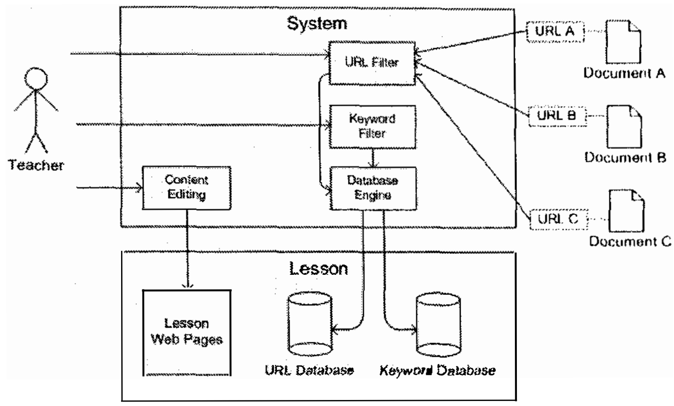


Figure 3.8: URL and text filtering being used by a teacher

When page requests from students were received during a lesson, the page's permission was searched by the URL filter by using a database engine and the page's URL, directories and domains. If permission was found, access to the page was granted accordingly. Otherwise, each word in the page was searched by the keyword filter in the keyword database using a database engine. Access to Web pages was then determined by the text filter depending on the presence of keywords in the page.

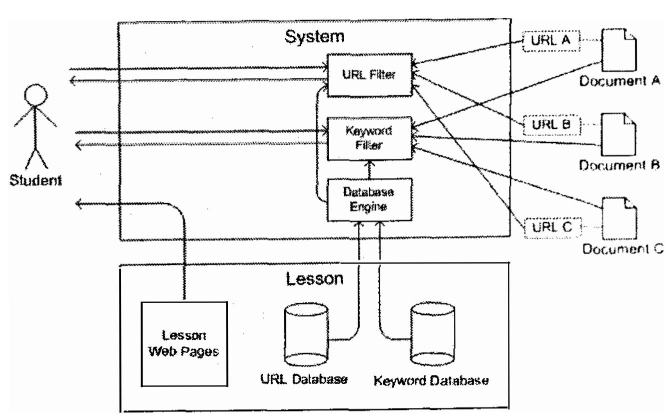


Figure 3.9: URL and keyword filtering system being used by students

3.3. Chapter discussion

This chapter described the design of a software system called "Caught In The Act" (CITA). CITA consisted of a server system implemented as ISAPI filters and extension, and a proprietary client that resembled a standard Web browser. A prototype was created to test the methodology and a number of filtering methods were considered and tested. Test results can be found in Chapter 5.

CITA server ran from a Web server and a proxy server, which involved establishing and maintaining a network infrastructure that was not available in many schools and colleges. Redeveloping existing technology in a proprietary software package was an ineffective way of developing the CITA client.

These limitations suggested a need for another type of software tool that provided structured, focused and controlled access to the Internet in an intuitive and non-intrusive way, relying on minimal network infrastructure. The research moved on to produce a system with these characteristics, called iLessons.

CHAPTER FOUR
ILESSONS

A novel set of tools called iLessons has been created by the author to overcome the limitations of systems described in Chapters 2 and 3. iLessons gave teachers the ability to structure the use of the Internet by reusing materials readily available on the Internet; to create a set of lesson Web pages; to restrict Internet access to keep students focused; and to control the use of the Internet by selecting lessons and restrictions per classroom, all from within a standard Web browser and without the need of server software. This Chapter describes the design, implementation and management of iLessons.

The Microsoft Windows operating system was selected because of its widespread use in educational institutions. The Microsoft Internet Explorer (IE) Web browser was selected because its functionality could be extended by using the Explorer Extensions described in Chapter 2. IE was freely available with the selected operating system and users did not have to install any other third party Web browser software. Software and hardware requirements needed to execute iLessons were the same as needed for IE and were met by most school and college computers at the time of writing.

Explorer Extensions were COM components and could be only created by using an object oriented programming language. Microsoft Visual C++ 6.0 was selected to create iLessons because it was an object oriented programming language widely used for the development of COM components. Technical guides about Explorer Extensions were written for Microsoft Visual C++ and technical support was available for the research.

4.1. Specifications

Specifications for iLessons were defined after researching the systems described in Chapter 2, gathering information from the marketing department at the collaborating company and receiving feedback from teachers about the first prototype system described in Chapter 3.

4.1.1. User model

The user model described in Chapter 3, Section 3.1.1 was utilised when defining the iLessons specifications. The model divided users in three categories: teachers, students and administrators. Only teachers and students were expected to use the system. Administrators installed and maintained iLessons by using the management tools provided with the system. In the following narrative, "users" means both teacher and student users. When a function was available only to a type of user, the term "teacher" or "student" is used.

4.1.2. System goals

The goal of the new system was to provide tools:

- That enabled teachers to:
  - Gather resources from the Internet such as text or images.
  - Create lesson Web pages.
  - Define student access to zones of the Internet.
  - Load lesson Web pages onto student computers and enforce access restrictions to defined zones of the Internet.
- That enabled students to:
  - Gather resources from the Internet such as text, images or video.
  - Create assignments using collected resources.

4.1.3. System attributes

The following attributes were required in the system:

Ease of use

As described in the user model (Section 3.1.1) teachers might have experience of common computer applications and Internet applications. iLessons was required to be intuitive and easy to use, in line with software applications that teachers might already know how to use.

Interface metaphor

iLessons' User Interface (UI) was to exist within IE using explorer extensions. User input and system output was to be through the use of the Dynamic HTML (DHTML) UI within the explorer extensions. Drag and drop was to be available for resources and the creation of lesson Web pages.

Number of students

iLessons was to support up to two students working on a single PC.

4.1.4. System functions

Functions that iLessons had to support to accomplish the stated goals were identified.

Resource collection functions (available to teachers and students)

Resource management: Functions were required to create resources by capturing drag and drop information; to delete resources and to assign a unique name and a description to them.

Resource collection management: Functions were required to create, save and load resource collections into a single file, including resource drag and drop information.

Lesson design functions (available to teachers)

Lesson management: Functions were required to create, save and load lessons into a single file, including lesson Web pages and Internet zone access rules granted to students.

Navigation zone: Functions were required to define the default Internet access permission and grant access to zones of the Internet.

Lesson page management: Functions were required to create, delete or modify lesson Web pages; and to import Web pages as lesson Web pages within a lesson.

Lesson page design: Functions were required to edit the contents of lesson Web pages using resources from a resource collection and to format the contents of a lesson Web page.

Lesson implementation functions (available to teachers)

To remotely load lessons in groups of computers, making the lesson Web pages available and restricting Internet access to the zone of the Internet defined in a lesson.

Assignment design functions (available to students)

To edit an assignment page using gathered resources and original contents; as well as to save and load assignments.

Security functions (available to all users)

To identify types of user by providing user login and apply appropriate rights and functionality to each user.

Administration functions (available to administrators)

Computer administration: To add or delete groups of computers and to specify the computers that form each group.

User administration: Functions were required to add, modify and delete log in information to manage the users.

4.1.5. iLessons architecture

The iLessons architecture can be seen in Figure 4.1. The iLessons UI is described in Section 4.2; resource collection is described in Section 4.3; lesson creation is described in Section 4.4; the navigation zone is described in Section 4.5; user mode control is described in Section 4.8; the iLessons filter is described in Section 4.5.4.

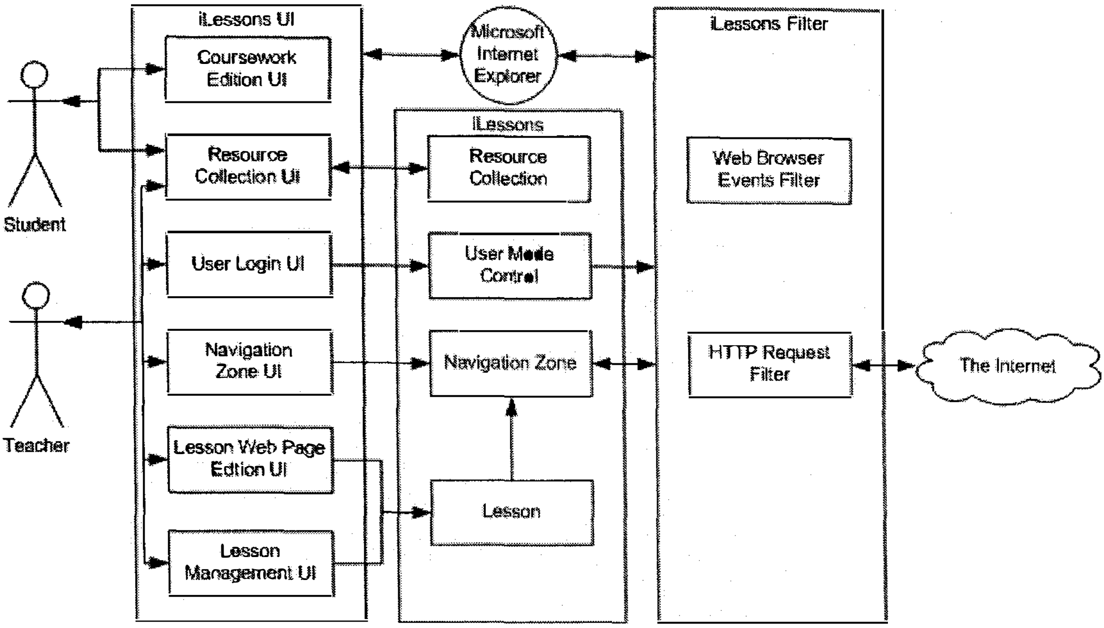


Figure 4.1: iLessons architecture

4.2. UI overview

Explorer Extensions described in Chapter 2 were used to create the iLessons UI to provide extended functionality within a standard Web browser.

The two main UI windows were the "iLessons toolbar" and the "infoPad" shown in Figure 4.2. The iLessons toolbar was always visible and users could show or hide the infoPad when needed.

4.2.1. The infoPad

The infoPad was an explorer bar located at the left side of the IE window. It could be shown or hidden from the "Views → Explorer bar" menu in IE or by clicking on the infoPad button in the iLessons toolbar. It was used to provide resource collection and lesson design functions in two views.

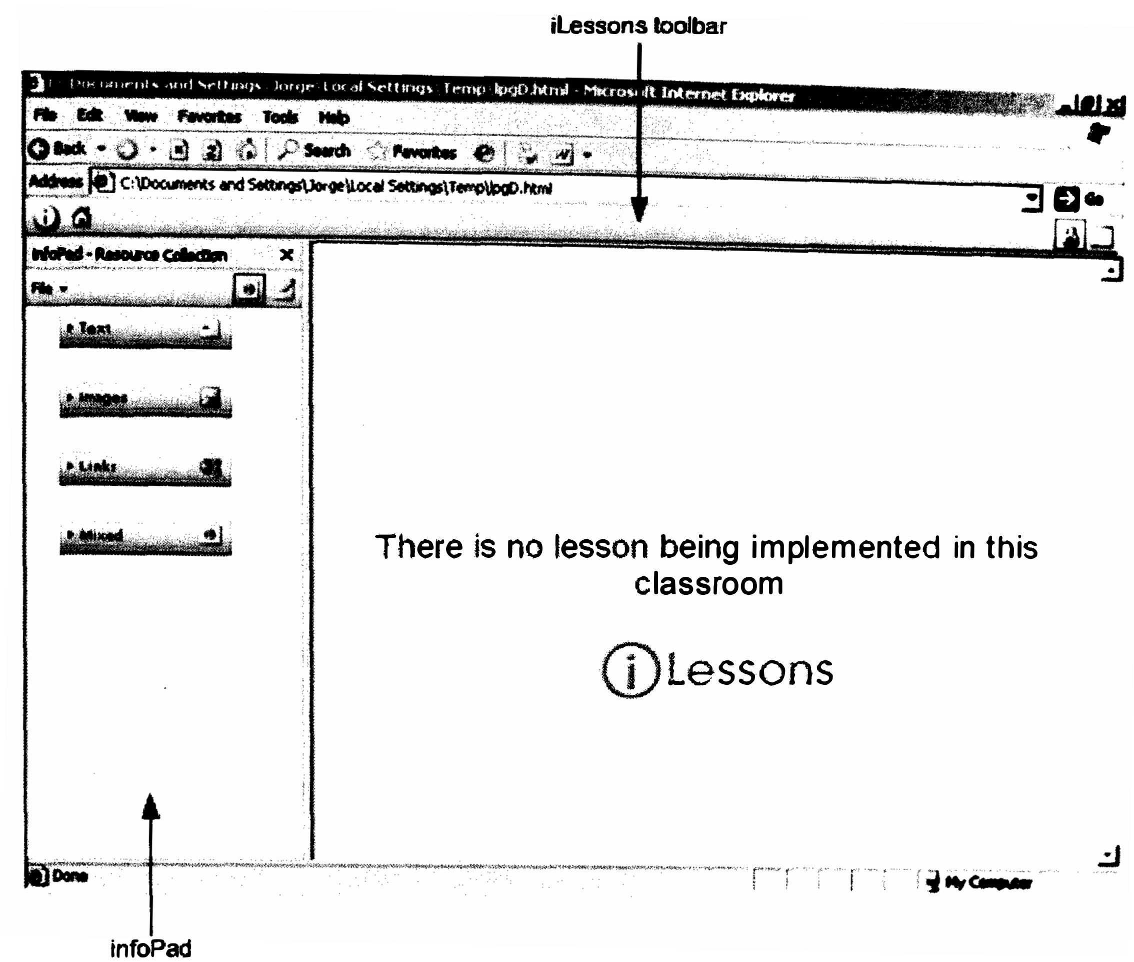


Figure 4.2: iLessons UI in student mode

Resource collection view

The resource collection view displayed resources collected by the user. It enabled users to collect resources from Web pages, modify the resource details, delete and manage resource collections. The resource collection view displayed four resource blocks as shown in Figure 4.3 (left):

- Text: Stored plain text resources.
- Images: Stored image resources.
- Links: Stored hyperlink resources.
- Mixed: Stored HTML fragment resources.

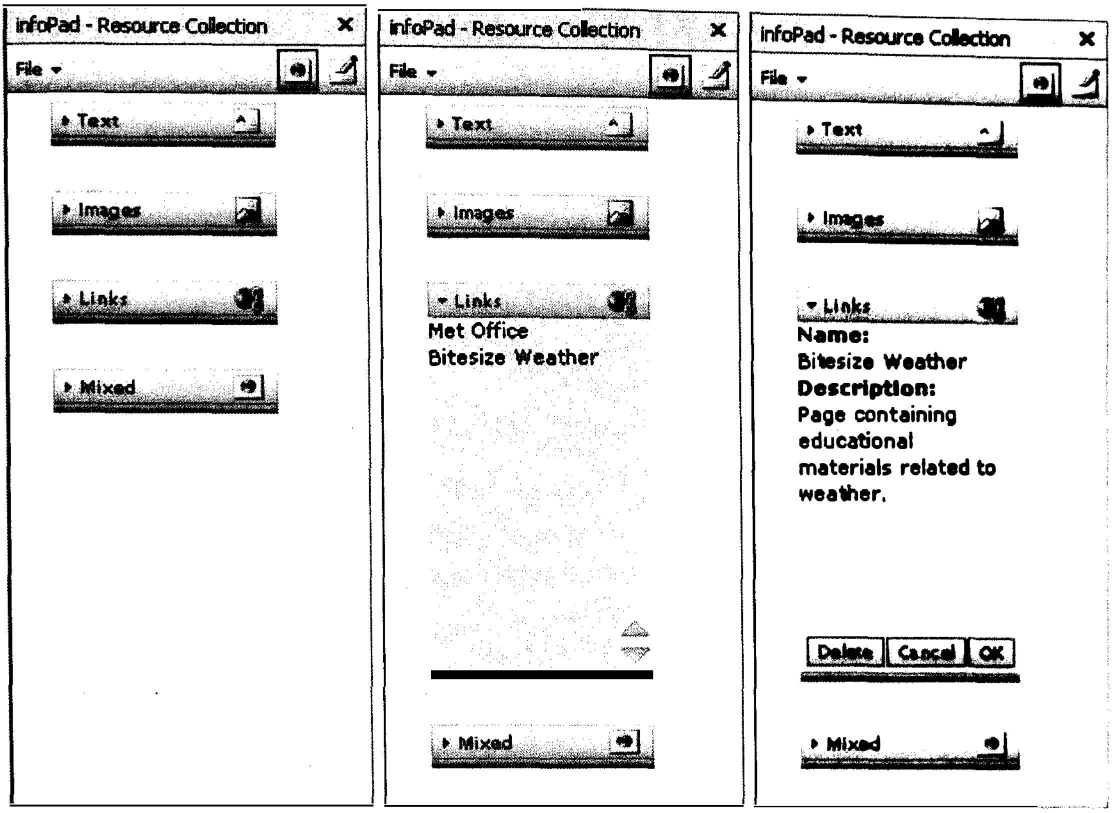


Figure 4.3: Resource collection view

When users clicked on any of the blocks they showed a list of resource names (Figure 4.3, centre). If users clicked on any of the resource names then resource information was displayed (Figure 4.3, right). Users collected resources from Web pages by dragging and dropping items into each block. The block expanded and allowed the users to modify the name and description of the new resource (Figure 4.3, right).

The "File" menu at the top of the resource collection view provided options to: create a blank resource collection; open a resource collection file; and save the current resource collection into a file.

Lesson view

The lesson view (Figure 4.4, left) displayed a list of lesson Web pages and it was available only to teachers. It enabled teachers to add new lesson Web pages; import Web pages as lesson Web pages; view lesson Web page contents; and to edit lesson Web pages from within IE.

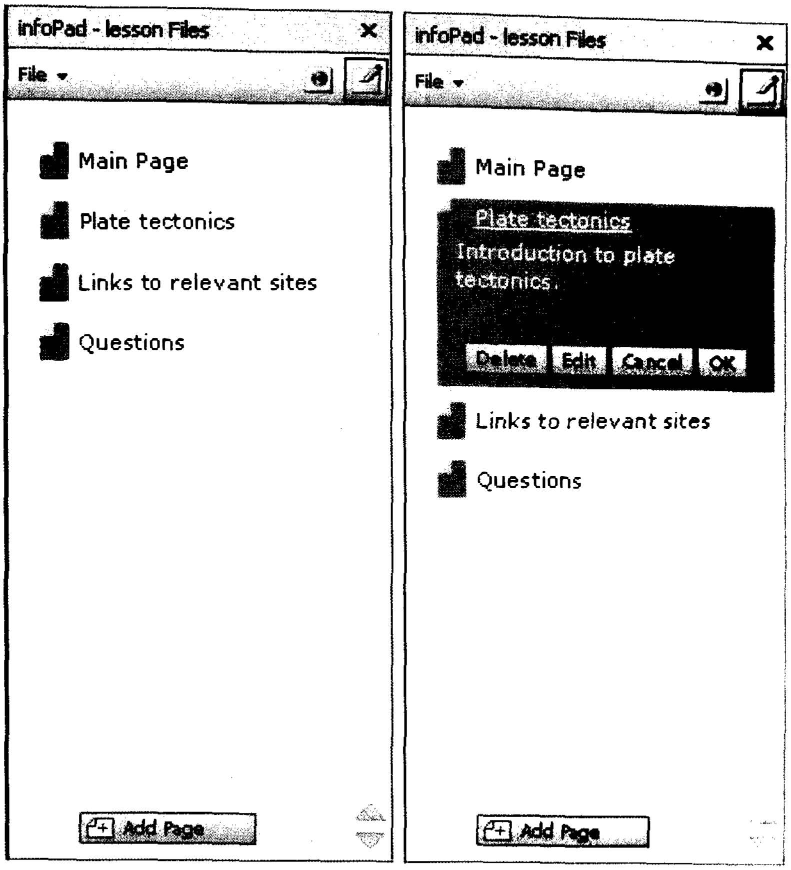


Figure 4.4: Lesson view

Teachers added new lesson Web pages by clicking on the “Add Page” button at the bottom of the lesson view. Internet Web pages could be imported by dragging and dropping Web hyperlinks onto the “Add Page” button. If teachers clicked on a page name, the Web page contents were displayed in the IE main window and the page name and description were displayed (Figure 4.4 , right). Teachers could modify page information or remove the Web page from a lesson. If teachers clicked on the “Edit” button, IE was set to editing mode and the lesson Web page could be edited from within IE. Other lesson Web pages in the list could be dragged and dropped onto a page being edited to create links between pages.

The “File” menu provided options to: create blank lessons; open lesson files; save lessons into files; and modify lesson properties, such as the default permission and to define the URL of the lesson’s main Web page.

4.2.2. The iLessons toolbar

The iLessons toolbar was an explorer toolbar located on top of the IE window. It could be shown or hidden from the “Views → toolbar” menu in IE. The iLessons toolbar provided access to lesson design, assignment design and security functions through two views.

Navigation toolbar view

The navigation toolbar was displayed by default when the iLessons toolbar was started. The functions provided by the navigation toolbar depended on whether users were students (Figure 4.5) or teachers (Figure 4.6). The home button was available to both kinds of users and displayed the main lesson page in the IE browser window.

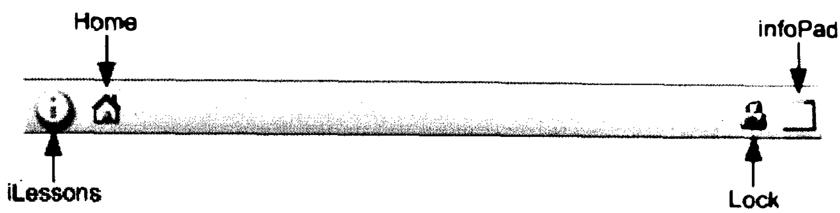


Figure 4.5: Navigation toolbar view - Student mode

The "iLessons", "lock" and "infoPad" buttons were common to all views. The "iLessons" button was disabled in student mode, but was used in teacher mode to navigate to the "iLessons resources" Web site or to display the iLessons version information if clicked on while pressing the shift key. The "lock" button was used to swap between teacher and student modes. A teacher user name and password was required to switch to teacher mode. The "infoPad" button was used to show or hide the infoPad.

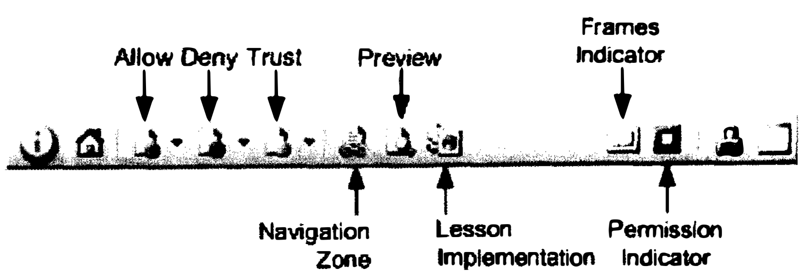
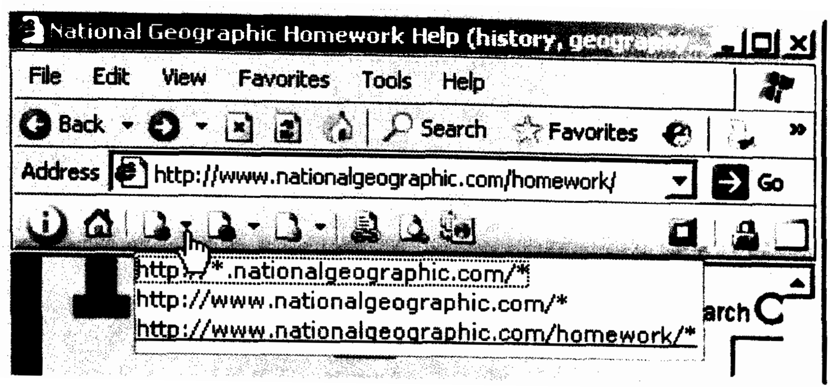


Figure 4.6: Navigation toolbar - Teacher mode

The navigation toolbar enabled teachers to grant access to zones of the Internet as described in Section 4.5. Teachers could assign permissions to pages being displayed by IE by using the "allow", "deny" and "trust" buttons. These buttons also provided a drop down list of directories and domains extracted from the page

URL (see 4.7), so that permissions could be assigned to Internet domains or directories.



4.7: Drop down list showing domains and directories for http://www.nationalgeographic.com/homework/

Domains and directories in the drop down list were colour-coded to display the permission assigned to each entry:

- Black: No permission assigned
- Green: Entry allowed.
- Red: Entry denied.
- Yellow: Entry trusted.

Colours were chosen in accordance to the colours used in traffic lights as users were already familiar with their meanings. Black was used to indicate that no permission has been assigned because it was a neutral colour used to display most text in GUIs.

Permission could also be assigned to images within Web pages by right-clicking on them and selecting "iLessons Allow", "iLessons Deny" or "iLessons Trust" in the context menu. A drop down list appeared as described before, and permissions could be set for the image URL or any of the directories or domains where the images were contained. When permissions were assigned to images, a colour coded border was displayed around the image.

The same colour scheme displayed the permission of any pages being displayed by IE in the navigation view's permission indicator. When permission for a page had been explicitly assigned by a teacher the permission indicator displayed a filled square. When permission for the page was not explicitly assigned, but a teacher had assigned permission to a domain or directory where the page was contained then the permission indicator displayed a hollow square. If permissions affecting the page were not set, the permission indicator displayed the default permission in a hollow square. The permission indicator displayed a grey square while pages were loading or if errors occurred.

The "Navigation Zone" button displayed a list of allowed, denied and trusted pages, directories and domains colour coded as described above (see Figure 4.8).

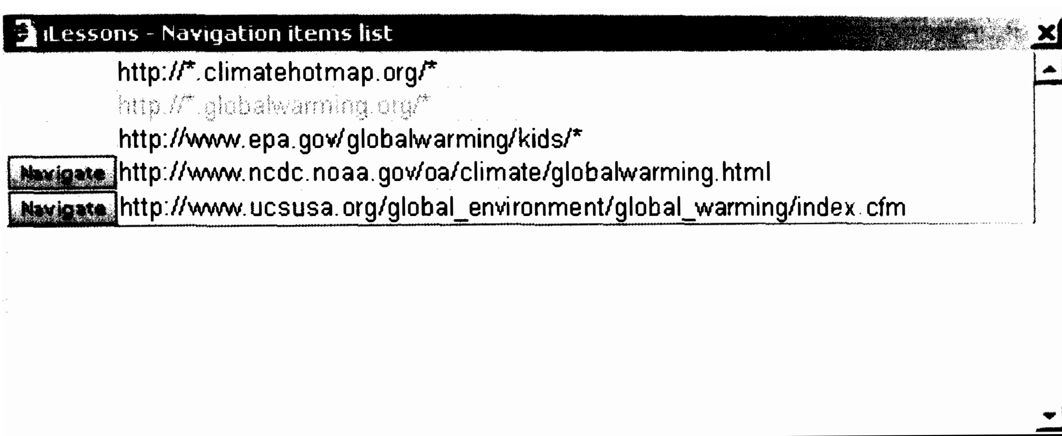


Figure 4.8: Navigation zone list

The "preview mode" button was used to test Internet access by setting Web page access restrictions to on. When preview mode was activated, teachers could only access zones of the Internet where access was granted, so that the restriction settings could be tested before implementing a lesson.

Lessons could be automatically loaded into computers grouped by classroom using the "Implement Lesson" button. A window showing available classrooms was displayed (Figure 4.9) and teachers were able to select default lessons for computer classrooms and to load or unload lessons into the classrooms.

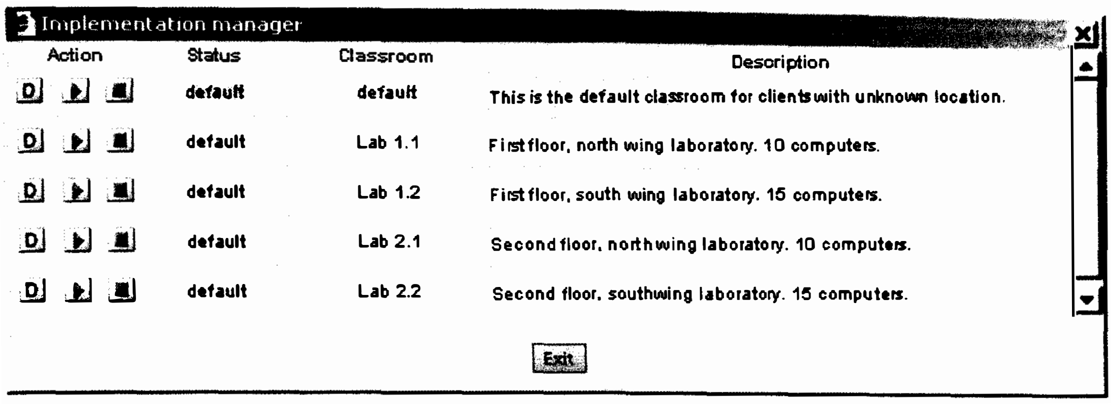


Figure 4.9: List of available classrooms

Lesson editing toolbar view

The lesson editing toolbar (Figure 4.10) was displayed when teachers selected a lesson Web page to edit in the infoPad. It provided teachers with tools to edit and format lesson Web pages within IE (similar to those found in standard text editors).

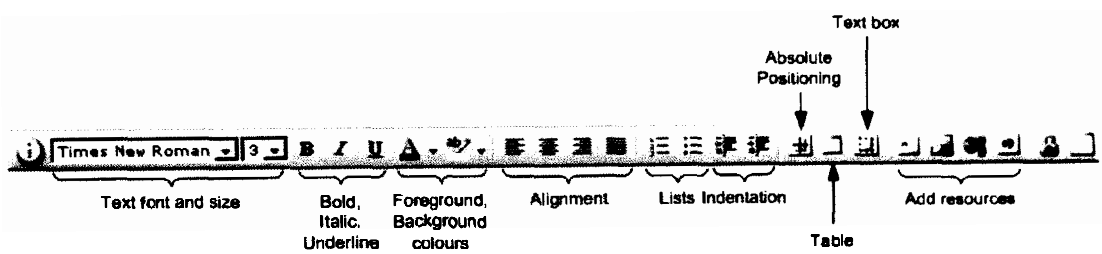


Figure 4.10: Lesson editing toolbar view

Resources could be added by dragging them from the infoPad and dropping them into the lesson page, or by using the four "Add resources" buttons, each corresponding to a resource block as described in Section 4.2.1. This enabled teachers to reuse resource collections without keeping the infoPad open, switching between the resource collection view and the lesson view. Figure 4.11 shows a lesson Web page being edited in iLessons.

Coursework editing toolbar view

Students were able to create resource collections and to use them to create Microsoft Word coursework files from within IE by clicking on the "Go to lesson / coursework editing" button in the infoPad. A Microsoft Word document opened in the IE main window (Figure 4.12) providing the standard text editing toolbars.

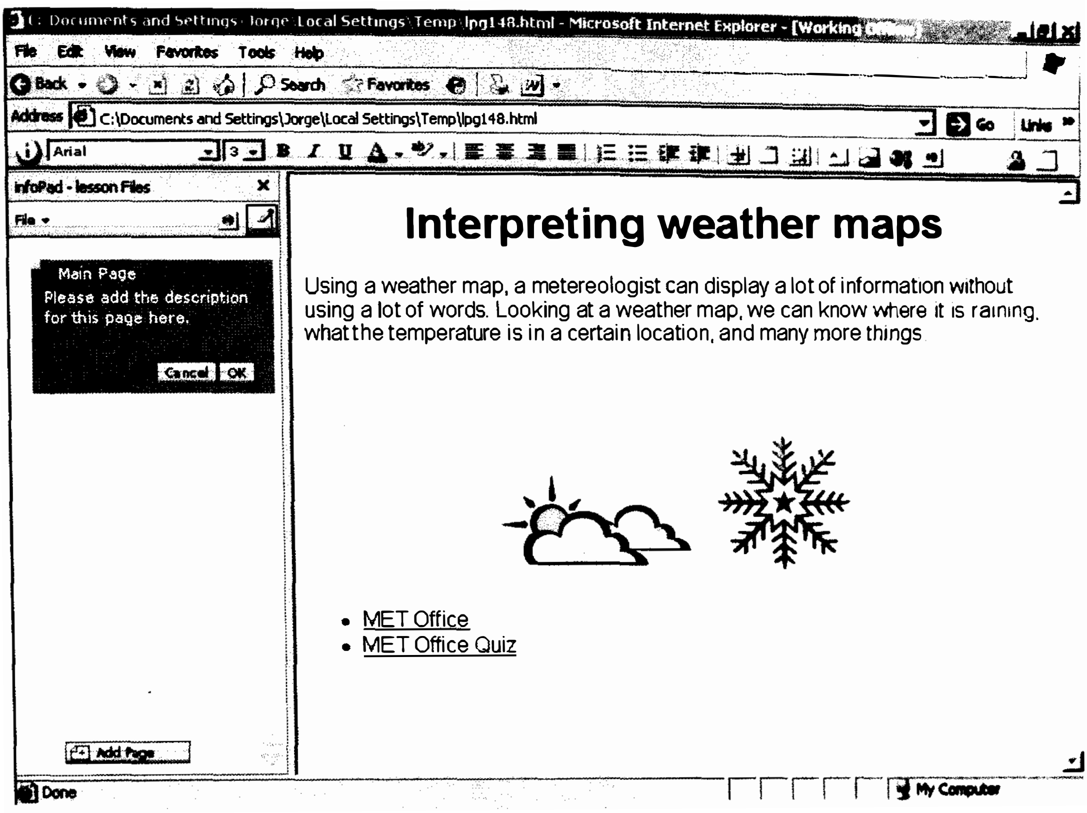


Figure 4.11: Lesson Web page being edited in iLessons from within IE

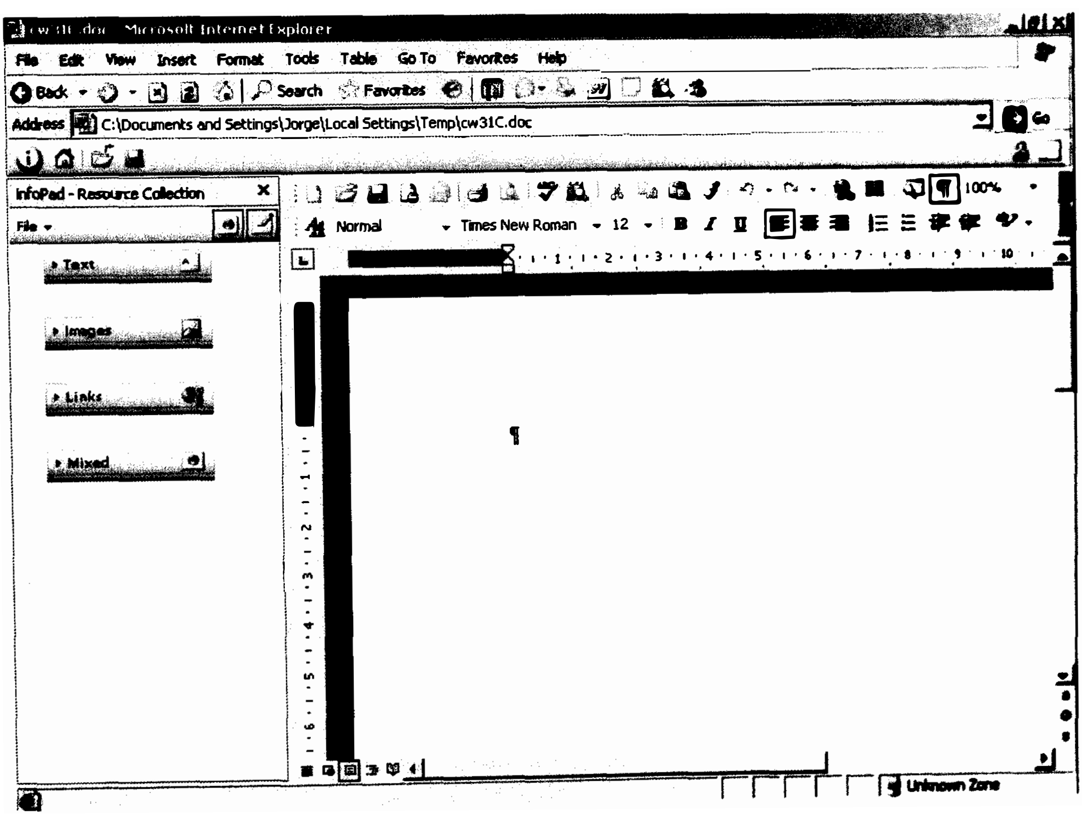


Figure 4.12: Coursework editing from within IE

The coursework editing toolbar view (Figure 4.13) provided buttons to save the coursework file or open a Microsoft Word coursework file within IE.

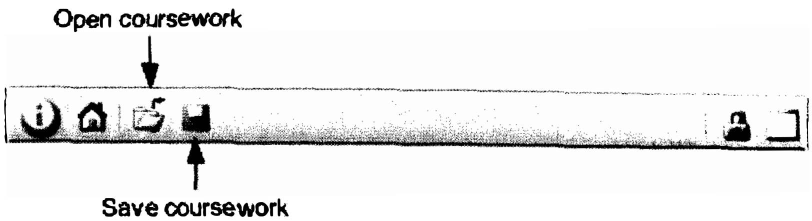


Figure 4.13: Coursework editing toolbar view

4.3. Resource collection

Resource collections contained a group of resources created by dropping Web page elements or fragments onto a resource collection UI block, as described in Section 4.2.1. When drag and drop was used, data from the source window (the "drop source") was selected then dragged to the desired destination (the "drop target"), and dropped. The operation eliminated the need for menus and was quicker than a copy/paste sequence. The only requirement was that both the drop source and drop target had to be open and at least partially visible on the screen [Chapell (1996)].

4.3.1. Resource types

Data in drag and drop operations was transferred using IDataObject interface pointers provided to the resource collection by the system when drag and drop operations completed successfully. The IDataObject interface specified methods that enabled data transfer and notification of changes in data [Chapell (1996)]. Data transfer methods specified the format of the transferred data and the medium through which the data was transferred. In addition to methods for retrieving and storing data, the IDataObject interface specified methods for enumerating available formats and managing connections for handling change notifications. Table 4.1 shows the resource types and the data formats required to create resources of each type.

Resource type	Required data formats	Valid page elements
Text	CF_TEXT (unformatted text)	Text from Web pages or any other source that provided the necessary formats.
Media	CF_HDROP (image file path) CF_DIB (image bitmap) CF_HTML (image HTML code)	Images from Web pages or any other source that provided the necessary data formats.
Links	CF_UniformResourceLocator (hyperlink URL)	Hyperlinks from Web pages or from IE's address bar or any other source that provided the necessary data formats.
Mixed	CF_HTML (HTML code)	Fragments selected from Web pages or any other source that provided the necessary data formats.

Table 4.1: Resource types and required data formats

4.3.2. Resource collection file format

Resource collections were saved as resource collection files (.rsc) using structured storage. Structured storage saved data into streams, and created nested substorages within storages. The file version was saved into a stream called "CMTCIPersistFileImplFileVersion" to prevent resource collections saved with a different file format from being opened.

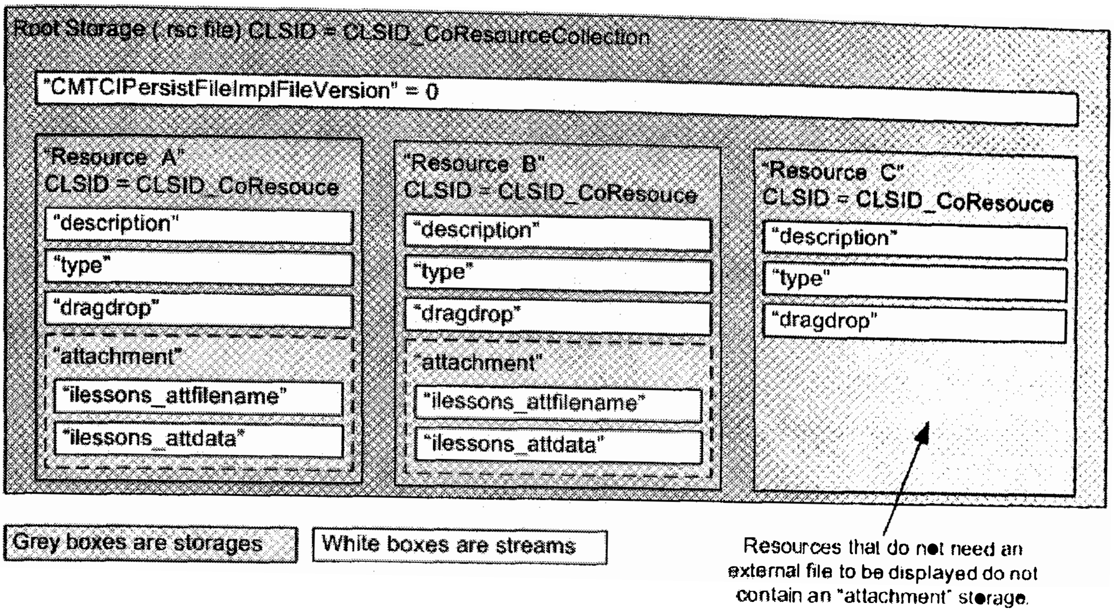


Figure 4.14: Resource collection file format

The root storage contained substorages for each resource in the resource collection, named as the resources that they contained. Each resource substorage contained three streams:

- "description" contained the resource's description.
- "type" contained the resource's type: Text, media, link or mixed.
- "dragdrop" contained the resource's drag and drop data formats.

Data in the "dragdrop" stream (Figure 4.15) started with the number of drag and drop formats stored in the stream. After this, the format name and drag and drop data was saved for each format.

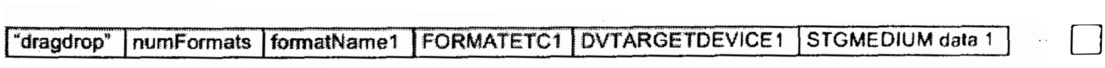


Figure 4.15: Drag and drop data stream format

External image files were necessary to display media resources correctly. Image file names and contents were saved in two streams called "ilessons_attfilename" and "ilessons_attdata" created inside an "attachment" substorage nested into the resource substorages. This storage was only created when the resource had an image file associated.

4.4. *Lesson creation*

Lessons contained a set of lesson Web pages and a navigation zone that specified the zones of the Internet that students could access during lesson implementation. The lesson Web page management UI is described in Section 4.2.1. Navigation zones are described in Section 4.5.

4.4.1. Lesson Web page editing

Web page editing was implemented by reusing the editing features available in the software component that IE utilised to display Web pages, called MSHTML. MSHTML editing provided the user with:

- Standard editing functionality such as caret positioning, keyboard navigation, drag-and-drop, and content selection.
- Copy, cut, delete, and paste operations.
- Multi-level undo and redo.
- The ability to toggle text between bold, italic, and/or underlined and change its typeface, size, foreground and background colour.
- The ability to remove formatting.
- The ability to increase or decrease indentation.
- Text justification (left, centre, right).
- The ability to create ordered and unordered lists.
- Creation of hyperlinks and bookmarks.
- Horizontal line insertion.
- Image insertion.
- The ability to insert a variety of controls such as buttons or text boxes.

[Tahir (2003)]

Standard editing functions were applied by executing standard MSHTML commands, such as Bold, Italic, or AbsolutePosition. Editing functions that were not standard had to be created and are described in Chapter 5. These were: table creation, absolute positioning and text boxes, links to other lesson Web pages, and resource inclusion

4.4.2. Importing Web pages from the Internet

Internet Web pages could be imported as lesson Web pages, modified and manipulated as any other lesson Web page. Imported Web pages were saved using the MIME Encapsulation of Aggregate HTML Documents (MHTML) file format. MHTML allowed the embedding in a single file of the HTML code of a Web page and the elements needed to display the Web page correctly, such as images. A third-party component was utilised to export Web pages to MHTML files.

4.4.3. Lesson file format

Lesson files (.les) were actually compressed files. A file containing lesson and navigation zone data as well as lesson Web pages saved as MHTML files were contained inside the compressed file.

Lessons data was saved using structured storage. Structured storage saved data into streams, and created nested substorages within storages. The file version was saved into a stream called "CMTCIPersistFileImplFileVersion" to prevent lessons saved with a different file format from being opened.

The root storage contained navigation zone substorage and a pages collection substorage. The pages collection substorage contained a stream where the file name of the main lesson Web page was stored. Substorages were created for each lesson Web page and were named after the page they contained. Streams contained the page description and the page ID used to resolve hyperlinks to lesson pages. In cases when the main lesson page was an Internet page, a stream contained the Internet page URL. Substorages inside lesson page substorages contained a stream with the MHTML file name corresponding to each page, which was saved in the compressed file. The navigation zone substorage is described in Section 4.5.3.

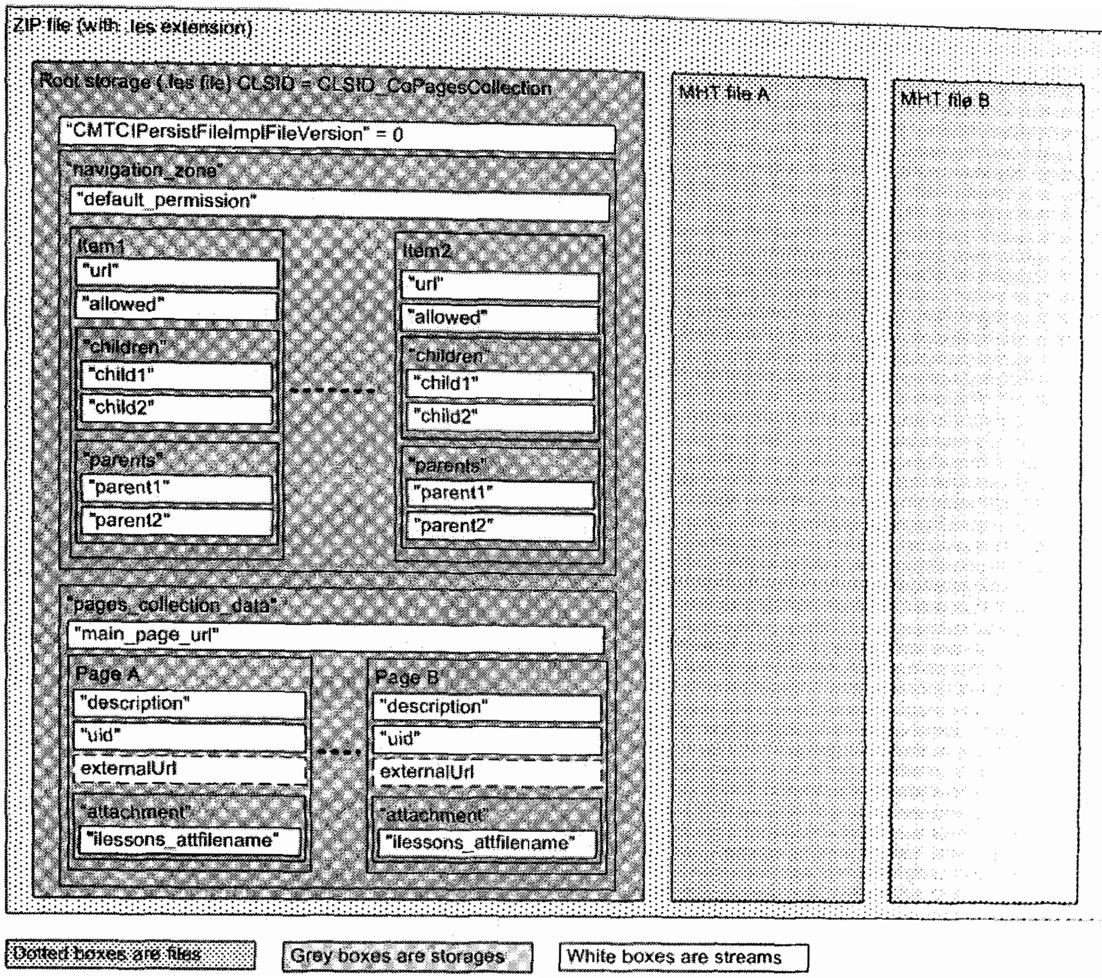


Figure 4.16: Lesson file format

4.5. Navigation zone

The navigation zone defined Internet pages, directories and domains that students were allowed to access. Navigation zones were part of lessons and were saved in the same file as lesson Web pages. Extended URL filtering was selected for iLessons because it was fast, simple and accurate.

Navigation zones defined a default permission that was applied to Web pages whose permission could not be resolved from the permissions defined by teachers. The default permission could be set to "allowed" or "denied" in the lesson properties UI. Allowed default permission granted full access to the Internet; denied default permission blocked access to the Internet. The default new lesson permission was "denied".

4.5.1. Defining navigation zones

Three kinds of permissions were available to define navigation zones: "allowed", "denied" and "trusted". Permissions could be set for individual Web pages or page elements as well as for directories or domains. This allowed teachers to create complex navigation zone structures, for example by allowing domains whose pages were relevant to a subject, then denying irrelevant directories or pages within allowed domains and finally trusting Web pages containing links to useful Web pages outside of the allowed domains.

Allowing zones of the Internet

Students were granted access to a Web page when allowed. Allowing directories or domains granted students access to Web pages within them.

Denying zones of the Internet

Student access was blocked to denied Web pages. Denying directories or domains blocked access to Web pages contained within them.

Trusting zones of the Internet

Trusting a Web page granted student access to the page and to any other page linked to the trusted Web page down to a specified level. For example, the educational resources for secondary students available in the Met Office Web site could be trusted during a lesson about weather forecasts, as all pages linked from this page were related to the subject. Figure 4.17 illustrates this principle: trusting a page and specifying level 2 allowed access to the trusted page and to any page linked from it and up to two links in depth. Pages beyond this were blocked.

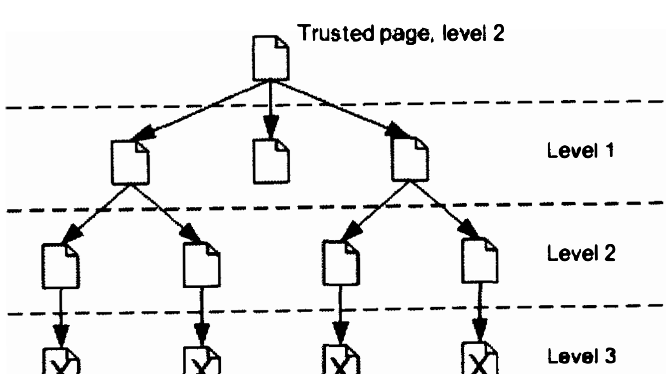


Figure 4.17: Access from a Web page trusted with level 2

Directories and domains could also be trusted. Access to pages inside trusted directories or domains was granted, as well as to pages outside the directory or domain up to a specified level.

4.5.2. Structure in memory

Navigation zone item pointers were held in a table, tagged by the URL, directory or domain that they represented (see Figure 4.18). Navigation items contained a URL, its permission, the URLs of the elements necessary to display the item correctly (children) and the URLs of the items where the item was displayed (parents). Only allowed items had associated children and parent items. Trusted items also contained their assigned trust depth.

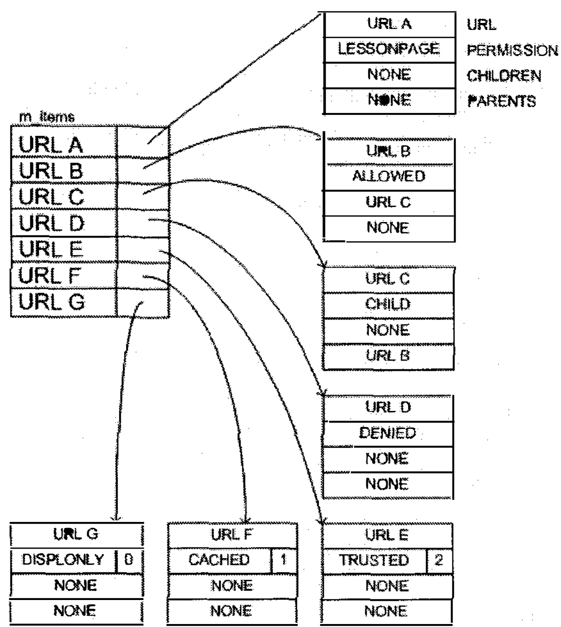


Figure 4.18: Navigation zone memory structure

4.5.3. File format

The navigation zone was stored in a substorage inside the lesson file main storage, as described in Section 4.4.3. The navigation zone substorage contained a stream storing the default permission. Substorages were created for each navigation item. Navigation item substorages contained navigation item data in two streams: "URL", containing the navigation item URL; and "allowed" containing the permission for the given URL. Two substorages inside each navigation item substorage contained streams storing children and parent item URLs.

4.5.4. Filtering algorithm

The iLessons filter monitored every request made from IE and granted access to pages or page elements as specified in the navigation zone. Filtering took place in three stages:

Stage I monitored the IE event that was fired each time that a Web page was requested.

Stage II monitored HTTP requests by implementing an Asynchronous Pluggable Protocol in which events were triggered when HTTP requests were made.

Stage III monitored the IE event that was fired each time a Web page started downloading.

It was necessary to use two IE events to detect server-side redirection and to update trusting information. Stage II was necessary to monitor Web page element requests because Stages I and III only captured Web page requests.

4.6. Lesson implementation

iLessons enabled teachers to load lessons remotely into computers grouped by class, making lesson Web pages available to students and restricting Internet access. iLessons did not rely on any server to provide lesson implementation. Lessons were copied to shared network folders named as the defined classrooms. When iLessons started up, the name of the classroom that the computer belonged to was sought in a file called “iLessons.ini” and the lesson stored in the folder with the same name was loaded. iLessons monitored the classroom folder for changes and reloaded the lesson file when changes occurred.

The iLessons implementation was the same for network and standalone versions. However the file structure did vary.

iLessons network file structure

When iLessons was utilised in computers over a network, the iLessons file structure was shared from a computer that acted as a file server, so that all computers could access the “iLessons.ini” file and lesson files. "iLessons Network

Tools" was the main installation folder and contained the administration utilities (see Figure 4.19).

"ilessons_root" contained files that were accessed by iLessons such as the iLessons.ini file and lesson files for each classroom. The iLessons setup application was located in the "ilessons_root" folder. It was executed from that folder to locate the "iLessons.ini" file where computers were registered.

A folder existed for each classroom in the "ilessons_root" folder. Classroom folders contained up to two lesson files: a default lesson file (default.les) that was loaded by iLessons when no lesson was implemented; and a lesson file being implemented (now.les). iLessons sought implemented lesson files first, loading the default lesson file if they were not found.

The "ilessons_root" folder contained a word document that was used as a template to create coursework files as described in Section 4.7.

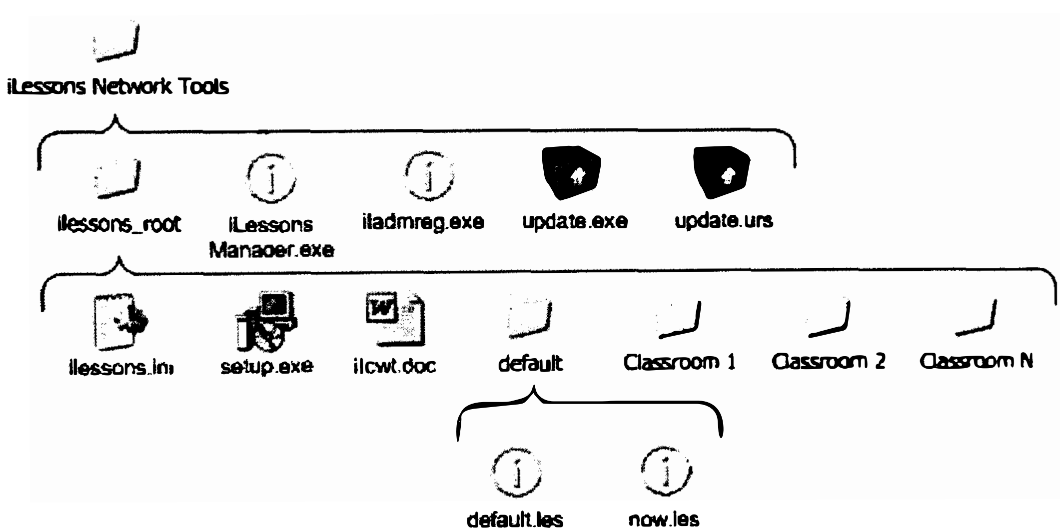


Figure 4.19: iLessons network file structure

iLessons files could be accessed from any computer in the network. Table 4.2 shows the necessary permissions to prevent students from tampering with the system.

Resource	Administrator	Teacher	Student
iLessons Network Tools	Read, Write, Execute	None	None
iLessons_root	Read, Write, Execute	Read, Write	Read
iLessons.ini file	Read, Write	Read	Read
setup.exe	Read, Write, Execute	None	None

Table 4.2: Permissions for the iLessons network file structure

iLessons standalone file structure

When iLessons was utilised in a single computer, the iLessons file structure was held in the application folder (see Figure 4.20). The application folder contained the administration utilities, as well as files accessed by iLessons such as the iLessons.ini file. Classroom folders did not exist and lesson files were stored in a "default" classroom folder. It contained up to two lesson files: a default lesson file (default.les) that was loaded by iLessons when no lesson was implemented and a lesson file being implemented (now.les). iLessons sought implemented lesson files first, loading the default lesson file if the implemented lesson files were not found.

The application folder contained a word document that was used as a template to create coursework files as described in Section 4.7.

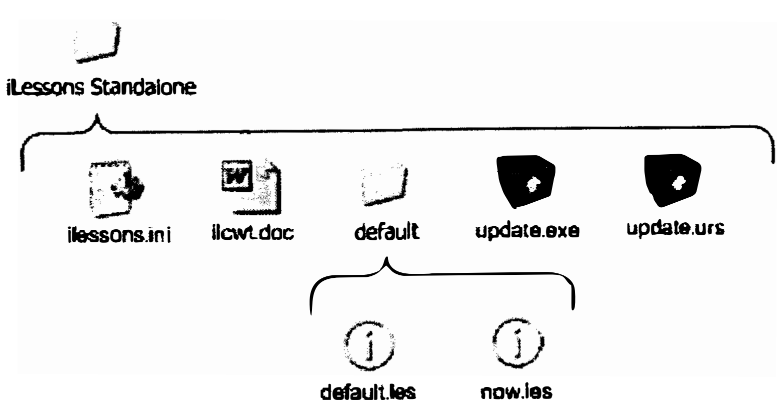


Figure 4.20: iLessons standalone file structure

4.6.2. iLessons INI file format

The iLessons INI file was read by iLessons at start up to determine the computer classroom or group and validate teacher passwords. The iLessons INI file contained information about the classroom or group assigned to each computer and the classrooms or groups available, as well as encrypted teacher login data, distributed as follows:

```
BEGIN_CLIENT_INFO
(Client location information here)
END_CLIENT_INFO
BEGIN_CLASSROOM_INFO
 (Classroom information here)
END_CLASSROOM_INFO
BEGIN_USER_INFO
 (Teacher login information here)
END_USER_INFO
```

BEGIN_CLIENT_INFO / END_CLIENT_INFO

Rows contained three columns separated by a tab: The computer's MAC address, the name of the classroom where the computer was located, and a description of the client, which was optional. For example:

```
BEGIN_CLIENT_INFO
00B121230102	Classroom 1A	FCC-CL1A-Workstation1
0029F880DB40	Classroom 1A	FCC-CL1A-Workstation2
00ABA70105CB	Classroom 1B	FCC-CL1B-Workstation1
000F90B1A25C	Classroom 1A	FCC-CL1A-Workstation3
445355400040	Classroom 1B	FCC-CL1B-Workstation2
END_CLIENT_INFO
```

If clients could not find their group in the list, they loaded the lesson in the "default" classroom folder. iLessons standalone always loaded the lesson in the default classroom folder.

BEGIN_CLASSROOM_INFO / END_CLASSROOM_INFO

Rows contained two columns separated by a tab: The classroom's name and a description of the classroom.

BEGIN_CLASSROOM_INFO
default For clients with unknown location.

Classroom 1A	Floor 1 Classroom A
Classroom 1B	Floor 1 Classroom B
Classroom 2A	Floor 2 Classroom A
Classroom 2B	Floor 2 Classroom B

END_CLASSROOM_INFO

The "default" classroom entry was compulsory. Classroom entries corresponded to folders with the same name stored in the same directory as the iLessons.ini file, which contained the default lesson for each classroom as well as the lesson being implemented in each classroom.

BEGIN_USER_INFO / END_USER_INFO

Rows contained three columns separated by a tab: The teacher's user name, the teacher's password and a description of the user, which was optional.

BEGIN_USER_INFO

Priscilla	CpyntHZ4	History teacher.
Victor	H5y34sAr5	Maths teacher.

END_USER_INFO

Passwords were encrypted by using the cryptography functions available within the Microsoft Windows Operating System, particularly the RSA encryption algorithm. The resulting encrypted passwords were modified to contain only alphanumeric characters. When users logged in, passwords were validated encrypting a string using the stored teacher password as key and then decrypting it with an encryption key generated from the password entered by the user at login. If the decrypted string matched the original the password was correct.

4.7. Coursework

iLessons enabled students to create coursework in Microsoft Word files from within IE using resources collected from the Internet as described in Section 4.2.2. An installation of Microsoft Word was required for this feature to be used.

4.8. Administration tools

iLessons provided a set of administration tools to manage classrooms, computer location and teacher login information. Administration tools were protected by an encrypted administrator password. This was achieved using the cryptography functions available within the Microsoft Windows Operating System, particularly the RSA encryption algorithm.

4.8.1. Administrator password registration utility.

The administrator password registration utility saved an encrypted administration password in the registry. The administration password protected access to other administration tools.

4.8.2. Teacher management utility.

The teacher management utility application was available in iLessons Standalone version only. It enabled administrators to create, delete and modify teacher user names and passwords. Passwords were encrypted and information was stored in the iLessons.ini file.

4.8.3. iLessons manager

The iLessons manager was available in iLessons Network version only. This enabled the administrator to manage classrooms, computer locations and teacher accounts, saving all the changes into the iLessons.ini file.

4.9. Chapter discussion

iLessons was created to allow teachers to structure the use of the Internet by reusing materials readily available on the Internet to create a set of lesson Web pages; to restrict Internet access to keep students focused; and to control the user of the Internet by selecting lessons and restrictions per classroom, all from within a standard Web browser and without the need of server software. Specifications for the new system were defined after researching the systems described in Chapter 2, gathering information from the marketing department at the collaborating company and receiving feedback from teachers about the first prototype system described in Chapter 3. Students were able to create resource collections and to use them to create Microsoft Word coursework files from within IE using resources collected from the Internet.

iLessons was required to be intuitive and easy to use, in line with software applications that teachers might already know how to use. The iLessons UI was created within IE. User input and system output was achieved by using DHTML UIs. Drag and drop was available for resources and lesson Web pages. The two main UI windows were the “iLessons toolbar” and the “infoPad”. The infoPad provided resource collection and lesson design functions. The iLessons toolbar provided access to lesson design, assignment design and security functions.

iLessons enabled teachers to load lessons remotely into computers grouped by class, making lesson Web pages available to students and restricting Internet access. iLessons did not rely on any server to provide lesson implementation. Lessons were copied to shared network folders named as the defined classrooms which were loaded at startup.

CHAPTER FIVE

TESTING OF THE CITA PROTOTYPE AND ILESSONS

5.1. Introduction

The Computer Aided Instruction (CAI) systems described in Chapter 2 provided limited functionality to clients as most tools were Web-based. They did not provide intelligent advice on potential sites, consider student activity or provide content-specific filtering of Web pages. Their limitations suggested a need for another type of software tool and Chapters 3 and 4 described Caught In The Act (CITA) and iLessons, two new systems that were designed and created by the author to overcome these limitations.

This Chapter describes the testing of the CITA prototype and iLessons and then presents results from the tests, as well as the feedback received from teachers and users. The Chapter begins with the testing of the CITA prototype. Testing and results of the server side of the system are described, followed by an explanation of the testing of the client side and testing of the system as a whole. The narrative then moves on to describe the testing of iLessons and the components described in Section 4.1.5: User Interface (UI), resource collection, Web page editing, navigation zone, filtering algorithm, lesson implementation, coursework editing and administration tools.

5.1.1. Software testing

White box testing was performed by the author after each development iteration, ensuring that all logical paths and data structures within the code were correct. The product of each iteration was a functional software system although it did not contain the full specification of the system until later stages. After each iteration, the software was tested by the testing team using black box testing methodology in two stages: In a first stage, testing was performed grouping system functionality by the UML Use Cases implemented or expanded during the iteration. Once that the system passed all testing cases, a second testing stage was performed by giving users tasks to complete using the system to test overall system usability and stability.

Three types of user were considered during this work: students with some experience of common computer applications; Administrators with broad experience in installation, use and maintenance of ICT; and selected teachers likely to use the system. Both systems were tested by users from each of these categories.

5.2. Testing of the CITA prototype

Testing of the CITA prototype was divided into server side testing and client side testing.

5.2.1. Server side Testing.

The CITA server prototype was created using ISAPI filters and extensions so that it ran within Microsoft Proxy Server 2.0 (MSPS) and Microsoft Internet Information Server (IIS). The CITA server prototype was used by teachers to test the efficiency of three filtering methods described in Chapter 3: URL filtering, text filtering and combined URL and text filtering. Feature-based filtering was not tested because it could only be applied to reduced sets of documents.

To test these filtering methods, teachers populated a Microsoft Access Database with allowed and denied URLs, directories and domains in the case of URL filtering; allowed and denied keywords in the case of text filtering; and both in the case of combined URL and text filtering. The subject chosen for the testing was "music scales". This was chosen because it was a familiar subject for the teachers but most students had little knowledge about it. The CITA server prototype successfully loaded the Microsoft Access Database and monitored requests made to the Internet through MSPS.

Students did not actually test the CITA server prototype but members of staff of the collaborating company pretended to be students to test the system; they tested the system indirectly by trying to load Web pages within and outside the specified URLs, directories and domains, as well as containing allowed and denied keywords during a 15-minute seminar on the subject. While Web pages were always allowed or blocked according to the information specified by teachers and the active filter method, teachers claimed that populating the keyword database when using text filtering was a time consuming task. Also, full text filtering was effective when blocking access to clearly unrelated Web pages, such as those displaying adult content or offering online games, but it proved to be ineffective when focusing students' attention on a subject, as unrelated pages could be allowed and related pages could be denied if keywords were not selected carefully. URL filtering was an easy to use method that enabled teachers to clearly define access for areas of the Internet, but both teachers and students mentioned that although URL filtering was efficient at focusing the use of the Internet when delivering a seminar or lecture, it was too restrictive to enable students to perform their own research. It was thought that flexibility would improve by combining full text filtering with URL filtering, but it was found that adding text filtering did not yield any improvement, as students were able to access unrelated pages that did not contain any blocked keyword but contained allowed keywords.

The testing of the CITA server prototype was successfully completed and the methodology was proven although filtering was not enforced depending on computer location at this stage. This was successfully achieved later during the creation of iLessons, as described in Chapter 4.

5.2.2. Client side testing.

The prototype implementation of the CITA client consisted of an application that received student activity notifications from the CITA server (see Figure 5.1). The CITA client prototype successfully notified teachers when students tried to access blocked pages, but it was found that it displayed too many notifications when students made mistakes or tried to access to related URLs that were not allowed by the database created by the teacher.

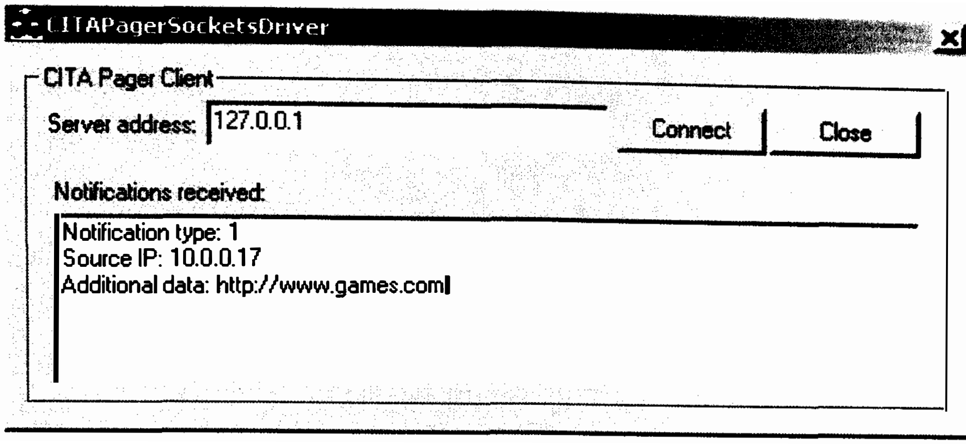


Figure 5.1: Notification client prototype UI

A mock version of the full CITA client UI (Figure 5.2) was created to test the concepts with teachers and receive feedback from them before proceeding to further development stages. The CITA client UI was a single window application similar to commercial Web browsers in order to make the system more intuitive and easy to use. It was comprised of three main areas: browser toolbar containing navigation buttons and an address text field; navigation window where requested pages could be displayed and where lesson Web pages could be edited; and an edit toolbar that could provide tools to edit lesson Web pages in a similar way to commercial text editors. User dialogs were implemented as a set of template Web pages stored locally. When a dialog was displayed, a template Web page was populated with the necessary information. A limitation was that information to populate templates was pulled from the CITA server when dialog pages were loaded, so the CITA server could not notify clients when events took place, such as students trying to access blocked pages. Java applets or ActiveX components were required to receive real time information from CITA server and display it in template Web pages.

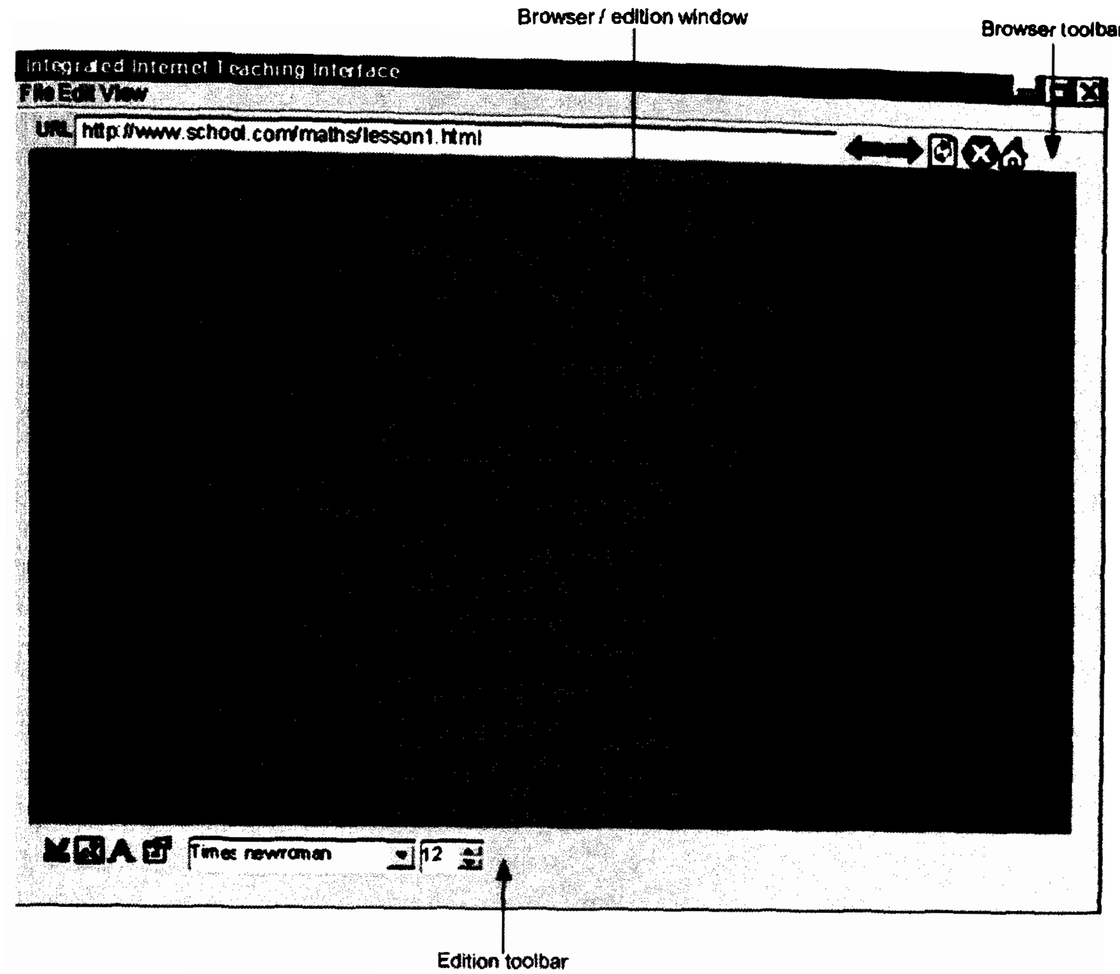


Figure 5.2: Model of the CITA client UI

After teachers tested the UI, it was found that teachers considered the UI and overall CITA system to be useful but not intuitive or easy to use, because using Web templates to display information was too intrusive and only one window was available to display all information. Also, although the UI was designed to resemble a commercial Web browser, it was found that teachers considered the CITA client UI as a proprietary application and did not find it familiar to use.

5.2.3. CITA Testing discussion

The testing of CITA prototype was divided in server side and client side. The CITA server prototype was created using so that it ran within Microsoft MSPS and IIS. It was used to test the efficiency of filtering methods:

- Full text filtering was effective when blocking access to clearly unrelated Web pages but unrelated pages could be allowed and related pages could be denied if keywords were not selected carefully.
- URL filtering was efficient at focusing the use of the Internet when delivering a seminar or lecture, but it was too restrictive to enable students to perform their own research.
- Combining URL filtering with text filtering did not yield any improvement, as students were able to access unrelated pages.

The prototype of the CITA client consisted of an application that received student activity notifications from the CITA server. It successfully notified teachers but it was found that it displayed too many notifications. A mock version of the full CITA client UI was created. It was considered useful but not intuitive or easy to use.

The author met with the collaborating company and the University supervisors to discuss these findings and it was decided that the approach taken with CITA was not correct: using a standard Web browser was a better solution than creating a proprietary application as teachers and students were already familiar with the UI and also it provided functionality such as Web page browsing and editing and HTTP event filtering. It was also found that using MSPS as a platform for CITA needed a network infrastructure that many schools were not able to afford or to migrate to. It was decided that the system had to work using only the standard Microsoft Windows network file system available. Notifying teachers of attempts to access denied content proved to be inefficient and was discarded.

After these decisions were taken, the development of CITA did not proceed any further. Instead, iLessons was created to address these issues and feature all the functions specified for CITA: resource collection; lesson editing; navigation zone; lesson implementation; and coursework editing.

5.3. The testing of iLessons

After white-box testing was performed by the author and UML Use Case testing was performed by testers at the collaborating company, iLessons was installed on a test network in the collaborating company. Staff in the collaborating company were then given tasks to accomplish using iLessons so that usability and black box testing could be performed. This included the reuse of materials readily available on the World Wide Web (WWW) to create a set of lesson Web pages; to restrict Internet access to keep students focused; and to control the user of the Internet by selecting lessons and restrictions per classroom, as well as to create assignments using collected resources. iLessons was then installed in a pilot testing secondary school and was tested by network administrators, teachers and students in a real teaching environment. Structured interviews with users were conducted regularly by the author to collect feedback. A user feedback questionnaire can be seen in Appendix B that was used to structure the interviews and assess iLessons.

5.3.1. Testing of the UI

The UI described in Chapter 4, Section 4.2 was tested by teachers and students and considered to be intuitive and easy to use, and in line with software applications that teachers already knew how to use. This was achieved by embedding the iLessons UI within Microsoft Internet Explorer (IE) using explorer extensions, allowing the addition of functionality while keeping a UI familiar to the user, and reusing functionality available within the Web browser. Using DHTML to create the UIs allowed to create dynamic, adaptive and attractive UIs in a way not available through standard Windows UIs, The iLessons design did not impose restriction in the number of students using the system simultaneously and it was successfully used by pairs of students working on a single PC.

Teachers and students found the resource collection and lesson UIs described in Chapter 4, Section 4.2.1 intuitive and easy to use, and they successfully collected resources from Web pages by using drag & drop, modified their details, deleted them and managed resource collections. Teachers claimed that collecting resources by using drag and drop was effective and easy to use as both the resource collection UI and the Web pages were in the same window; it successfully eliminated the need for menus; and it was quicker than a copy/paste sequence. However, using drag and drop to add resources to lesson pages was slow and ineffective, because users had to constantly switch between the resource collection and lesson views in the infoPad. Also, the infoPad sometimes limited the editing area. Buttons were added to the edit toolbar UI to enable teachers to add resources to lesson Web pages without having to display the infoPad.

The navigation toolbar described in Chapter 4, section 4.2.2 displayed tools depending on the type of user (teacher or student) and the edit toolbar was available to teachers only. Teachers granted access to zones of the Internet using the navigation toolbar buttons and the context menu. Teachers found the way of representing the permissions of viewed pages with a square coloured depending on the permission was effective and easy to understand, but they found that they had to navigate to each page to find out its permission. A button was included that showed a list of all the Web pages, directories and domains with an assigned permission. Teachers suggested that colouring the hyperlinks within a page depending on their permission would make it easier to grasp which zones of the Internet were allowed. All teachers found the edit toolbar similar to most text editors and therefore intuitive and easy to use. It was found that when absolute positioning was applied to elements, page contents could be distorted when the infoPad was closed as the absolutely positioned elements did not reposition with the rest of the page when the dimensions of the window changed. Teachers found it was simpler to use absolute positioning for all elements, or none of them, than to use absolute positioning in only certain elements.

The coursework edit toolbar successfully enabled students to create, open and save Microsoft Word coursework files from within IE.

5.3.2. Testing of the resource collection

Resource collections were used by teachers and students to reuse Internet resources such as images, text, hyperlinks and HTML content by dragging resources from the IE window and dropping them to the resource collection UI. Data was successfully transferred from IE to the resource collection using memory pointers. Automatic notifications of changes in IE data were not supported because resources were snapshots of the data being collected, rather than dynamic data containers.

The drop effect on the resource collection view was determined by the location of the drop point within the UI and the contents of the data being dropped. Dropping was only allowed onto the four resource block headers when the data being dropped was the necessary to create a resource of the type contained in the resource block.

Resource types

Resources were grouped in four types depending on the type of data that they stored. If Web page elements did not contain the required data types, resources of the specified type could not be created from a given page element. For example, a "hyperlink" resource could not be created from an image. When creating "mixed" resources, HTML code was copied from the data provided by IE. External files needed to display selected page fragments such as images were not downloaded. The resource's HTML code pointed to the original locations of the files instead.

It was found during testing that images surrounded by hyperlinks provided data corresponding to the hyperlink but not to the image. This prevented users from creating media resources from images surrounded by hyperlinks. This problem was solved by detecting which Web page element was dragged when creating a media resource. If it was an image, it was downloaded to a file and drag and drop data was created from it.

Reusing resources

When users dragged a resource from the resource collection, the memory pointer to the resource was searched and the drag and drop operation was successfully handled by the system, copying the resource data to the drop target. Using standard drag and drop mechanisms enabled resources to be successfully reused not only within iLessons but also by applications that supported drag and drop, such as Microsoft Word.

Saving and loading resource collections

Resource collections were saved using structured storage. Resources were successfully saved as substorages containing resource data and external image files in the case of resources containing images.

5.3.3. Testing of the lesson Web page editing

Web page editing was successfully implemented by reusing the editing features available in IE. Standard editing functions were successfully implemented by executing standard IE commands, such as Bold or Italic.

Tables

IE included the ability to manipulate tables but it did not provide a simple and standard way of creating tables or modifying their properties such as background and border colour, or merging cells within the table. ACE editor was a JavaScript-based Web page editor that allowed editing Web pages from a host Web page. It included advanced table creation and manipulation functions that were embedded into iLessons to provide support for table editing. A licence of ACE editor that allowed reusing its JavaScript code was purchased.

The ACE editor table creation UI (Figure 5.3) was displayed when teachers clicked on the "Table" button in the editing view of the iLessons toolbar. Teachers claimed during testing that media resources could not be used as table or cell backgrounds, so the UI and underlying JavaScript code were modified to support media resources as table and cell backgrounds.

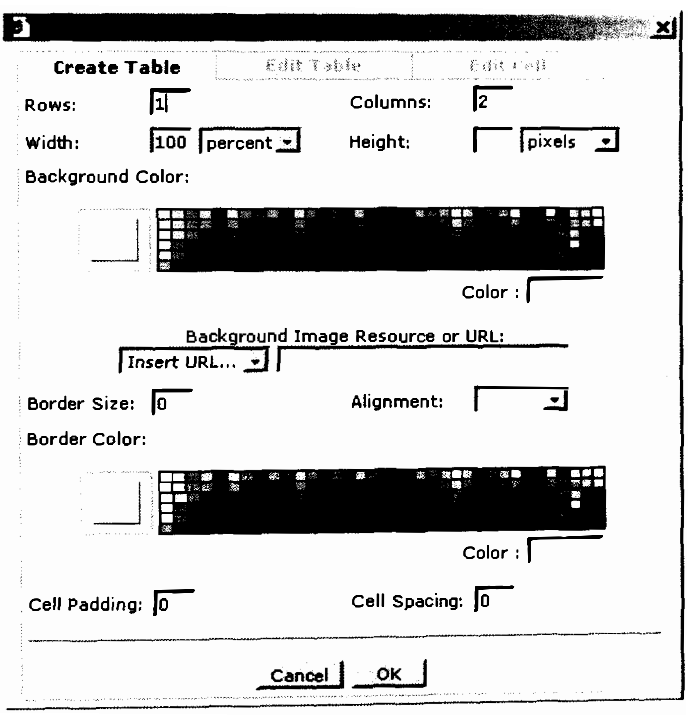


Figure 5.3: Table creation UI

If teachers clicked on the "Table" button after positioning the cursor inside a table, then the table and cell manipulation UI (Figure 5.4) was displayed.

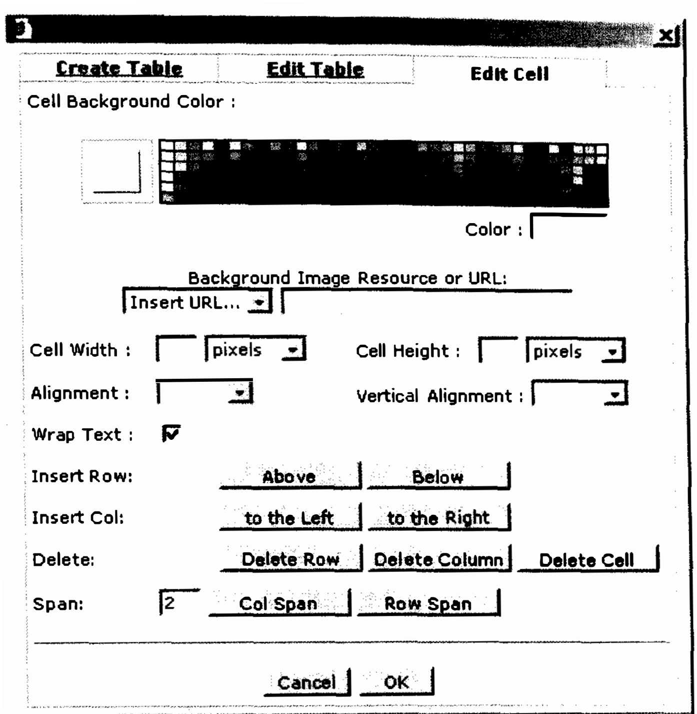


Figure 5.4: Cell manipulation UI

Absolute positioning, text boxes and editing glyphs

Elements in Web pages were positioned by default following the flow of the page text. Absolute positioning enabled teachers to position images and tables freely anywhere in a lesson Web page, but it was found during testing that absolute positioning was not a useful feature if text could not be positioned freely as other elements. A "text box" tool was successfully created to enable teachers to position text blocks anywhere in the lesson Web page (Figure 5.5). When teachers clicked on the "text box" button in the edit toolbar, an absolutely positioned layer was created in the lesson Web page. Layers could contain any HTML code and be absolutely positioned, so text could be written in them. Text boxes were transparent and displayed a dashed border around them in editing mode. The border was removed when teachers finished editing the page.

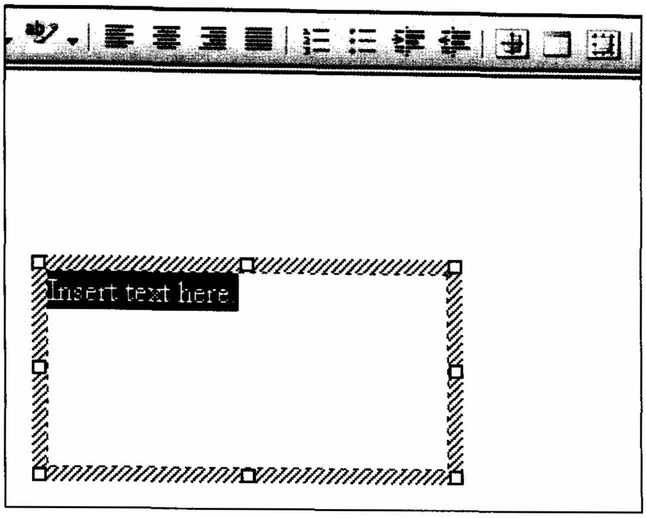


Figure 5.5: Text block created with the "text box" tool

Using absolute positioning enabled teachers to position images, tables and text boxes anywhere in the lesson Web page, but the elements' HTML code was invisible and remained in the original position. Teachers found this very confusing because absolutely positioned elements could be accidentally deleted when text surrounding the invisible code defining absolutely positioned elements was removed, even if the elements were in a different location within the page. This issue was solved by adding editing glyphs. Editing glyphs were images that represented HTML tags formatting a Web page [Tahir (2003)]. Editing glyphs gave users visual clues about the structure of a page by marking with a small icon the position where the HTML code defining absolutely positioned elements was placed (Figure 5.6). If a glyph was deleted the element that it represented was also deleted. Glyphs were moved to the top of the page to facilitate the editing of non-absolutely positioned content without deleting absolutely positioned elements accidentally. Editing glyphs were created for absolutely positioned images, tables and text boxes.

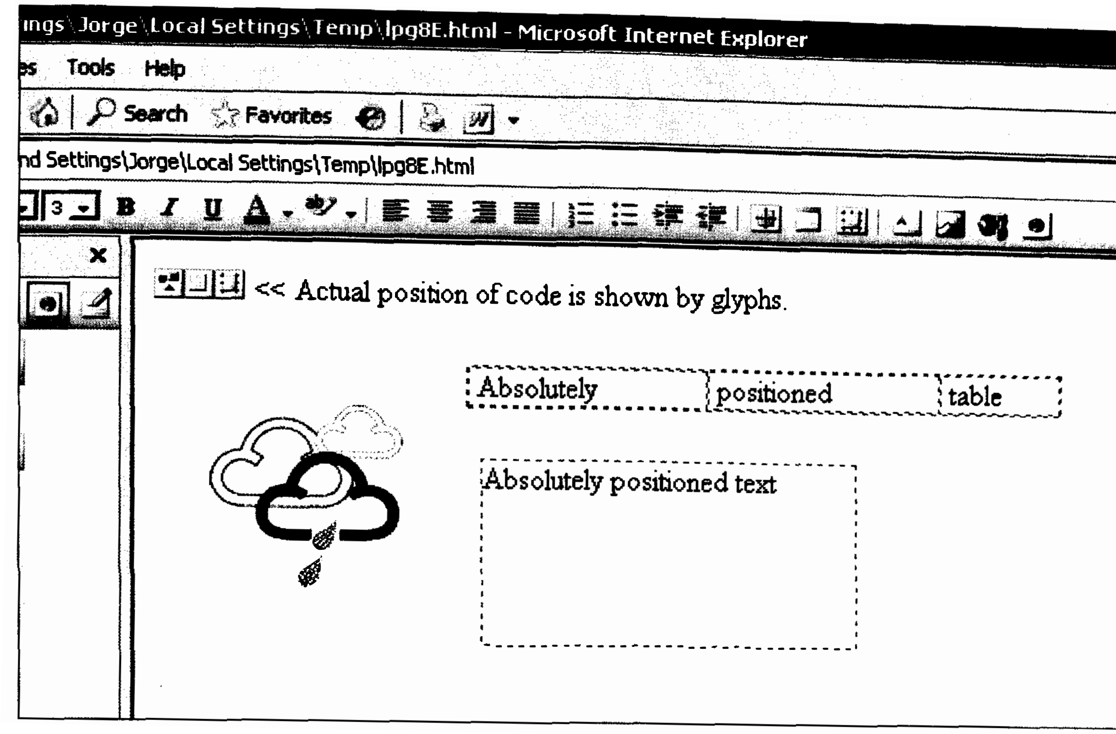


Figure 5.6: Absolutely positioned elements and editing glyphs

Adding links to other lesson Web pages

Hyperlinks to other lesson Web pages within the lesson could be successfully added to lesson Web pages. Lesson Web page objects implemented the necessary drag and drop functions to provide a hyperlink pointing to the lesson Web page file that they represented. When users dragged and dropped lesson pages from the lesson UI the lesson page was searched in memory and the hyperlink information was passed to the operating system. The operating system then handled the standard drag and drop operation.

Hyperlinks to lesson Web pages did not point to the lesson Web page file directly because it could change each time that the lesson was loaded. Instead, a custom addressing protocol was created. Lesson Web page hyperlinks had the format "ilessons:value". Three kinds of values were defined:

- *"main":* The ilessons:main address was resolved to the path of the lesson main page.
- *"block":* The ilessons:block address was resolved to the path of the iLessons blocking page.

- *{pageuid}*: Each lesson Web page was assigned a constant and unique identifier (UID). Hyperlinks containing an ilessons*{pageuid}* address were resolved to the path of the lesson Web page with a matching page UID. Lesson Web page names were not used because they could be modified by teachers.

Adding resources

Resources could be successfully added to lesson Web pages by using drag and drop (Figure 5.7). Resources could also be added by using the "Add resource" buttons in the editing view of the iLessons created after feedback was received from teachers as described in Section 5.3.1.

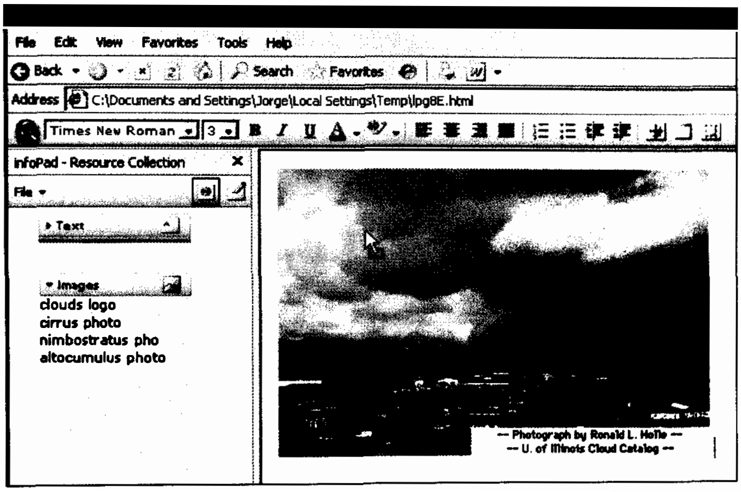


Figure 5.7: Adding a resource to a lesson Web page

Importing Web pages

A third-party component was utilised to import Web pages into files that could be used as lesson Web pages. Teachers found this function useful because network traffic was reduced by storing relevant pages locally in the lesson file.

Saving lessons

Lesson Web pages and navigation zone data were saved in compressed files changed to the ".les" extension and using structured storage. Saving lessons as single files allowed teachers to carry them using removable data storage such as USB flash memory cards and share them with other teachers by email or other means.

5.3.4. Testing of the navigation zone and filtering algorithm

Extended URL filtering proved to be a fast, simple and accurate filtering method. iLessons enabled teachers to successfully create complex navigation zone structures by allowing, denying or trusting domains, directories, Web pages and Web page elements.

Allowing zones of the Internet

When Web pages were allowed, external components such as images, applets or video streams were allowed to display the page correctly when requested by a student. It was necessary to retrieve the URLs of the elements needed to display the page correctly. A parser was created that retrieved the tags of the elements to be retrieved and the attributes of the elements where relevant URLs were located from a text resource. Table 5.1 shows the tags of external elements and the attributes that contained URLs to be allowed to display the element correctly.

Denying zones of the Internet

When Web pages, directories or domains were denied, student access to them was successfully blocked.

Element tag	Attributes	Description
APPLET	codebase, code	Applet source code.
BGSOUND	src	Background sound file.
BODY	background	Page background image.
EMBED	src, code, codebase	Object source code files.
IMG	lowsrc, src, dynsrc	Image file.
LAYER	background, src	Layer background image.
LINK	href	Linked file, usually CSS.
OBJECT	code, codebase, data, usemap	Object source code files.
SCRIPT	src	Script source code file.
TABLE	background	Table background image.
TD	background	Cell background image.
TH	background	Header background image.
TR	background	Row background image.

Table 5.1: External elements retrieved by the parser

Trusting zones of the Internet

URL filtering was extended with a new kind of permission called "trusted". Trusting a Web page granted student access to the page and to any other page linked to the trusted Web page down to a specified level. In order to support trusting, two new permission types were added: "cached" and "display only". These permission types were used internally by the navigation zone and they were not available to users.

"Cached" permission was assigned to pages navigated from a trusted page, directory or domain, or to pages navigated from another cached page. Cached pages were effectively trusted pages and their trust level was one level less than the trusted or cached page where the navigation started. Cached pages could change from one session to another and they were not saved in lesson files.

"Display only" permissions were assigned to pages navigated from a trusted or cached page when navigating to any other Web page from them was not allowed. They were effectively cached pages with zero trust level.

Frames

Navigation zone permissions were based in Uniform Resource Locators (URLs) because they identified single Web resources uniquely and permissions could be set unambiguously. Web pages containing frames did not comply with this standard. URLs of pages containing frames identified the frame set uniquely, but URLs did not change when navigation within a frameset occurred. This supposed a limitation in handling framesets: it was found during testing that if teachers allowed Web pages containing frames after having navigated to other frames from the original frame, the allowed frames were not the same as the original frames contained in the frameset. This led to allowed frame pages being unreachable as frame pages needed to navigate to the allowed frame pages were not allowed. Teachers were advised to allow the directories where frames were stored or to use trust permissions to grant access to frames within a frameset.

iLessons filtering algorithm

The iLessons filtering algorithm was divided in three stages. Stages I and III occurred within IE browser events and Stage II took place when HTTP requests sent by IE were captured.

a) *Filtering stage I*

Filtering stage I (Figure 5.8) was triggered when a Web page was requested from IE. The following steps were successfully performed:

1) iLessons: requests were processed and resolved to lesson Web page file paths. IE navigated to the requested lesson Web page.

2) Request URLs were stored to be compared with request URLs in stage III to detect server-side redirections.

3) The teacher login window was displayed when it was detected that the navigation occurred because an IE window was opened by another application to display a Web page. This gave users the chance to log in as teachers before the Web page was blocked.

4) Explicitly denied pages were blocked.

b) *Filtering stage II*

Stage II (Figure 5.9) was triggered when HTTP requests were made by IE. The following steps were successfully performed:

1) "Cached" permissions were added to request URLs in the navigation zone if request referrers were trusted or cached to a valid level, as specified in "Trusting zones of the Internet" in this Section.

2) Explicitly denied elements were blocked.

Step 2 was different to Step 4 in Filtering stage I because Stage I only blocked explicitly denied Web pages and Stage II blocked Web page elements that could not be detected by monitoring IE events.

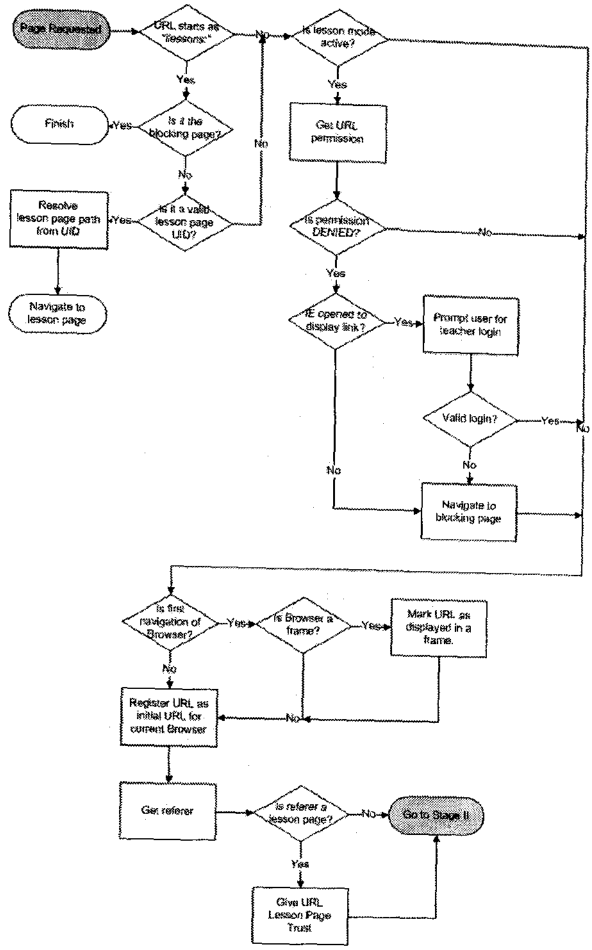


Figure 5.8: iLessons filtering algorithm, stage I

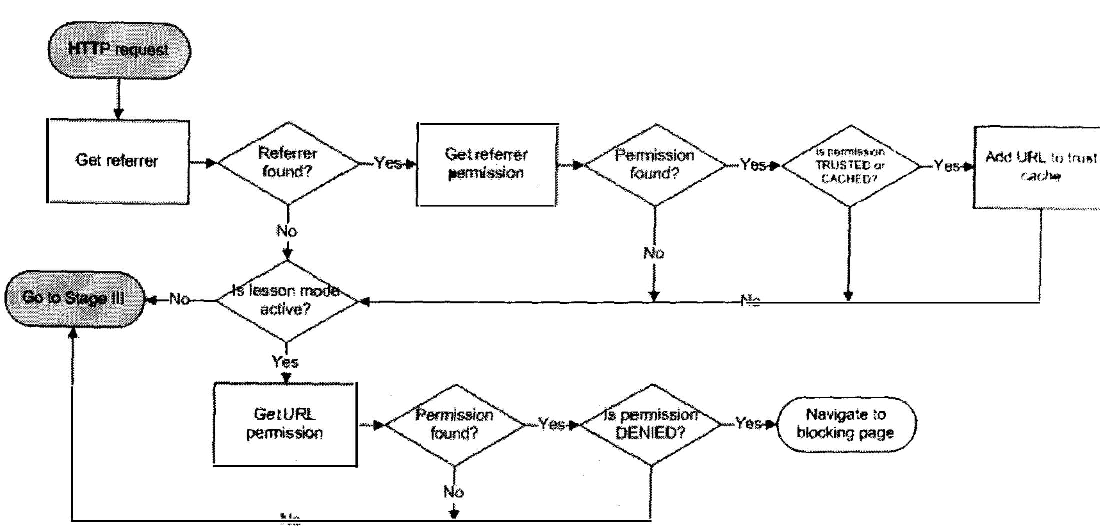


Figure 5.9: iLessons filtering algorithm, stage II

c) *Filtering stage III*

Stage III (Figure 5.10) was triggered when IE started downloading Web pages. The following steps were successfully performed:

1) The lesson main page was displayed the first time that IE was opened and iLessons was started.

2) The navigation zone resolved Web page permissions and Web pages were blocked if their permission was denied.

3) Server-side redirections were detected by comparing the URL stored at stage I with the URL provided by IE in this stage. If redirections occurred the trust information was updated to include final URLs.

Step 1 was different to step 4 in stage I and step 2 in stage II because stage I only blocked explicitly denied Web pages and stage II blocked Web page elements that could not be detected by catching IE events. Stage III did not check explicitly set Web page permissions only, but resolved Web page permissions depending on permissions set to directories and domains where pages were contained.

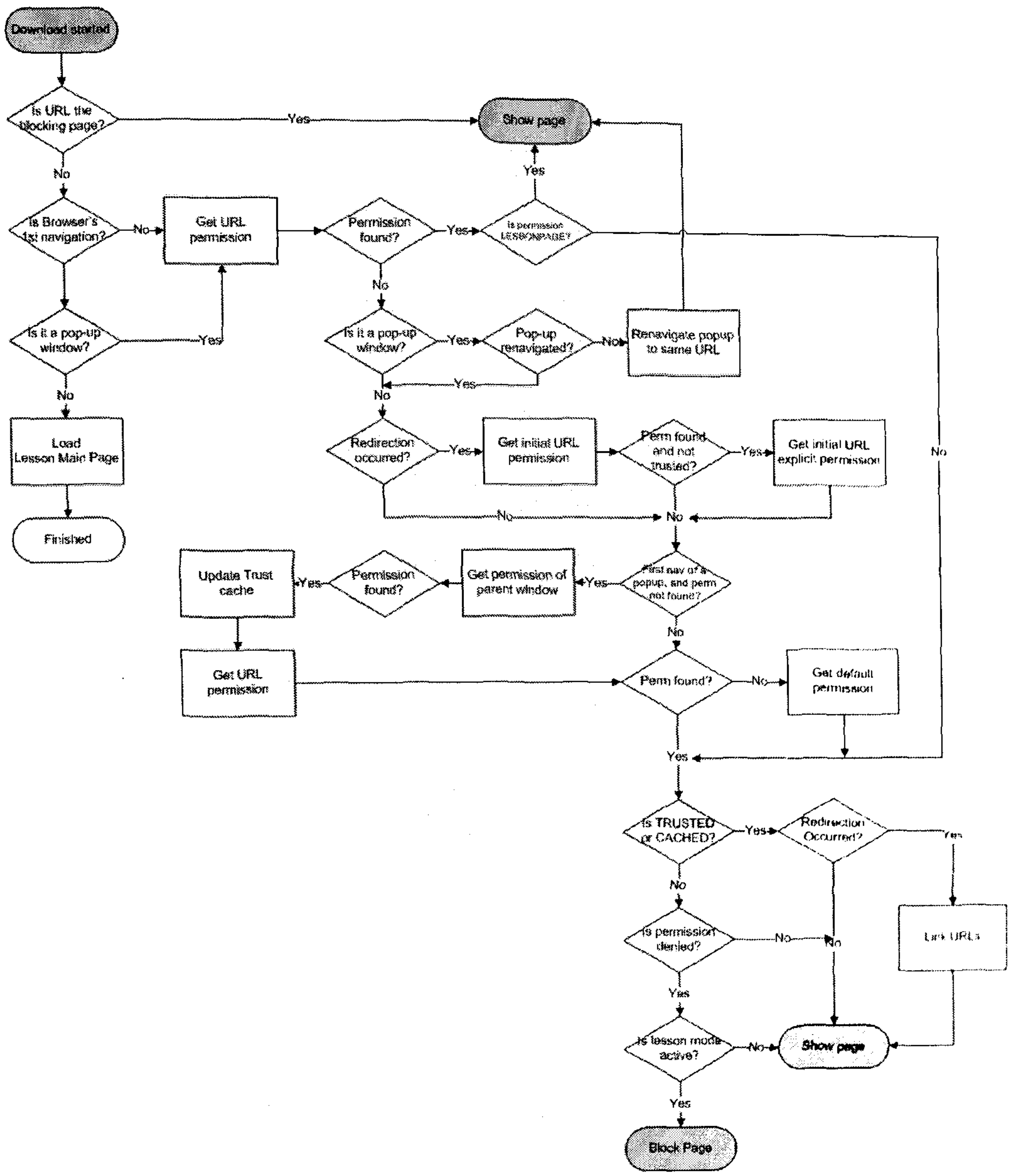


Figure 5.10: iLessons filtering algorithm, stage III

Resolving permissions

Different permissions could affect Web pages or page elements. If Web pages or page elements were assigned permissions and the directories and domains containing Web pages or elements were assigned different permissions, ambiguities could arise when determining which permission to apply. An algorithm to resolve Web page and page element permissions was created (Figure 5.11).

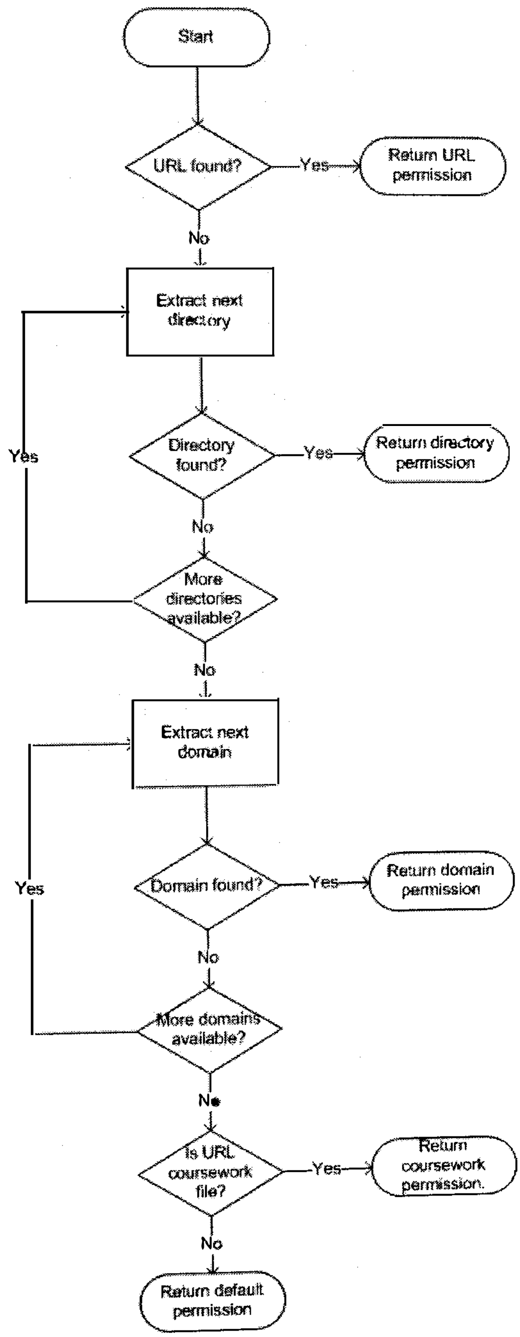


Figure 5.11: Algorithm to resolve Web page and page element permissions

The algorithm first searched the permission for the Web page or page element URLs. If permission was not found, permission for the directories containing the Web page or page element was searched from the closest directory to the most general. If permission was not found, permission for the domains containing the Web page or page element was searched from the closest domain to the most general. If permissions were not found, it was checked that the URL was a coursework file URL. If the URL was not a coursework file URL, the default permission was applied.

5.3.5. Testing of lesson implementation

Teachers were able to load lessons remotely into computers grouped by classroom, making lesson Web pages available to students and restricting Internet access without relying on any server. Lessons were successfully copied to network folders named as the defined classrooms. When iLessons started up the lesson stored in the folder corresponding to the classroom where computers were located was loaded.

iLessons monitored the classroom folder for changes and reloaded the lesson file when changes occurred by using a system function to automatically receive notification from the operating system when changes to classroom folders were made. It was found during testing that this method was unreliable when monitoring network folders in other operating systems than Microsoft Windows XP. As many educational establishments used different versions of Microsoft Windows, a hybrid method was developed: If the operating system was not Microsoft Windows XP or a latter version, the folder details were polled every 10 seconds. Otherwise, the system function was used. iLessons successfully monitored classroom folder changes using this method.

5.3.6. Testing of coursework editing

Students were able to create coursework in Microsoft Word files from within IE using resources collected from the Internet. Microsoft Word was required to be installed to make this feature available. Registry settings were modified when iLessons was installed to force IE to display the coursework file in the browser window, instead of opening it in a Microsoft Word window. Coursework files were successfully generated from a Microsoft Word template file stored in a network folder. When students created a new coursework file, the template was copied into the student's computer. This enabled educational establishments to provide customised coursework templates.

5.3.7. Testing the administration tools

The administrator password registration utility successfully saved an encrypted administration password in the registry and verified the current administrator password.

The teacher management utility application successfully created, deleted and modified teacher user data. The teacher management utility enforced teacher passwords to be at least eight characters long and contain both upper and lower case characters and also numbers. Administrators that tested the teacher management utility pointed out that passwords created in this way were too complicated to remember for most teachers, so this requirement was not included in the final version.

A first version of iLessons manager was enabled administrators to manage classrooms, computer locations and teacher accounts, saving all the changes into the iLessons.ini file. This version was tested by administrators, who did not find it intuitive or easy to use. Administrators requested several features to make the system easier to use, such as:

- Sorting of teacher users, computers and classrooms by name
- The ability to add computers from a Windows network domain
- The ability to license batches of computers
- The ability to relocate computers visually by using drag & drop.

A new version of iLessons manager was created that successfully featured the requests made by systems administrators.

5.4. Chapter discussion

This chapter described how the CITA prototype and iLessons were tested by final users and members of staff in the collaborating company, and the outcomes of the testing.

Testing of the CITA prototype was divided into server side testing and client side testing. The CITA server prototype was used by teachers to test the efficiency of three filtering methods described in Chapter 3: URL filtering, text filtering and combined URL and text filtering. While Web pages were always allowed or blocked according to the information specified by teachers and the active filter method, teachers claimed that populating the keyword database when using text filtering was a time consuming task. Also, full text filtering was effective when blocking access to clearly unrelated Web pages, such as those displaying adult content or offering online games, but it proved to be ineffective when focusing students' attention on a subject, as unrelated pages could be allowed and related pages could be denied if keywords were not selected carefully. Both teachers and students mentioned that although URL filtering was efficient at focusing the user of the Internet when delivering a seminar or lecture, it was too restrictive to enable students to perform their own research. It was thought that flexibility would improve by combining full text filtering with URL filtering, but it was found that adding text filtering did not yield improvement, as students were able to access unrelated pages that did not contain any blocked keyword but contained allowed keywords.

The prototype implementation of the CITA client consisted on an application that received student activity notifications from the CITA server. The CITA client prototype successfully notified teachers when students tried to access blocked pages, but it was found that it displayed too many notifications when students made mistakes or tried to access to related URLs that were not allowed by the database created by the teacher. A mock version of the full CITA client UI was created to test the concepts with teachers and receive feedback before proceeding to further development stages. Teachers considered the UI and overall CITA system to be useful but not intuitive or easy to use, because using Web templates to display information was too intrusive and only one window was available to display all information. Also, although the UI was designed to resemble a commercial Web browser, it was found that teachers considered the CITA client UI as a proprietary application and did not find it familiar. It was decided that the approach taken with CITA was not correct and the development of CITA did not proceed any further. Instead, iLessons was created to address the issues raised in CITA and feature all the functions specified for CITA: resource collection; lesson editing; navigation zone; lesson implementation; and coursework editing.

iLessons accomplished its goals by using Explorer Extensions to reuse functionality available within IE to provide teachers and students with tools to

- *Gather resources from the World Wide Web such as text or images:* A resource collection tool was successfully tested.

- *Create lesson Web pages:* A lesson Web page editing tool was successfully tested. The tool enabled teachers to use resource collections to successfully assist them in creating educational content.

- *Define student access to zones of the Internet:* A navigation zone tool was successfully tested to enable teachers to specify zones of the Internet that students could access during a lesson. The navigation zone was attached to a set of lesson Web pages.

- *Load lesson Web pages into student computers and enforce access restrictions to defined zones of the Internet:* A lesson implementation tool was successfully tested.

- *Create assignments using collected resources:* A coursework editing tool was successfully tested.

Local Educational Authority advisors from the UK Department for Education and Skills investigated and trialled iLessons and strongly supported the new systems. iLessons was asserted as an easy-to-use, novel and effective tool to deliver guided learning using the Internet in a classroom but it lacked flexibility, adaptability and collaboration facilities. During a lesson, students were able to access the supporting material created or trusted by the teacher, but further access to the Internet was blocked.

Feedback from teachers using iLessons suggested that while allowing and denying specific areas of the Internet was an effective way of controlling the misuse of the Internet during a lesson and of focusing their attention, students were not able to use the Internet to carry out their own research. Research moved on to the creation of a new model of an intelligent system to provide a less restrictive filtering mechanism based on the relevance of WWW pages to a subject, and to consider individual student learning styles, using iLessons as a platform.

CHAPTER SIX
THE NEW INTELLIGENT AGENT SYSTEMS

After creating iLessons and receiving feedback from teachers, the research on software systems to assist in using the Internet moved on to the creation of new intelligent agent systems to provide less restrictive filtering based on the relevance of Web pages to a subject, and to consider individual student learning styles, using iLessons as a platform.

This Chapter describes the creation of a new model of a collaborative agent system. The new system recommended Web pages from the Internet to students based on page contents, students' learning style and activity. This Chapter also introduces two intelligent agent systems used to record user activity and page structure information from users while navigating the Internet. The experimental results are described in Chapter 8. The experiment was designed to find patterns in the way users interacted with standard Web browsers that predicted a user's learning style.

6.1. Document classification and filtering

Document classification algorithms described in Chapter 2, Section 2.4.5 could be used to filter document collections such as the Internet more effectively by granting access only to documents classified as relevant to a subject. During training, teachers defined page categories, such as "relevant" and "irrelevant", and specified example Web pages for each category using the document filter (see Figure 6.1). Terms from Web pages text were extracted using a feature extraction algorithm and a document classification algorithm generated a classification pattern from the training set. Teachers could also create lesson Web pages using a content editing subsystem similar to iLessons.

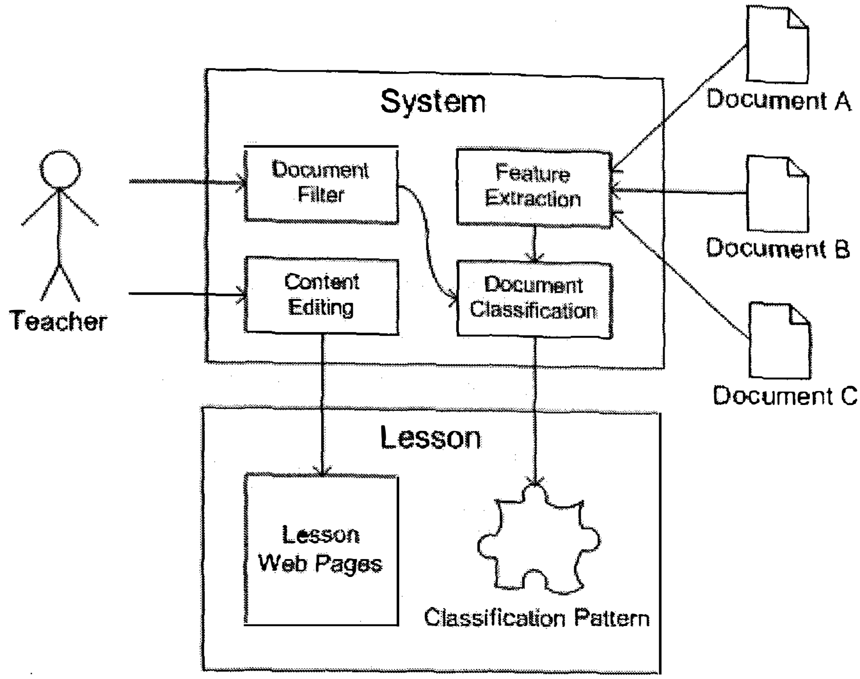


Figure 6.1: Training of the content-based filtering system

The classification pattern was loaded into student systems during a lesson. When students requested Web pages a feature extraction algorithm extracted page terms and a document classification algorithm returned the likelihood that the page belonged to each category (such as "relevant" or "irrelevant" using the classification pattern created by the teacher (see Figure 6.2). Access to pages was granted by the document filter based on the likelihood of it belong to a certain category (such as "relevant") within a predefined threshold. Students could also access lesson Web pages created by teachers.

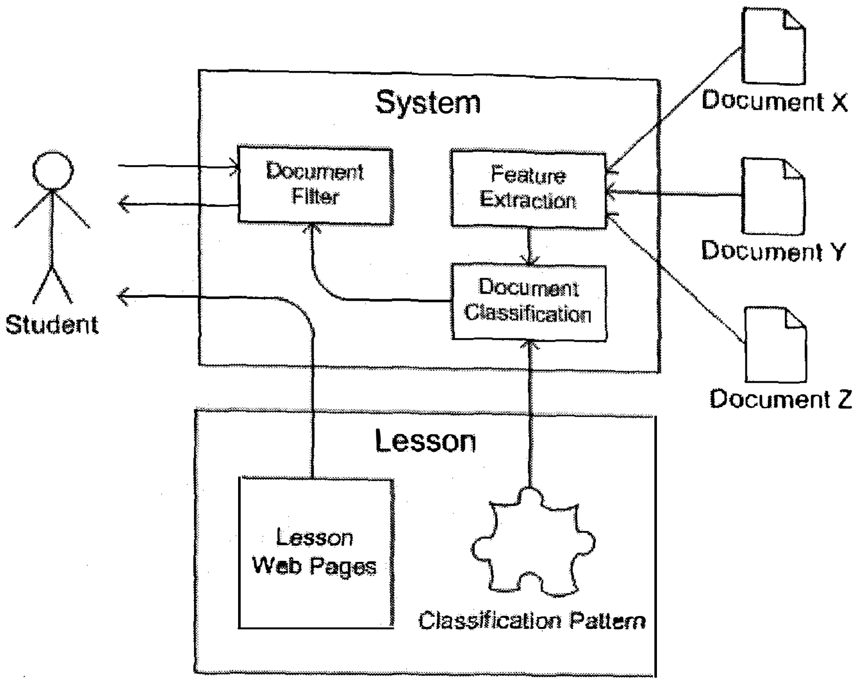


Figure 6.2: Content-based filtering system being used by students

Yang & Pedersen (1997) found that the best feature selection algorithms for document categorisation were IG and χ^2. Term scores calculated using IG, χ^2 and DF were strongly correlated. This suggested that DF was simpler and could be used instead of IG or χ^2 when the computation of these measures was too time consuming. Based on these findings, DF was selected as the feature extraction algorithm for the model of the new intelligent system.

Yang & Liu (1999) found that the best text document classification algorithms were SVM and kNN, both described in Section 9.512.5. Based on these findings, kNN was selected as the document classification algorithm for the new intelligent system. Yang & Liu (1999) reported that 20 documents had to be rated in each category to reach 60% of accuracy.

6.1.1. Enhancements to document classification algorithms

Document classification algorithms were enhanced using URL filtering, semantic networks and collaborative agents to create new intelligent filtering models that also assisted users in researching using the Internet.

Enhancements using URL filtering

A drawback of using content-based document filtering was that feature extraction and document classification had to be performed each time a document was requested, which was processor-intensive. URL filtering was combined with document classification to store the category of retrieved documents in a URL database. When documents were requested, the URL database was queried first, and if a classification was found, content-based classification was not performed.

During training, teachers defined page categories, such as "relevant" and "irrelevant", and provided training Web pages for each category using the document filter (see Figure 6.3). Terms from Web pages text were extracted using a feature extraction algorithm and a document classification algorithm generated a classification pattern from the training set. Categories of retrieved documents were automatically stored in a URL database using a database engine. Teachers could also create lesson Web pages using a content editing subsystem similar to iLessons.

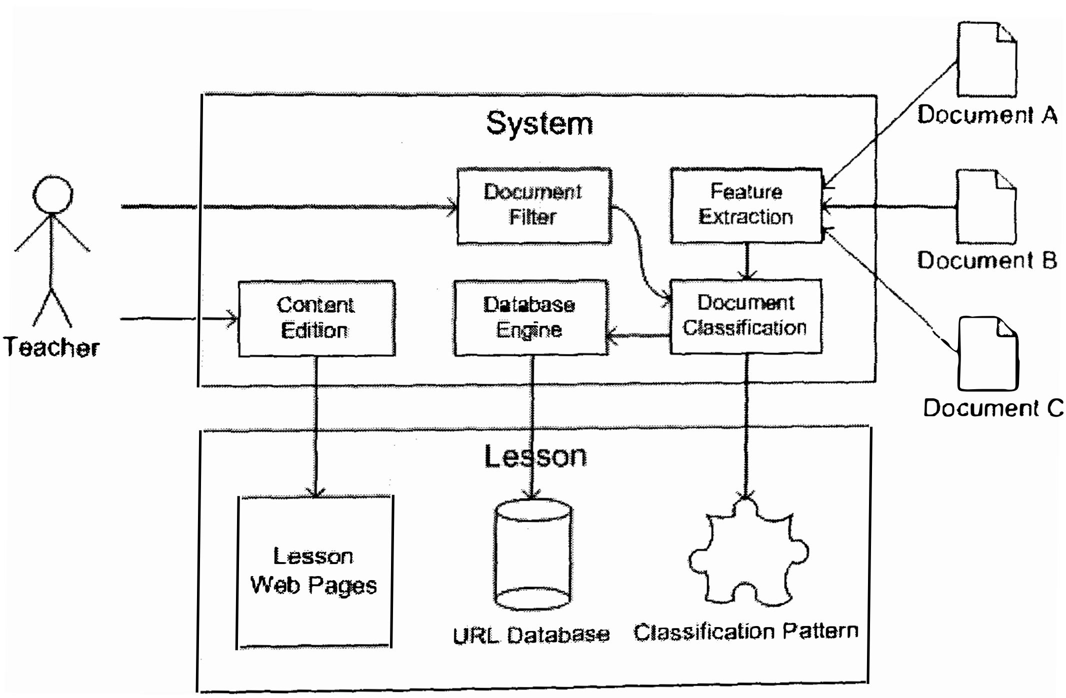


Figure 6.3: Training of a content-based filter enhanced with a URL database.

The classification pattern and URL database were loaded into student systems during a lesson. When students requested Web pages, the URL database was searched for each Web page category using a database engine (see Figure 6.4). If an entry was found, the category stored in the database was used to filter the Web page. Otherwise, a feature extraction algorithm extracted page terms and a document classification algorithm returned the likelihood that the page belonged to each category (such as "relevant" or "irrelevant") using the classification pattern created by a teacher. Access was granted by the document filter to pages likely to belong to a certain category (such as "relevant") within a threshold and Web pages categories were stored in the URL database. Students could also access lesson Web pages created by teachers.

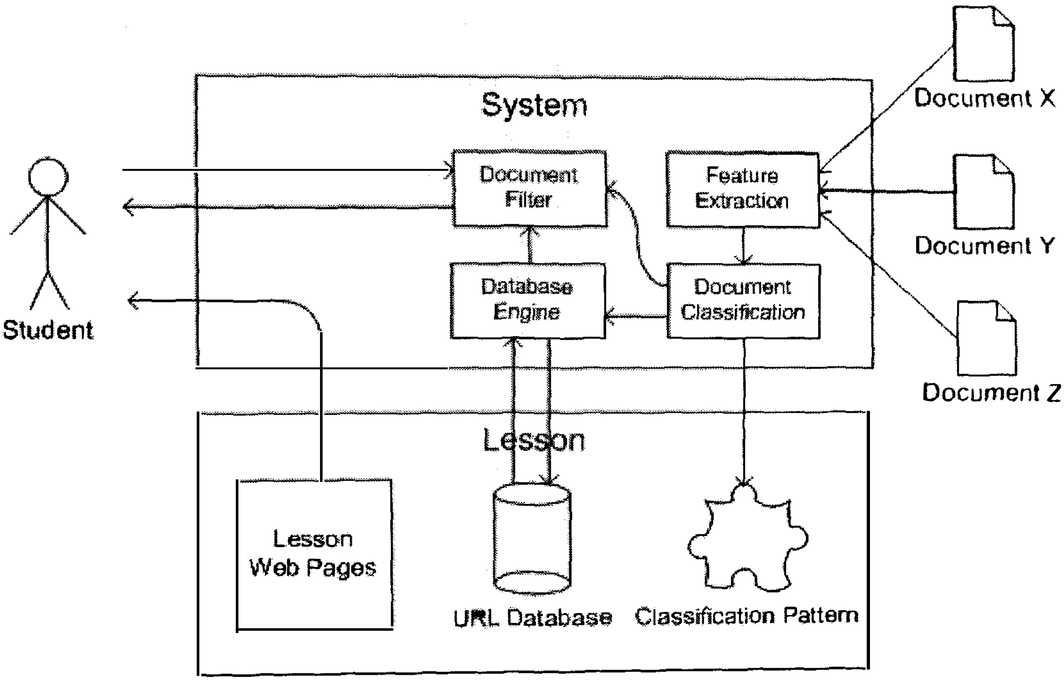


Figure 6.4: Content-based filtering enhanced with URL filtering being used by students

Enhancements using semantic networks

Semantic networks were a graphic notation for representing knowledge in patterns of interconnected nodes and arcs [Sowa (2001)]. Semantic networks could be used either to represent knowledge or to support automated systems for reasoning about knowledge. Document classification algorithms were enhanced by using a semantic network of related documents to recommend related pages to users.

During training, teachers defined page categories, such as "relevant" and "irrelevant", and provided training Web pages for each category using the document filter (see Figure 6.5). Terms from the text on Web pages were extracted using a feature extraction algorithm. A document classification algorithm then generated a classification pattern from the training set. Relationships between related documents were determined by a semantic network engine and stored in a semantic network. Teachers could also create lesson Web pages using a content editing subsystem similar to iLessons.

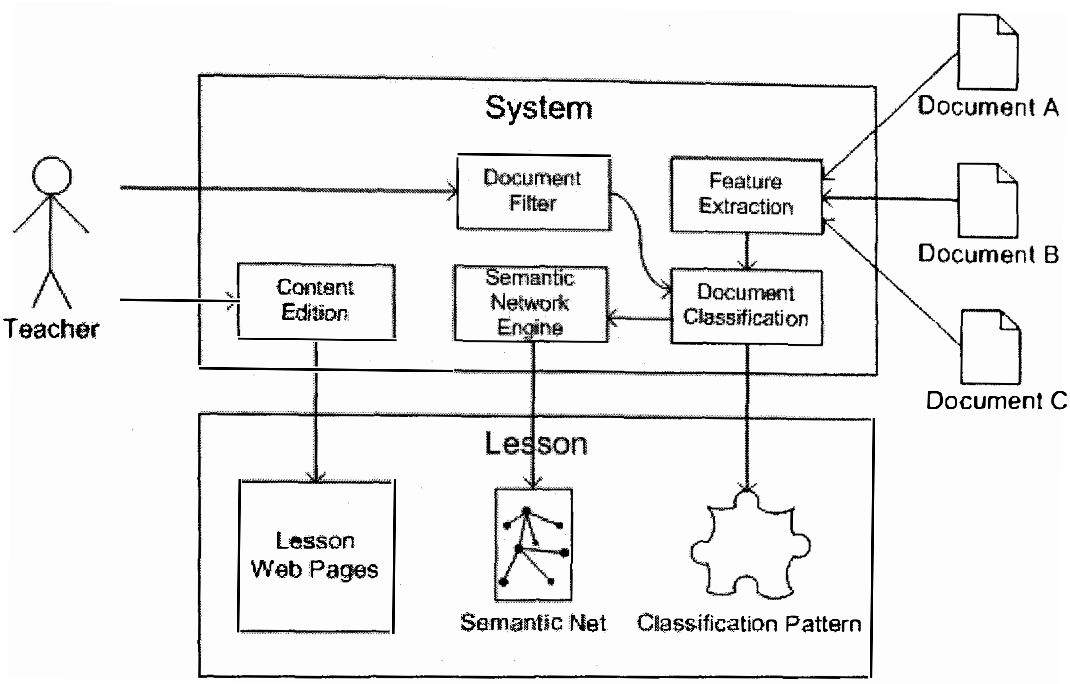


Figure 6.5: Training of a content-based filter enhanced with a semantic network.

The classification pattern and semantic network were loaded into student systems during a lesson. When students requested Web pages (see Figure 6.6), a feature extraction algorithm extracted page terms and a document classification algorithm returned the likelihood that the page belonged to each category using the classification pattern created by a teacher. Access was granted by the document filter to pages that were likely to belong to a selected category (for example, the "relevant" category) within a predefined threshold. Relationships between documents were included in the semantic network by the semantic network engine and a list of related pages was shown to the user. Students could also access lesson Web pages created by teachers.

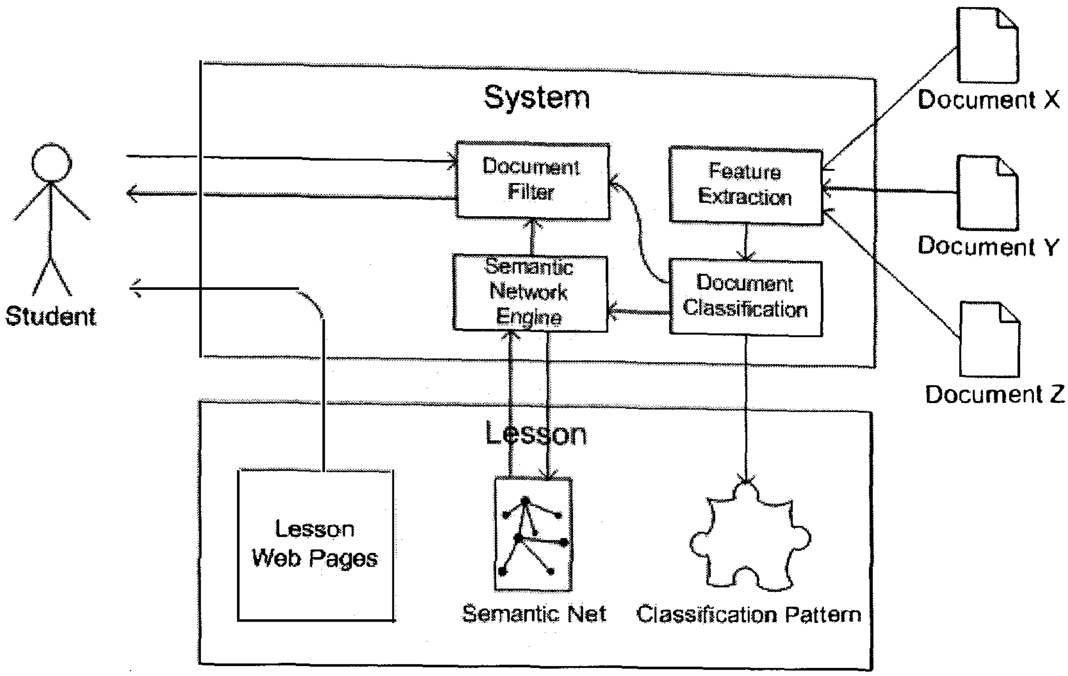


Figure 6.6: Content-based filtering enhanced with a semantic network being used by students

Enhancements using collaborative agents

Autonomous software agents were utilised to analyse and react to user behaviour. Agents assisted users by recommending Web sites or assessing the relevance of a page. Agents could also perform pre-emptive analysis of outgoing hyperlinks, or use network idle time to conduct searches based on user behaviour. Agents did not need to be trained and they made search and navigation through documents more effective, although their learning curve was slow.

Agent-mediated collaborative document filtering involved a group of user agents communicating between themselves. User agents compared user interests in order to enhance overall group performance. Green *et al. (*1998) and Papaspyrou *et al. (*1999) describe such systems. In a similar way, collaborative agents could improve group performance by sharing and upgrading content-based filtering patterns between users in a research group.

a) Content based filtering enhanced with URL filtering and collaborative agents

Document classification algorithms enhanced with URL filtering were combined with a system of collaborative agents (see Figure 6.7). Collaborative agents broadcasted new URL database entries and updated the URL database with entries received from other agents. In this way, each document was classified only once within the research group.

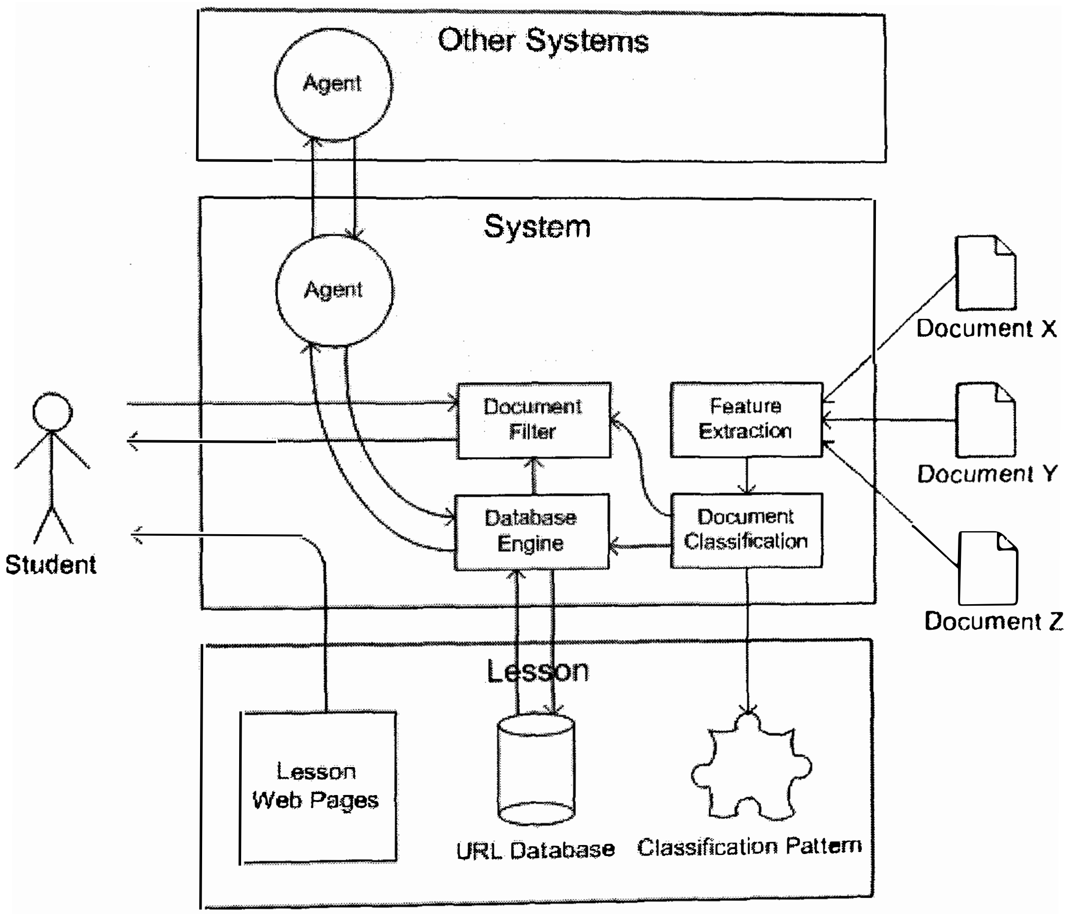


Figure 6.7: Content-based filtering enhanced with URL filtering and agents.

b) Content based filtering enhanced by semantic networks and collaborative agents

Document classification algorithms enhanced with semantic networks described in page 123 were combined with a system of collaborative agents (see Figure 6.8). Collaborative agents broadcasted semantic network updates; updated the semantic network with entries received from other agents and recommended students related pages found by peers.

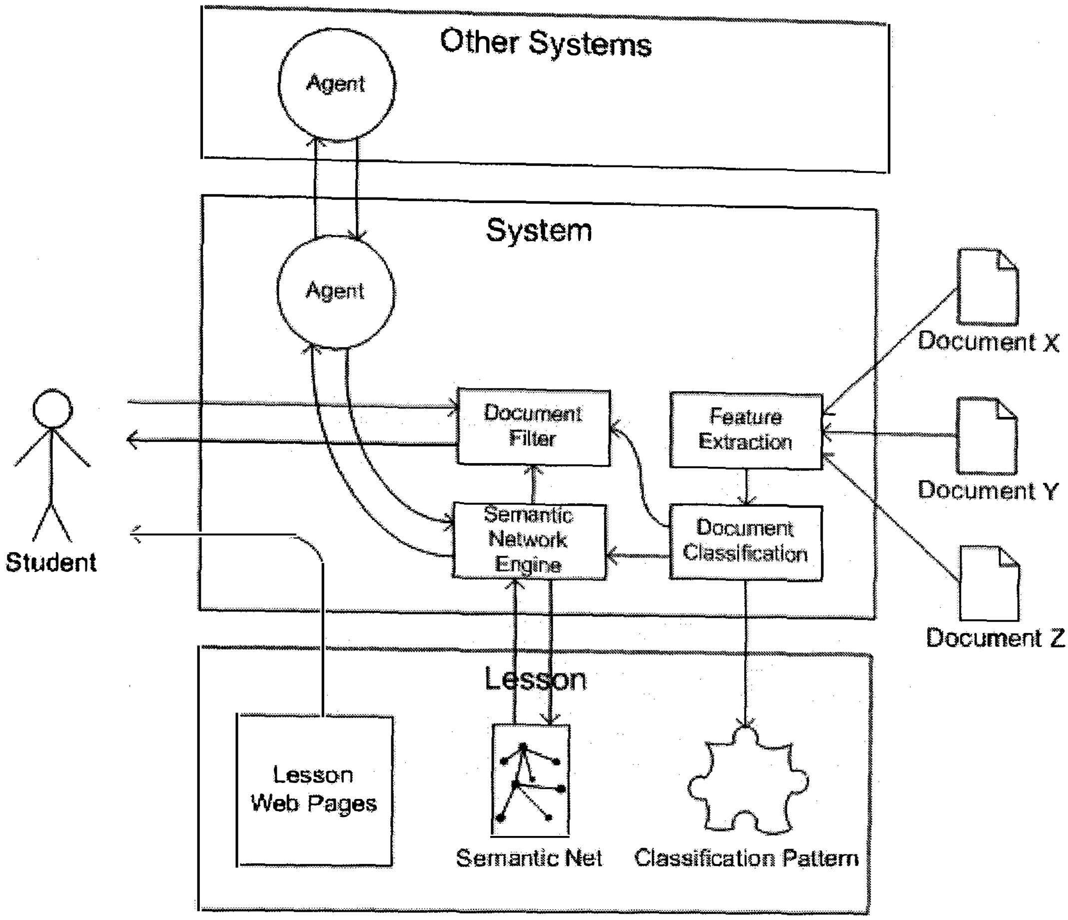


Figure 6.8: Content-based filtering enhanced with semantic networks and agents.

6.2. A new collaborative agent system model

Devedžić (2003) stated that "*Next-generation Web-based educational applications should exhibit more theory and content-oriented intelligence and adaptability, pay more attention to interoperability, reusability, and knowledge sharing issues, and look more closely to general trends in Web development*". Subject-specific filtering using document categorisation was flexible enough to enable students to use the Internet as a research tool while keeping them focused on a subject, but the model lacked adaptability to meet student learning styles and did not provide any collaboration facilities. The research moved on to the creation of a model of a new collaborative agent system that adapted to users depending on their learning style and enabled them to collaborate by automatically recommending relevant and suitable pages found by other students.

CAI systems described in Section 2.4.5 used content-based document classification and agents to assist users in navigating the Internet by providing page ratings, suggesting query words and compiling information from interesting pages. None of these systems provided Internet access control based on the relevance of page contents to a subject. CAI systems described in Section 2.4.5 provided intelligent content adaptation based on learning style and previous knowledge. These systems worked with Web-based adaptive material created with proprietary tools. The systems assessed students' learning styles through questionnaires or colour tests in the case of CITS [Razek *et al.* (2003)]. iWeaver [Wolf (2002)], TANGOW [Paredes *et al.* (1999)] and CITS dynamically adapted to preferences by monitoring user feedback and navigation patterns. None of these systems used Web pages readily available on the Internet, or inferred students' learning styles by analysing the way users navigate and interact with standard Web browsers.

In the research presented in this thesis a new model of collaborative agent system was designed (Figure 6.9). The new system filtered and recommended Web pages from the Internet to students based on three different dimensions:

- Page relevancy, based on contents.
- Page layout based on student learning style.
- User activity (active or inactive).

When students requested Web pages, page contents were retrieved by a document filter and access to the page was granted if it matched a subject relevance pattern within a threshold as described in Sections 6.1.2 and 6.1.3. Relevant Web pages' structure was compared with a document learning style pattern to find the suitability of the page for each dimension of learning style and this information was shared with other systems in the group by a collaborative agent. A UI agent determined user dimensions of learning style and activity by monitoring the way in which the user interacted with Web pages. To encourage users to join the learning experience after periods of inactivity, pages found by other students that suited their learning style were recommended to them by a recommender agent.

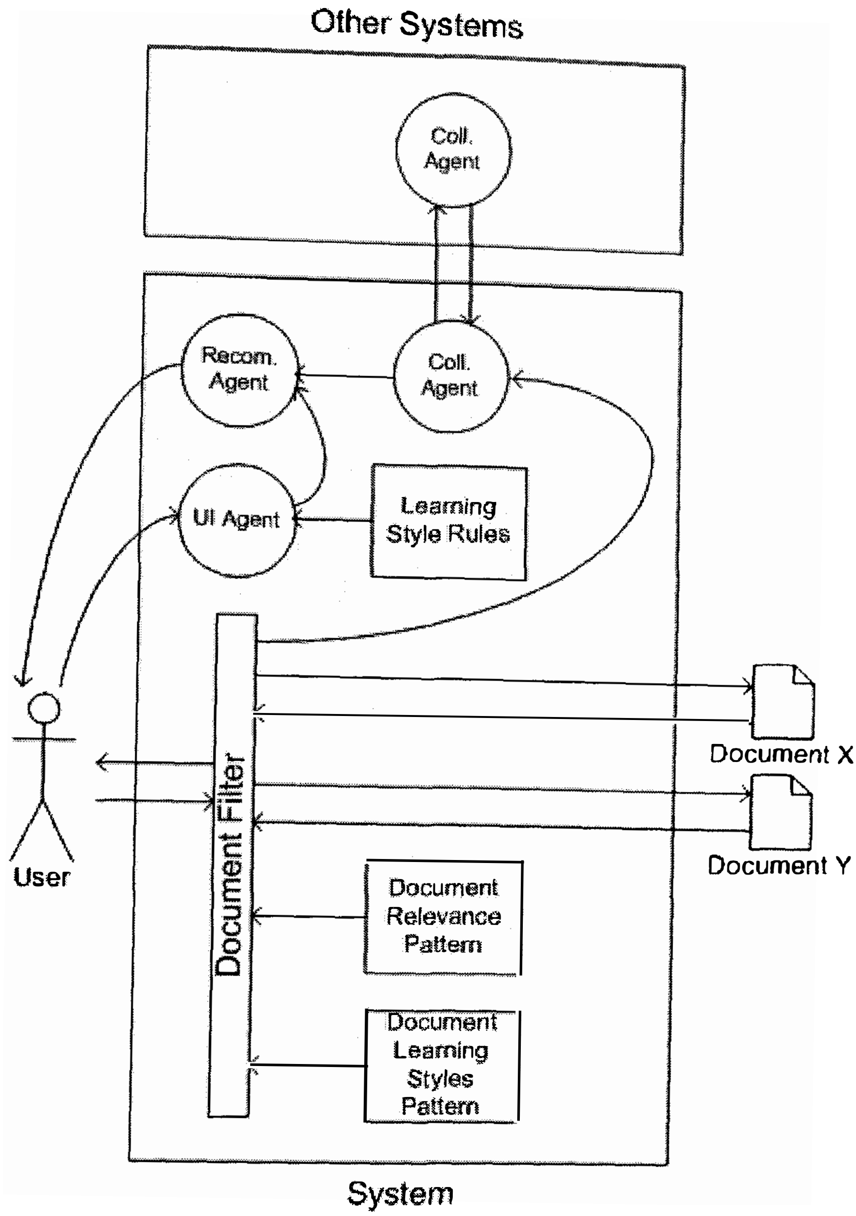


Figure 6.9: Model of the new collaborative agent system

The new model of collaborative agent system enabled students to use the Internet to freely investigate a subject. Teachers trained the system by ranking a set of Web pages with a relevancy rating for a subject. The most significant features to determine whether a page is relevant or not were automatically selected using DF (described in Section 9.512.5), and kNN (described in Section 9.512.5) was used to determine the relevance of new pages based on their contents.

The Felder-Silverman dimensions of learning style model was a well-accepted model used in several adaptive hypermedia applications such as LSAS [LSAS (n.d.)], CS388 [Carver *et al.* (1999)] and Tangow [Paredes *et al.* (2002)]. It was selected because it provided four dimensions of learning style that could be measured from data obtained from the computer systems such as timings, actions, locations, etc.

Rules to infer user learning style and determine the suitability of web pages for each learning style could also be used to enhance the distance-learning WBT systems described in Chapter 2 to provide adaptation based on learning style without the need of questionnaires.

6.3. The new intelligent agent systems

In order to automatically determine the learning style of a student, patterns needed to be found in the way users with different learning styles interacted with a standard Web browser. It was also necessary to find patterns in the layout and elements of Web pages that were easier to understand by students depending on their learning style.

Two new intelligent agent systems were created to record user activity and Web page structure while using Web browsers. Data was then analysed to find rules to determine student learning style and the suitability of Web pages for each learning style depending on their layout and contents.

6.3.1. Solstice: A Web browser agent

Solstice was a browser agent prototype created by the author to test the ability to retrieve user activity and document layout information from a standard Web browser such as Internet Explorer (IE).

The Solstice UI was built on the same technology as the iLessons UI using Microsoft Visual C++ 6.0 and Explorer Extensions. It consisted of an explorer toolbar displaying a DHTML UI (Figure 6.10).

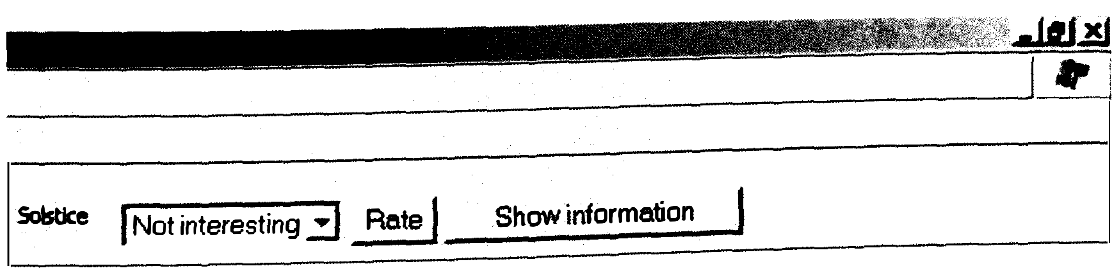


Figure 6.10: Solstice UI

Users could rate the page being displayed as "interesting" or "not interesting" by selecting an option in the drop-down list and clicking on the "rate" button. Solstice displayed recorded information when users clicked on the "Show information" button.

User activity data collected by Solstice was: Timing of navigation events; scrolling activity; and page rating. Page structure data collected by solstice was: Page terms and Outgoing hyperlinks.

6.3.2. The intelligent agent system: BUCAgent

A new intelligent agent system called BUCAgent (Browser User and Contents Agent) was created by the author using Microsoft Visual C++ 6.0 and Explorer Extensions to record UI activity information that could be used to find rules that helped to infer users' dimensions of learning style, as well as document structure features and user ratings that could be used to infer the suitability of documents for each learning style (Figure 6.11).

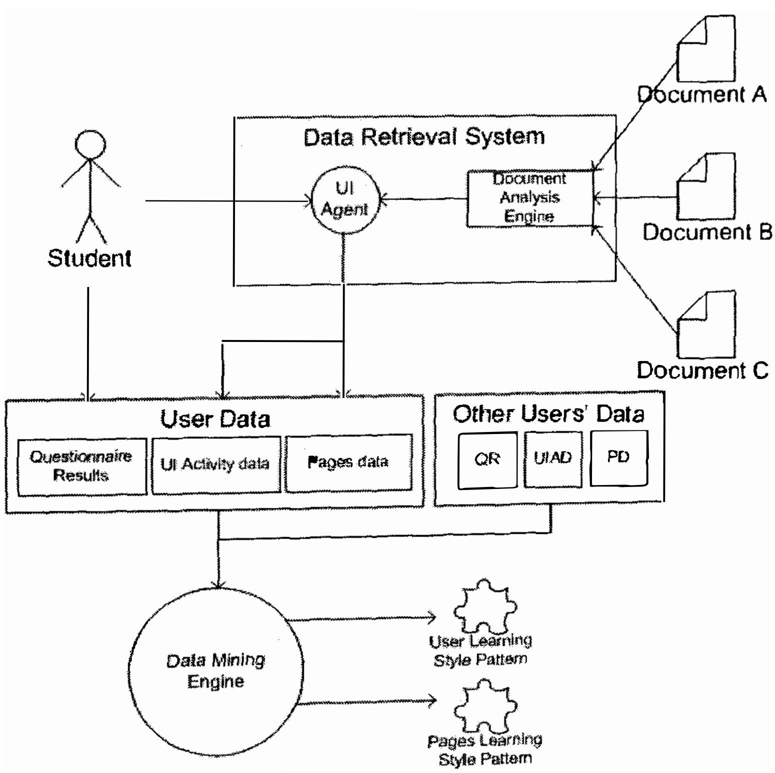


Figure 6.11: Model of BUCAgent

A user agent stored user dimensions of learning style; monitored UI activity; and analysed the Web pages visited and rated by users using a document analysis engine. User agents could be saved into a file and imported into a database to be combined with data from other users. Data was analysed to create rules that could infer user learning styles from the way users utilised the Web browser, and find the suitability of pages for each dimension of learning style.

The Microsoft Access database system was selected to save the information collected by BUCAgent, because easy access from Microsoft Visual C++ code was provided and this was available for the research.

The BUCAgent UI (Figure 6.12) was built using Explorer Extensions because it could be integrated with iLessons and it was easy to retrieve user activity and page information. The UI consisted of an explorer toolbar displaying a DHTML UI.

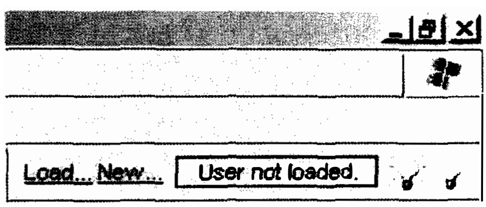


Figure 6.12: The BUCAgent UI

Two links, "Load..." and "New..." enabled researchers to load user agents previously saved to a file and to create new user agents. A lit bulb and switched off bulb buttons were utilised by users to rate pages as "easy to understand" or "difficult to understand".

When researchers created new user agents, a user profile window (Figure 6.13) was displayed so that users could enter their name and dimensions of learning style. This information was added to the new user agent, and was imported to the database with the rest of the information recorded by the agent. "AR" meant "Active/Reflective"; "SI" meant "Sensing/Intuitive"; "VV" meant "Visual/Verbal" and "SG" meant "Sequential/Global".

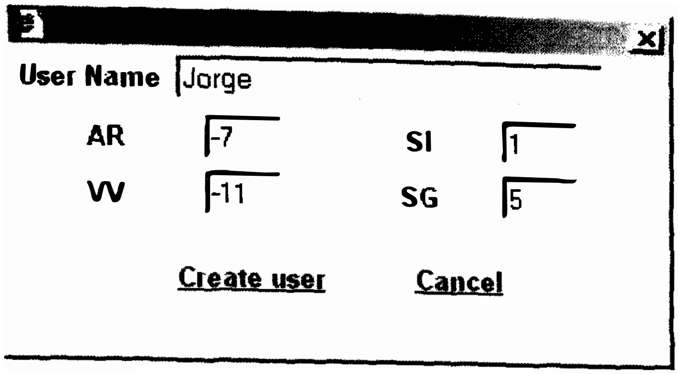


Figure 6.13: User profile creation UI

Scores were taken from ILS questionnaire [Felder & Spurlin (2005)]. A negative number was used for the first element of each dimension pair, and a positive element for the second. For example, in Figure 6.13 it can be seen that VV is equal to -11, which meant that the user was "visual" with a score of 11; SG is equal to 5, which meant that the user was "global" with a score of 5. Initials were used instead of dimension names to prevent users from knowing their dimensions of learning style as it was thought that this could bias their behaviour. When a user agent was loaded, the user name was displayed in the BUCAgent UI (Figure 6.14).

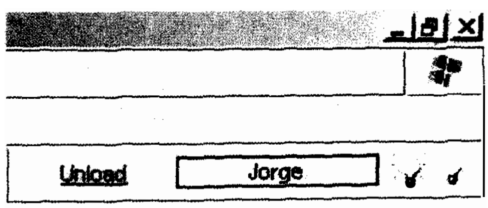


Figure 6.14: BUCAgent UI with user profile loaded

User agent information was imported into five tables in a Microsoft Access database using a database importer created by the author:

A "users" table contained user names and dimensions of learning styles.

A "userAnalysis" table contained user activity data retrieved by BUCAgent while users interacted with Web pages. Each entry linked with an entry in the "documentAnalysis" table, representing the pages that users interacted with.

A "documentAnalysis" table contained Web page data recorded by BUCAgent. If data for the same URL was entered twice, it was compared to check that the document had not changed, and only unique documents were imported. Relational data was updated so that different user activity data recorded from the same page pointed to a unique record in this table.

A “userRatings” table contained user ratings for Web pages stored in “documentAnalysis”.

A “dataObjectAnalysis” table contained user clipboard activity data recorded by BUCAgent.

For a detailed description of the tables and their relationships, see Appendix C.

6.4. Chapter discussion

Allowing and denying specific areas of the Internet was an effective way of controlling the misuse of the Internet during a lesson and of focusing attention, but students were not able to use the Internet to carry out their own research.

Research moved on to investigate subject-specific filtering using document categorisation. A number of feature extraction and document classification algorithms were considered, and DF and kNN were selected. Content-based document filtering was flexible enough to enable students to use the Internet as a research tool while keeping them focused on a subject, but the system lacked adaptability to meet student learning styles and did not provide any collaboration facilities.

A number of learning style models were considered, and the Felder-Silverman dimensions of learning style model was selected because it provided four dimensions of learning style that might be measured from data obtained from the computer systems. CAI systems providing content adaptation based on user learning styles were described, but none of them provided content-based document filtering. These systems worked with Web-based adaptive material created with proprietary tools. The systems assessed students' learning styles through questionnaires and some adapted dynamically to preferences by monitoring user feedback and navigation patterns, but none of these systems used Web pages readily available on the Internet, or inferred students' learning styles by analysing the way users navigate and interact with standard Web browsers.

A model of a new collaborative agent system to provide a less restrictive filtering mechanism based on the relevance of Internet pages to a subject, and to consider individual student learning styles was created using iLessons as a base platform within Internet Explorer. In order to automatically determine the learning style of a student, patterns needed to be found in the way users with different learning styles interacted with a standard Web browser. It was also necessary to find patterns in the layout and elements of Web pages that were easier to understand by students depending on their learning style. These patterns could also be used to enhance distance-learning WBT systems described in Chapter 2. Two new intelligent agent systems were created to record user activity while using Web browsers and Web page structure. Data could then be analysed to find patterns to determine student learning style and the suitability of Web pages for each learning style depending on the page layout and content.

CHAPTER SEVEN

TESTING OF THE NEW INTELLIGENT AGENT SYSTEMS

This Chapter describes the testing and results of the two new intelligent agent systems described in Chapter 6: Solstice and BUCAgent. The new intelligent agent systems were used to record user activity and page structure information from users while navigating the Internet. This information was then used to find rules to predict user learning style. The experimental results are described in Chapter 8.

7.1. Testing of Solstice

Solstice was created using Explorer Extensions and integrated with iLessons. A model of the Solstice system can be seen in Figure 7.1.

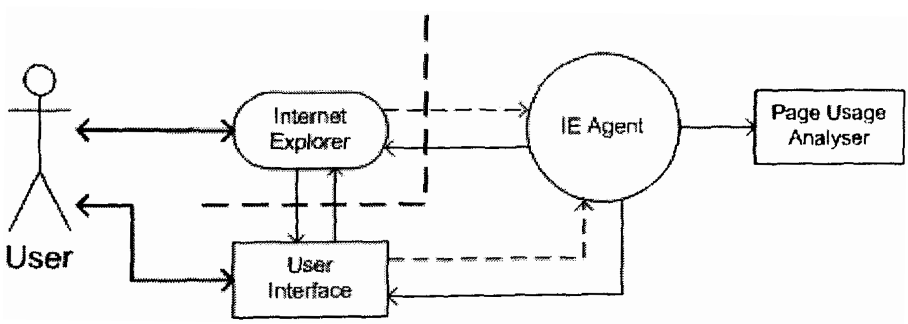


Figure 7.1: Model of Solstice

An Internet Explorer (IE) agent successfully monitored navigation events raised by IE and page information was retrieved by a page usage analyser. The page usage analyser also stored page ratings provided by the user through the User Interface (UI), and recorded the timing of navigation and scrolling events. Web pages were generated (Figure 7.2) showing the information retrieved by Solstice when users requested it by clicking on the "Show information" button.

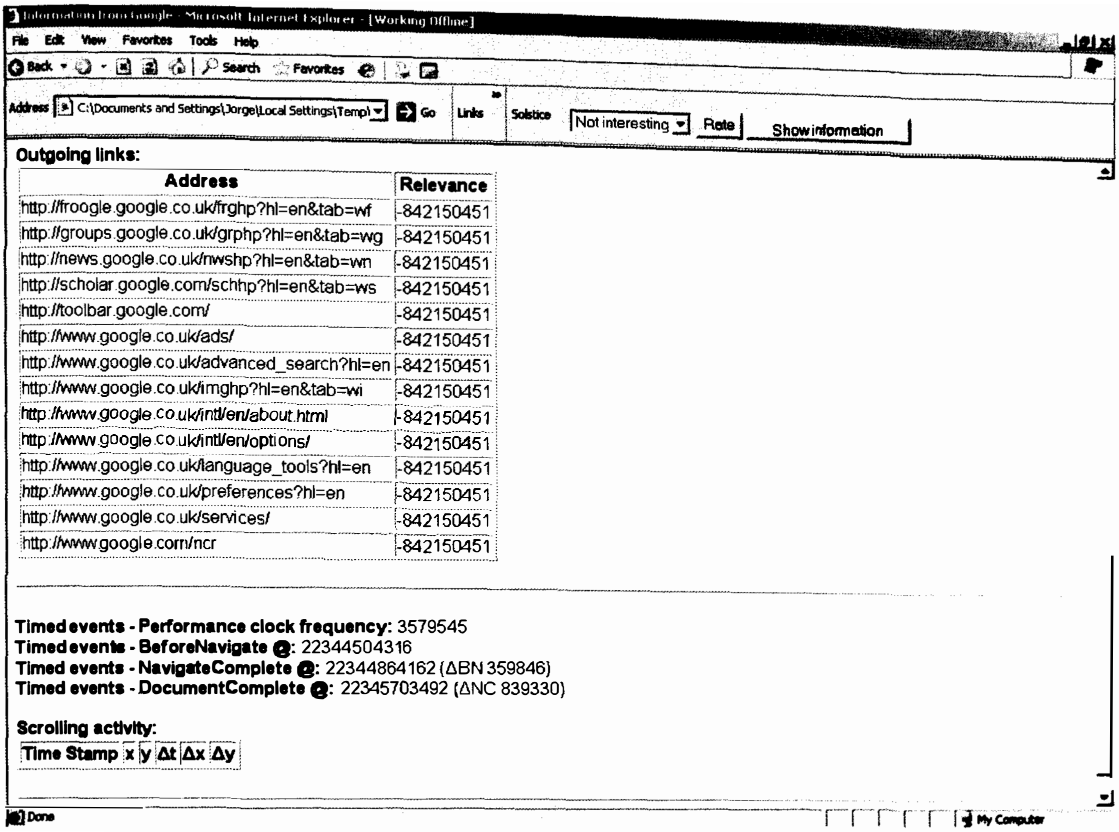


Figure 7.2: Solstice displaying data collected from page

7.1.1. Testing of user and page data recording

Solstice was entirely created and tested by the author. White box testing was performed over each of the three main modules: IE Agent, User Interface and Page Usage Analyser, ensuring that all logical paths and data structures within the code were correct. Once that Solstice passed white box testing, black box testing was performed by navigating to simple pages; pages that were redirected to other pages; and pages containing frames. The author then checked that the information retrieved by Solstice was correct.

Timing of navigation events

The time when the navigation process started, the page download started and the navigation process finished was correctly measured using the operating system's high precision clock.

Scrolling activity

When Scroll events were received, the x and y scroll coordinates were correctly captured as well as the scrolling distance since the previous Scroll event. The time in which the scroll took place was correctly recorded using the system's high precision clock.

Page rating

The page rating given by the user was correctly recorded as "interesting", "not interesting" or "not rated".

Page structure data

Terms found in pages and the outgoing hyperlinks from pages were correctly recorded and counted (Figure 7.3).

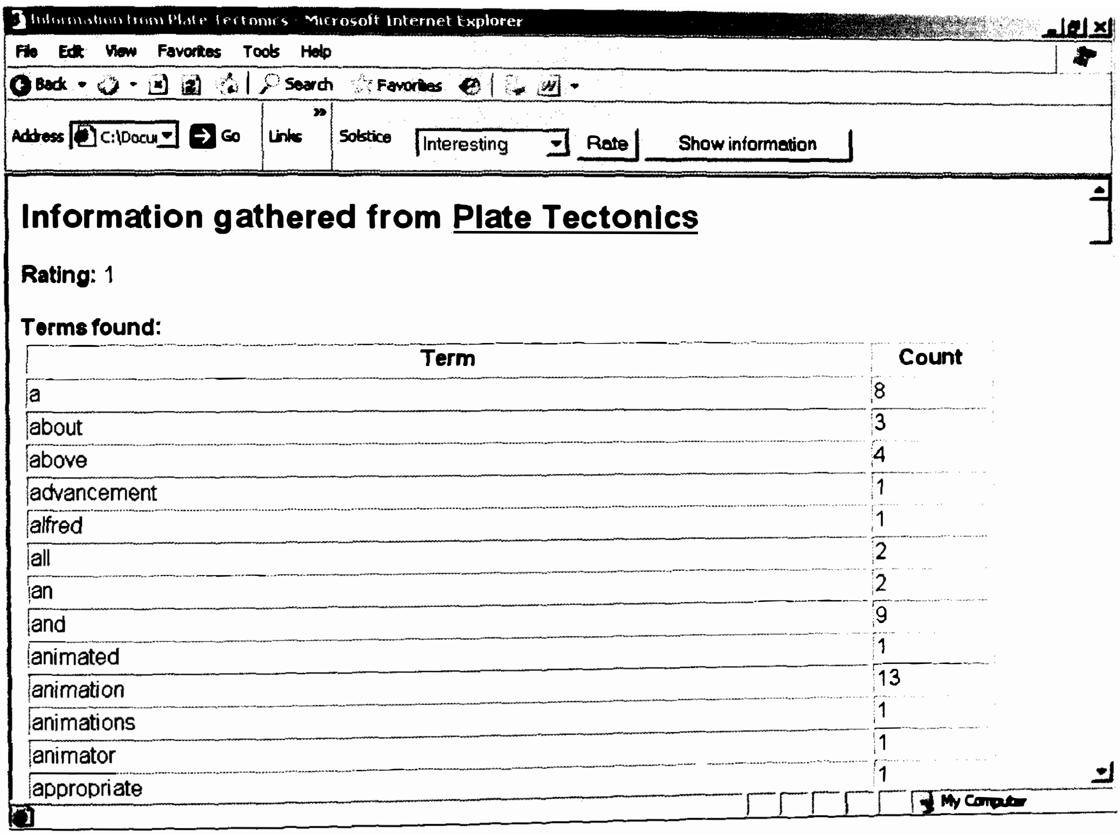


Figure 7.3: Solstice displaying data collected from page

7.2. Testing of BUCAgent

BUCAgent was implemented as a multi-agent system (Figure 7.4) based on technology created in iLessons and Solstice. BUCAgent comprised two types of agent:

- IE agents were created for each IE window and monitored IE events, retrieving page and user activity data.

- A single user agent was created in the system. The user agent kept the user profile and recorded user activity information and document contents analysis from IE agents.

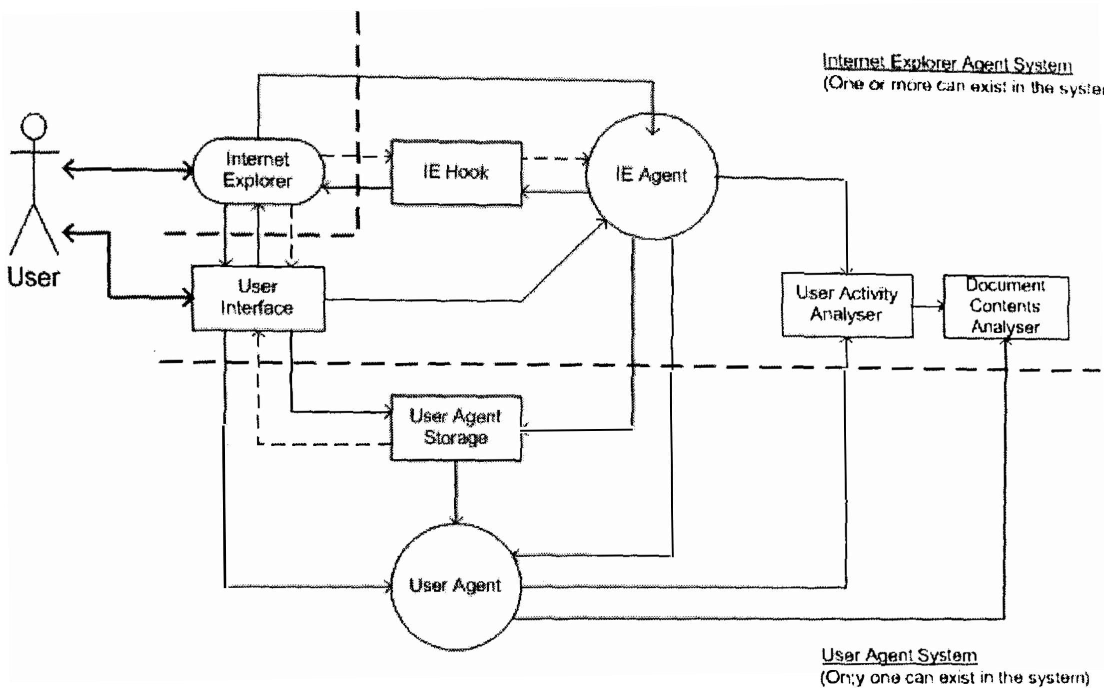


Figure 7.4: Model of BUCAgent

White box testing was performed over each of the BUCAgent modules shown in Figure 7.4:

An IE Hook monitored the events fired by IE when users navigated to a Web page, and signalled the IE Agent when IE started and finished navigating to a page. Information was successfully retrieved about how users navigated to each page: By typing a URL in the address bar, by clicking on a link in the previous page, or by using the back and forward buttons. This was tested by navigating to simple pages; pages that were redirected to other pages; and pages containing frames and checking the values returned by the IE agent. As explained in Chapter 5, Section 5.3.4, pages containing frames did not provide a URL for each combination of frame contents, so only navigation events on the main frame of pages containing frames was monitored.

When Web pages were loaded, IE Agents created User Activity Analysers and Document Contents Analysers. User Activity Analysers monitored UI events and recorded parameters such as mouse movements and scroll activity. Document Contents Analysers successfully recorded information such as the number and position of tables, or the area of the images contained in the page. If users rated Web pages, the UI passed this information to the IE agent, which successfully included it into the document content analysis. Details about the testing of the User Activity and Document Contents Analysers are described in Sections 7.2.1 and 7.2.2.

When new pages were loaded or IE windows hosting IE agents were closed, User Activity and Document Content analysis were sent to the User Agent. The User Agent saved into a file at the end of the session in a predetermined directory in the computer hard disk. Data was saved into the file by using Structured Storage functions. Structured storage allowed data to be saved into streams, and created nested substorages within storages. Data was saved in a single stream: User Agent data such as user name and dimensions of learning style was saved first, followed by the user activity data for each page visited, coupled with contents data from the page.

IE agents and UIs communicated with the User Agent by a User Agent Storage that successfully controlled the creation, load and unload of user agents in the system. The User Agent Storage and User Agent were tested by saving User Agent files and loading them and then checking that the data in memory was the same.

7.2.1. Testing of the user activity data collection

UI interaction parameters recorded by the agent were: time when the parameters where recorded; time viewing a page; mouse activity; scrolling activity; use of back and forward buttons; and clipboard activity. The successful recording of these parameters was tested by navigating to different kinds of pages, performing a number of actions such as moving the mouse at different speeds and scrolling up and down, and checking that the values were as expected.

Time

The time when users navigated to a page and when the agent started to record user activity were correctly recorded using the operating system's high precision clock, as well as the time that users spent viewing each page.

Mouse activity

Mouse movement events were captured. Total mouse movement distance within a page (d_m) was recorded relative to the size of the IE window (see Equation 7.1), because distance in pixels could vary depending on the size of the window or screen resolution. Δx and Δy were the mouse distance in pixels recorded in each mouse movement event. W_w and H_w were the window's width and height in pixels.

$$d_m = \sum \sqrt{\left(\frac{\Delta x_m}{W_w}\right)^2 + \left(\frac{\Delta y_m}{H_w}\right)^2}$$

Equation 7.1: Mouse distance relative to window size (d_m)

The amount of movement in the X and Y axis (d_x and d_y) were recorded as normalised values using Equation 7.2 and Equation 7.3. This was a measurement of how the total distance was distributed in the X and Y axis.

$$d_x = \frac{\sum \frac{|\Delta x|}{W_w}}{d_m}$$

Equation 7.2: Normalised distance in the X axis (d_x)

$$dy = \frac{\sum \frac{|\Delta y|}{H_w}}{d_m}$$

Equation 7.3: Normalised distance in the Y axis (d_y)

Average mouse speed (s_m) was first calculated using Equation 7.4. This speed measurement was not adequate because it tended to zero when the user did not move the mouse for long periods of time, not giving an accurate indication of the average mouse speed.

$$s_m = \frac{d_m}{t}$$

Equation 7.4: First mouse speed equation

Average instant mouse speed (s_{im}) was used instead. Instant speed was calculated by measuring the mouse distance and the elapsed time between two mouse movement events, as illustrated in Equation 7.5. Δx and Δy were the mouse distance in pixels recorded in each mouse movement event for the x and y axis. W_w and H_w were the window's width and height in pixels. Δt was the time taken to cover the measured distance between two consecutive mouse movement events. N was the total number of mouse movement events captured. Δd was the normalised distance as described previously.

$$s_{im} = \frac{\sum_{i=1}^{n} \frac{\sqrt{\left(\frac{\Delta x}{W_w}\right)^2 + \left(\frac{\Delta y}{H_w}\right)^2}}{\Delta t}}{n} = \frac{\sum_{i=1}^{n} \frac{\Delta d}{\Delta t}}{n}$$

Equation 7.5: Average instant mouse speed

S_{im} was not affected by periods of inactivity, and modelled mouse usage more accurately than average mouse speed: Figure 7.5 shows that when fast mouse movements are captured, s_m remains more or less constant, while s_{im} increases with speed.

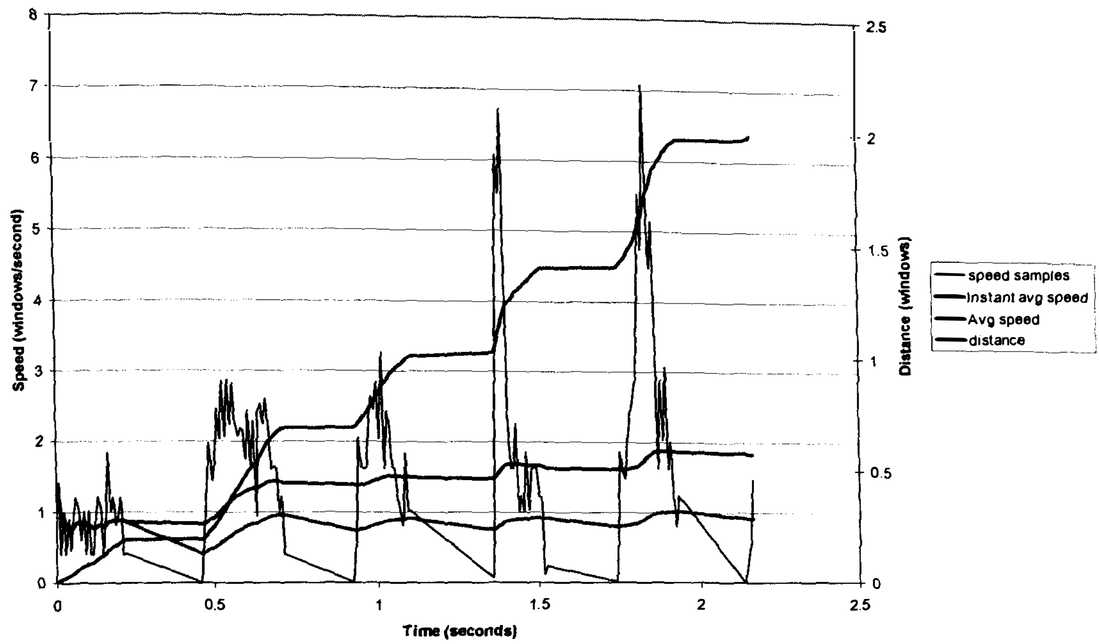


Figure 7.5: Fast mouse movement measures

Figure 7.6 shows the effect of 35 seconds of inactivity on both measurements. While s_m decreases, s_{im} remains constant.

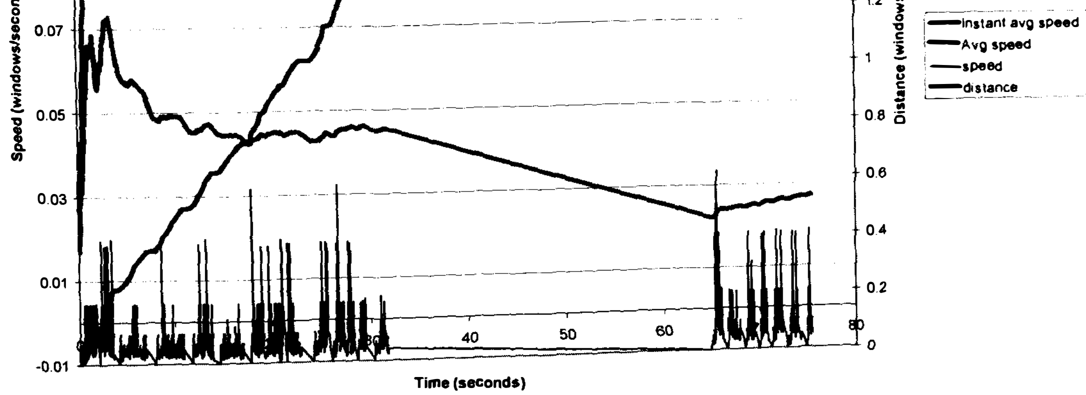


Figure 7.6: Slow mouse movement measures

Figure 7.7 shows both measures in a pattern of fast mouse movements followed by periods of slow mouse movements. s_{im} takes less time to show the changes in speed patterns than s_m.

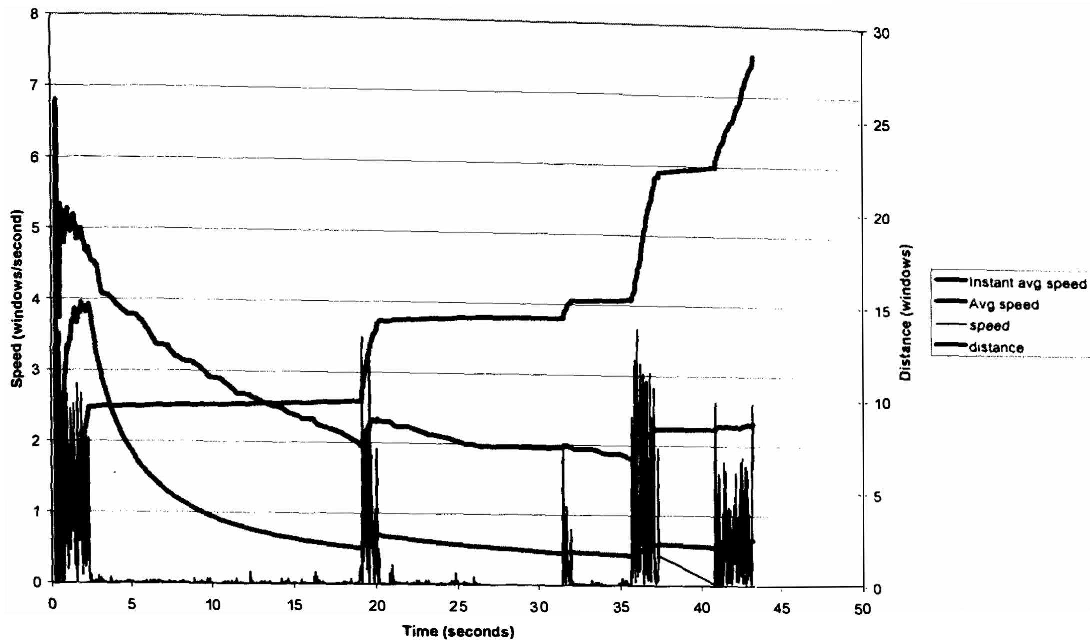


Figure 7.7: Mouse movement measures of fast and slow intervals

Scrolling activity

Scroll events were captured in each page. Only vertical scrolling was recorded because most pages were rendered to fit in the width of the IE window. Scrolling distance (d_s) was recorded relative to the size of the IE window (see Equation 7.6). Δy_s was the scroll distance in pixels recorded in each Scroll event. H_w was the window's height in pixels.

$$d_s = \sum \frac{\Delta y_s}{H_w}$$

Equation 7.6: Scroll distance relative to window size (d_s)

Average instant scrolling speed (s_{is}) was used instead of average scrolling speed for the same reasons described for s_m and s_{im}. s_{is} was calculated by measuring the scrolling distance and time elapsed between two Scroll events, as illustrated in Equation 7.7. Δy_s was the scroll distance in pixels recorded in each scroll event for the y axis. H_w was the window's height in pixels. Δt was the time taken to cover the measured distance between two consecutive scroll events. N was the total number of scroll events captured.

$$s_{is} = \frac{\sum_{i=1}^{n} \frac{|\Delta y_s|}{\Delta t \times H_w}}{n}$$

Equation 7.7: Average instant scroll speed (s_{is})

Changes in scrolling direction, called "scroll peaks" were successfully recorded. Scroll peaks were an indicator of whether the user scrolled down to the bottom of the page once, or scrolled up and down looking for information.

Use of back and forward buttons

In a first approach, use of back and forward buttons was successfully recorded in a vector of characters. Navigations performed by entering a URL or clicking on a link were represented with the character "N", navigations performed by clicking on the "back" button were represented with the character "B" and navigations performed by clicking the "forward" button were represented by the character "F". Vectors from each IE window were concatenated when the user agent was unloaded to form a single string that was then concatenated with a string from previous navigations in the user profile.

This option was dismissed because no meaningful information could be extracted from it and there was no reliable means of capturing "back" and "forward" navigation events. Instead, the way pages were entered and left was recorded. Three different ways of entering or leaving a page were defined: typing the URL in the address bar; clicking on a hyperlink; or pressing the back / forward buttons. Back / forward events were not captured, but detected by discarding the other two options.

Clipboard activity

Copy, Cut and Drag and Drop events were successfully captured. When users cut, copied or dragged fragments of Web pages, these fragments were analysed in the same way as documents. Also, the number of times that clipboard operations took place were recorded.

7.2.2. Testing of the page structure data collection

Recorded page structure parameters were: length of page text; number and area of images; ratio of text to images, presence and location of elements; presence and location of special characters and keywords. The HTML code of each page was also saved so that additional information about elements, characters of keywords could be queried if needed. The successful recording of these parameters was tested by navigating to different kinds of pages and checking that the values were as expected by comparing them with the HTML code of each page.

Length of page text

The text length of pages in characters was correctly recorded in memory while the User Agent was active. Page lengths were saved into a file with the rest of User Agent data when the User Agent was unloaded.

Images area

The area of all the images in each page was correctly calculated in pixels and recorded in memory while the User Agent was active. Image areas were saved into a file with the rest of User Agent data when the User Agent was unloaded.

Number and location of elements

The number and location of images, tables, lists, sound files, video files, animations and ActiveX components was successfully recorded in memory while the User Agent was active and into a file when the User Agent was unloaded. Page height was divided in three parts: top, middle and bottom, and the number of elements in each part of the page was recorded as an array of three integers.

Number of special characters and keywords

The number of question marks, exclamation marks and keywords such as: “example”, “figure”, “question” and “diagram” was correctly recorded in memory while the User Agent was active and into a file when the User Agent was unloaded.

7.2.3. Testing of the database importer

An application was created by the author to import data from user agent files into a database, so that data could be analysed using a data mining engine. The application UI (Figure 7.8) was a single dialog that allowed users to specify paths to user agent files. A folder path could also be entered to import all user agent files found in the specified folder. The application showed detailed information of the import process.

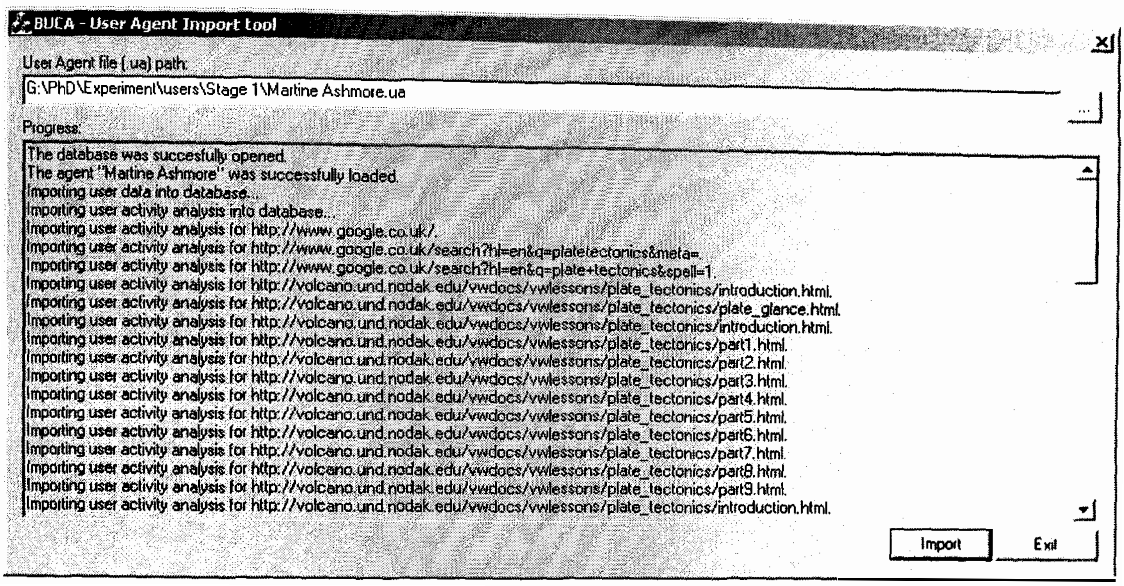


Figure 7.8: Database importer UI

The database importer was tested by importing a User Agent file into the database and then checking that the values in the database were the same as the values stored in the file. Once that this was tested, several files were imported to check that records were not duplicated. For example, if two users accessed the same page and the page contents were identical, only one record was created for the page.

7.3 *Chapter discussion*

This Chapter described the testing and results of the two new intelligent agent systems described in Chapter 6: Solstice and BUCAgent.

Solstice was created using Explorer Extensions and integrated with iLessons. Solstice successfully navigation events raised from IE and page information, event timings and user ratings were retrieved. Web pages were generated showing the

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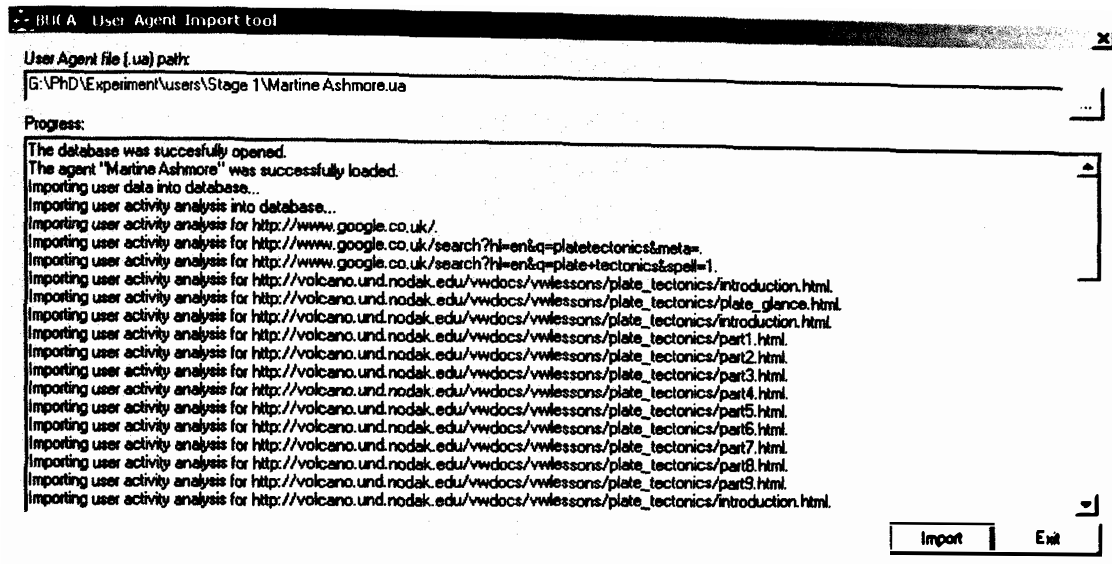

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Solstice was created using Explorer Extensions and integrated with iLessons. Solstice successfully navigation events raised from IE and page information, event timings and user ratings were retrieved. Web pages were generated showing the information retrieved by Solstice. Solstice was entirely created and tested by the author. White box testing was performed over each of the three main modules: Internet Agent, User Interface and Page Usage Analyser. Once that white box testing was passed, black box testing was performed by navigating to different kinds of pages and checking that the information retrieved by Solstice was correct.

BUCAgent was implemented as a multi-agent system based on technology created in iLessons and Solstice. BUCAgent comprised two types of agent: IE Agents and a single User Agent. White box testing was performed over each of the BUCAgent modules. Each module was tested by navigating to a number of different pages and performing a number of actions, checking that the values recorded by BUCAgent were as expected. The User Agent Storage and User Agent were tested by saving User Agent files and loading them, checking that the data in memory was the same.

An application to import data from user agent files into a database was tested by importing a User Agent file into the database and then checking that the values in the database were the same as the values stored in the file. Once that this was tested, several files were imported to check that records were not duplicated.

CHAPTER EIGHT
EXPERIMENT AND RESULTS

WBT systems described in Chapter 6, Section 2.5.1 provided intelligent content adaptation based on learning style and previous knowledge. These systems worked with Web-based adaptive material created with proprietary tools. The systems assessed students' learning styles through questionnaires, and dynamically adapted to preferences by monitoring user feedback and navigation patterns. None of these systems used Web pages readily available on the Internet, or inferred students' learning styles by analysing the way users navigate and interact with standard Web browsers.

A new model of collaborative agent system described in Chapter 6, Section 6.3 took a new approach to the use of learning styles in WBT systems: The collaborative agent filtered and recommended readily available pages from the Internet to students based on student learning style, page relevance and student activity, automatically inferring their Felder-Silverman dimensions of learning style described in Chapter 6, Section 6.2 by the way users interacted with a standard Web browser User Interface (UI). Proprietary tools or questionnaires were not needed. Rules were searched to automatically determine the learning style of students by analysing the way students with different learning styles interacted with standard Web browsers. Rules to determine the Active/Reflective, Sensing/Intuitive and Visual/Verbal dimensions of learning style were successfully found. Rules for the layout and elements of Web pages were also investigated to determine which layouts students found easier to understand, so that suitable Web pages could be recommended to students based on their learning style, but rules were not found due to a lack of data from the experiment.

BUCAgent, described in Chapter 6, was utilised in a controlled environment to retrieve UI activity and document structure data while volunteers completed an experiment task. This Chapter describes how the experiment to retrieve data was designed and implemented, how the data was cleaned and analysed, and what the results of the analysis were.

8.1. Experiment design

The experiment was designed to retrieve user dimensions of learning style, UI activity data and Web page structure data. Collected data was analysed using the PolyAnalyst data mining engine to find rules to predict user dimensions of learning style and the suitability of Web pages for each dimension of learning style.

Data retrieval and recording was performed by BUCAgent described in Chapter 6. Data was saved into files that could be imported into a Microsoft Access Database using the database importer described in Chapter 7, Section 7.2.3. Data cleaning was performed in the database and was then imported into a data mining engine called PolyAnalyst, where it was analysed.

The experiment was designed to be implemented in three stages:

a) *Stage I: Population sampling*

During Stage I, volunteers were requested to complete the Index of Learning Styles (ILS) questionnaire [Felder & Spurlin (2005)] and results were entered into a Microsoft Excel Spreadsheet so that their dimensions of learning style were known before the experiment. Information about the results was not given to the volunteers at this stage, as it was suspected that knowledge about dimensions of learning style could bias user behaviour during the second stage of the experiment.

b) *Stage II: Data retrieval*

During Stage II, volunteers investigated a subject for 15 minutes using Internet Explorer (IE) and BUCAgent embedded within it. Volunteers were asked to optionally rate pages using the agent's UI depending on how easy they were to understand. It was emphasised that this was optional as user behaviour could have been biased if they were given the task to rate each page that they visited.

Volunteers were given a briefing sheet at the beginning of the experiment, outlining what knowledge they were expected to gain during the activity. A copy of the briefing sheet is in Appendix D. The subject was "Plate tectonics: What they are, different types, their effects on the landscape". This subject was selected because all the volunteers were likely to have similar levels of background knowledge and motivation towards it, and also because pages on the subject could be found displaying just text, text and images or text, images and interactive elements, as well as varied layouts.

After volunteers finished investigating, a debriefing sheet was handed to them containing the results of the ILS questionnaire completed in Stage I, as well as a description of the dimensions of learning style.

c) *Stage III: Rule creation*

Data from volunteers was imported into a database, cleaned and imported into PolyAnalyst to seek rules to automatically determine the learning style of users by the way they interacted with standard Web browsers. Rules were also sought in the layout and elements of Web pages so that suitable Web pages could be recommended to students based on their learning style.

8.2. Implementation

The experiment took place from the 27th of October to the 15th of December 2004. 67 people volunteered included staff from the University of Portsmouth and the collaborating company, fellow researchers and friends. The experiment was performed in two stages as described in the previous Section.

a) *Stage I: Population sampling*

The original version of the ILS questionnaire available on the World Wide Web (WWW) was unsuitable for the experiment because information about dimensions of learning style was provided to volunteers and server-side code was required to calculate the questionnaire results, also an active Internet connection was needed. A version of the ILS questionnaire was created using JavaScript to calculate questionnaire results in a Web browser, so that it could be executed locally or sent by e-mail. The questionnaire was also uploaded to a Web server as a back up. Questionnaire results were displayed at the bottom of the page using "AR" for "Active/Reflective", "SI" for "Sensing/Intuitive", "VV" for "Visual/Verbal", and "SG" for "Sequential/Global". This was so that clues were not given to volunteers about their dimensions of learning styles, as described in Section 8.1a.

The JavaScript version was sent by email to 91 potential volunteers. The email described the nature of the research and the experiment stages. Volunteers were requested to complete the ILS questionnaire and send the results to the researcher by email. The address of the ILS questionnaire in the Web server was also given. 67 volunteers completed the ILS questionnaire and results were entered into an Excel spreadsheet. Data statistics are described in Section 8.4.1

b) Stage II: Data retrieval

The data retrieval stage took place in a University of Portsmouth laboratory and in the collaborating company. Both sites were quiet, free of distractions, and provided high speed broadband Internet connections. Tests run at the University were performed using a laptop computer equipped with a mouse. Tests run at the collaborating company were performed using a desktop computer equipped with a mouse. Both systems were configured using the same screen resolution and appearance settings.

20 volunteers from the previous stage volunteered to take part in further stages. BUCAgent was loaded into Internet Explorer on both computers. Volunteers were given a briefing sheet and questions were answered before each test. A user profile was created in BUCAgent containing the dimensions of learning style which had been derived from answers to the ILS questionnaire.

Volunteers were given freedom to decide how to approach the experiment task. Most volunteers read through the task sheet before starting to browse the Internet and others preferred to start browsing while reading it. Some volunteers took notes on paper, others used the clipboard and drag and drop to take notes, and some did not take notes at all.

Volunteer actions and the computer screen were recorded using a digital video camera. A frame from the video capture can be seen in Figure 8.1. In some cases volunteers were observed while performing the experiment and notes were taken on user interface interaction. After 15 minutes, volunteers were asked to finish their activity and the user agent was unloaded, saving data into user files.

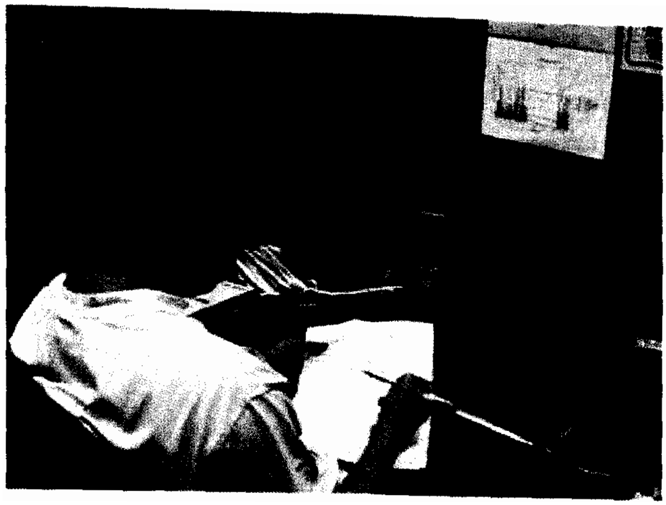

Figure 8.1: Volunteer carrying out experiment task

c) *Stage III: Rule creation*

The rule creation stage took place at the University of Portsmouth. Data from volunteers was saved into files, transferred into a database, cleaned and imported into the PolyAnalyst data mining engine. Rules were successfully found by the data mining engine.

8.3. The data mining process

The data mining process was designed as a series of phases during the three stages of the experiment (Figure 8.2). Data collection encompassed Stages I and II of the experiment and consisted of gathering data from volunteers and importing it into a database using the ILS questionnaire and BUCAgent. Data cleaning consisted of removing inconsistent and erroneous data from the database, as well as transforming data so that it could be manipulated by PolyAnalyst to improve the data mining accuracy.

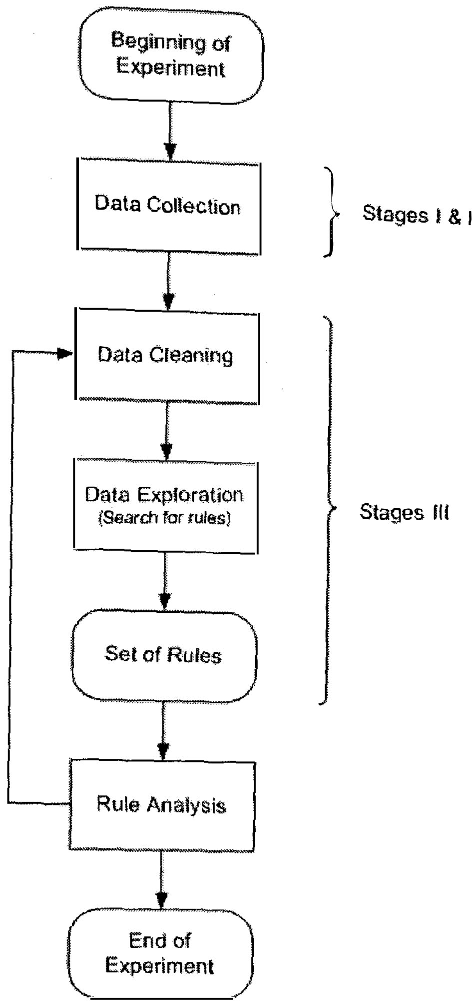

Figure 8.2: The data mining process

PolyAnalyst's data mining algorithms were run during the data exploration phase, providing a set of rules as a result that were analysed during the rule analysis phase to verify that the rules found were accurate and significant. The process from data cleaning to rule analysis was repeated based on the findings of previous iterations in order to improve the accuracy and significance of rules.

8.4. Preliminary statistics and data preparation

8.4.1. ILS questionnaire

The distribution of dimensions of learning style over the initial 67 volunteers can be seen in the first column of Table 8.1. Response data for ILS was collected from a number of studies performed across a wide range of disciplines [Felder & Spurlin (2005)]. The average distribution of dimensions of learning style from these studies can be seen in the second column of Table 8.1. It can be seen that the distribution of dimensions of learning styles in the volunteer population was similar to findings of other studies, apart from the "Sequential/Global" dimension. 75% of other studies were performed in Engineering Faculties, where "Sequential" learning skills were favoured [Felder & Spurlin (2005)], while the sample population in this research came from more diverse backgrounds. This caused the statistics to skew towards the opposite dimension as the proportion of "Global" learners grew.

Dimension	This study	Other studies
Active	**57%**	**60%**
Reflective	43%	40%
Sensor	**52%**	**65%**
Intuitive	48%	35%
Visual	**76%**	**77%**
Verbal	24%	23%
Sequential	34%	**60%**
Global	**66%**	40%

Table 8.1: Distribution of dimensions of learning style over sample population

8.4.2. Data cleaning and transformation

Data retrieved from volunteers was imported into a database composed of five tables as described in Chapter 6 and Appendix C. Data imported into tables was cleaned to improve the data mining accuracy and transformed into two SQL views to be imported to the data mining engine:

A view called *__UserData* contained user dimensions of learning style as well as user activity parameter averages as recorded by agents for each user, so that rules could be found to predict user learning style from the averages of monitored parameters.

A view called *__DocumentData* contained average ratings given by users to documents for each dimension of learning style, as well as document layout parameters, so that rules could be found to predict document suitability for each dimension of learning style.

Data cleaning in the document analysis table

Document entries were removed when they contained URL fragment identifiers; belonged to non-http transactions; were duplicates; or belonged to page redirections. When document entries were removed, associated entries in the user activity table were also removed. In case of URL fragment identifiers or duplicates, user activity entries were modified to point to the right entry in the document analysis table.

a) URL fragment identifiers

Document entries in the document analysis table that contained fragment identifiers were removed, as they represented different sections of a same page. Fragment identifiers (Figure 8.3) were located at the end of URLs and started with a '#' character. Fragment identifiers were used to point to sections of a Web page and enabled Web developers to create hyperlinks within pages.

http://www.domain.com/page.html#section

Figure 8.3: URL fragment identifier

A single entry representing the page was left, and user activity entries associated to document entries containing URL fragment identifiers were modified to point to remaining the entry.

b) Duplicates

Duplicate entries in the document analysis table were removed. User activity entries were modified to point to unique entries. As contents of the same page could vary over time, only entries that had exactly the same URL and attributes were removed. Entries that had the same URL but different attributes were left, as they represented the same page at different moments.

c) Non-http requests

Document entries not representing http requests were removed, as well as associated user activity entries. Non-http entries were pages retrieved using the "res" protocol to display pages stored as resources in an application or DLL in a local machine instead of the "HTTP" protocol. They were, for example, error pages displayed by Internet Explorer when a page was not found.

d) Redirections

Document entries representing redirection pages were removed. Redirection pages were identified because all their recorded parameters were zero. Related user activity entries were also removed.

Data cleaning in the user activity analysis table

User activity entries that contained zero mouse distance or time spent on page were removed. When the scrolling distance was zero, the user activity entry was not removed but scrolling parameters were not taken into account when calculating average scrolling values.

Time values were converted to seconds by dividing them by the frequency of the high precision system clock, so that time values were easier to read and interpret.

8.4.3. Data mining

Once data were retrieved, cleaned and transformed, it was imported into PolyAnalyst in order to generate rules to predict user learning style from the way users with different learning styles interacted with a standard Web browser, as well as rules to predict the suitability of pages to each learning style from the layout and elements of Web pages.

PolyAnalyst 4.6 was a versatile suite of data mining tools. It was selected to perform the data mining because it provided tools for data importing, cleaning, manipulation, visualization, modeling, scoring, and reporting [PolyAnalyst (n.d.)] and it was available for the research. PolyAnalyst provided algorithms for general statistical analysis; association rules; classification rules; predictive analysis and text analysis. Also, the "Classify" tool could be used to transform algorithm output into rules to split a dataset in two groups, such as "Active" and "Reflective" or "suitable" and "unsuitable", by calculating a threshold value for the output using a genetic algorithm. A number of classification algorithms and accuracy measures were considered.

Classification algorithms

Two algorithms were selected: "Linear Regression" and "Find Laws". The output of these algorithms was a human-readable model that could be used to predict a continuous target variable from a set of input attributes.

a) Linear regression

"Linear Regression" was a well known method of statistical prediction. In the case of dependence of y on x, "Linear Regression" could be considered as the process of drawing a line in the plane (x, y), such that the sum of the squares of the distance between this line and each data point was minimized. It provided good models of linear functions, but produced models of nonlinear functions that were accurate only at parts of the function and inaccurate at predicting other parts. PolyAnalyst's multi-parametric stepwise linear regression could work with any number of attributes.

b) Find Laws

The "Find Laws" algorithm generated complex symbolic rules that represented nonlinear dependencies. "Find Laws" was computationally intensive and could take extended periods of time to solve a problem. The number of attributes used in "Find Laws" had to be minimised by using "Linear Regression" beforehand and then running "Find Laws" including only the attributes found to be relevant.

Accuracy measures

PolyAnalyst provided statistical indicators to assess the quality of rules, such as standard error, r-squared, standard deviation and significance index. When "Classify" was utilised, the statistical indicators of rules found by the underlying algorithm were provided, as well as the classification probability, classification efficiency and p-value of the classification rule incorporating the threshold.

Standard Deviation (σ, s or stdev) was a measure of the degree of dispersion of data from its mean value. A large standard deviation indicated that data points were far from the mean and a small standard deviation indicated that they were clustered closely around the mean [Jordan & Smith (2002)]. The standard deviation for a given population can be seen in Equation 8.1. The standard deviation for a sample of values from a larger population can be seen in Equation 8.2. The square of the standard deviation was called *dispersion*.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - \overline{x}\right)^2}{N}}$$

Equation 8.1: Standard deviation

$$s = \sqrt{\frac{\sum_{i=1}^{n}\left(x_i - \overline{x}\right)^2}{n-1}}$$

Equation 8.2: Standard deviation for a sample from a larger population

Standard Error (stderr) was the standard deviation of the predicted values of a target variable with respect to the real values of the target variable for each sample. Let N be the number of data samples and let p_i and P_i be the predicted and real values for the target variables in each sample. The standard error is defined in Equation 8.3.

$$stderr = \sqrt{\frac{\sum_{i=1}^{N}(p_i - P_i)^2}{(N-1)}}$$

Equation 8.3: Standard Error

PolyAnalyst approximated a normalised value of the standard error that was usually in the interval [0...1] by dividing the standard error by the dispersion.

R-Squared (RSq) was equal to $1 - r^2$, where r was the standard error. Its values also lay in the interval [0, 1] , but in contrast with the standard error, it was equal to 1 in the case of an absolutely accurate model.

Significance Index (SIn) was evaluated by PolyAnalyst by comparing the standard deviation for the target variable to standard deviations obtained for artificially generated randomised data with the same distribution of values of independent and dependent variables. This procedure was called *randomised testing.* Randomised datasets were generated using a random permutation of the values of the target attribute between different records. If the standard deviation of the results of the rule obtained from the real data (S_{real}) was similar to the standard deviations obtained from randomised data sets (S_{rand}), it could be concluded that the rule was not significant and had no predicting power. The significance index expressed the degree of difference between S_{real} and S_{rand}, and it was calculated according to Equation 8.4.

$$SI = \frac{S_{real} - S_{rand}}{\sigma_{rand}}$$

Equation 8.4: Significance Index

For this work a rule was considered significant only when its significance index was greater than three.

Classification Probability (Rule) was the percentage of correctly classified records using a classification rule. Let $N_{correctA}$ and $N_{correctB}$ be the number of correctly classified records for classes A and B, and let N_A and N_B be the total number of records of class A and B. The classification probability of the classification rule was calculated as seen in Equation 8.5.

$$cp = 100 \times \frac{N_{correctA} + N_{correctB}}{N_A + N_B}$$

Equation 8.5: Classification probability

The percentage of users of each dimension in the test dataset determined the minimum accuracy required by the found rules. For example, a naïve prediction rule that considered every user as Active would have an accuracy of 80% if 80% of the users in the test dataset were Active. Any algorithm that claims to learn detail about all the inputs must always do better than the naïve prediction [Adriaans & Zantinge (1996)].

Classification Efficiency (ce) provides a measure of the accuracy of a classification rule with respect to a naïve prediction Let $N_{correctA}$ and $N_{correctB}$ be the number of correctly classified records for classes A and B, and let N_A and N_B be the total number of records of class A and B. The classification efficiency of the classification rule was calculated as seen in Equation 8.6.

$$ce = 100 \times \frac{N_{correctA} + N_{correctB} - \max(N_A, N_B)}{\min(N_A, N_B)}$$

Equation 8.6: Classification Efficiency

If 90% of records in a dataset were from class A and 10% were from class B, a naïve classification rule that classified all records as "class A" would have a classification probability of 90%, but a classification efficiency of 0% (see Equation 8.7, ce_{naive}). A classification rule that classified all records correctly regardless of their class had a classification efficiency of 100% (see Equation 8.7, $ce_{accurate}$).

$$ce_{naive} = 100 \times \frac{90+0-90}{10} = 0\% \qquad ce_{accurate} = 100 \times \frac{90+10-90}{10} = 100\%$$

Equation 8.7: Classification efficiency for naïve and accurate classification rules

The *p-value* (PVal) indicates the probability that the result obtained in a statistical test was due to chance rather than a true relationship between measures. The closer p-value was to zero, the more significant the reported dependence was. The p-value was calculated as the probability that a variable would assume a value greater than or equal to the observed value strictly by chance.

The *F-Ratio* (Equation 8.8) was used to determine to what extent independent attributes in a linear regression influenced the target variable. Greater values of F-Ratio (above 3) indicated that the presence of the independent attribute in the linear regression was important to determine the target variable. F-Ratio was calculated as the squared division of the term's regression coefficient by the standard deviation of the regression coefficient.

$$F - Ratio = \left(\frac{RC_{term}}{\sigma_{RC_{term}}} \right)^2$$

Equation 8.8: F-Ratio

8.5. Experiment results

8.5.1. First exploration

A first exploration of the retrieved data involved the use of the algorithm "Classify" to find rules to predict user learning style using the "Linear Regression" underlying algorithm. The input parameters were:

- Average time on page
- Average mouse distance
- Average mouse speed
- Average mouse movement in the X axis
- Average mouse movement in the Y axis
- Average scroll distance
- Average scroll speed
- Average number of changes in scroll direction
- Average document length
- Average image area

The detailed rules can be seen in Appendix F Statistical indicators can be seen in Table 8.2. AR1 could classify users accurately. SI1, VV1 and SG were accurate to some degree but their ce was low. The statistical indicators of underlying linear regressions showed that AR1 was significant, but only slightly above of the minimum significance index threshold, which was set to 3.

	"Classify"			Linear Regression			
Rule	**cp**	**ce**	**PVal**	**StdErr**	**RSq**	**StdDev**	**SIn**
AR1	100%	100%	2.50E-05	0.4038	0.837	0.1898	3.379
SI1	65%	30%	9.80E-01	0.9367	0.1225	0.4805	-1.167
VV1	80%	20%	8.06E-01	0.9557	0.08657	0.4246	-1.01
SG1	75%	38%	7.92E-06	0.9814	0.03685	0.4933	-1.28

Table 8.2: Statistical indicators for first set of rules using "Classify" and "Linear Regression" (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

"Find Laws" was better than "Linear Regression" at finding non-linear dependencies in data. More accurate and significant rules were sought using "Find Laws" and binary values as input, such as 1 for "Active" and 0 for "Reflective". Rules were only found for Active/Reflective (AR2) and Sensing/Intuitive (SI2).

	Find Laws			
Rule	**StdErr**	**RSq**	**StdDev**	**SIn**
AR2	1.00E-05	1	4.58E-06	> 100
SI2	5.49E-05	1	2.75E-05	2.612

Table 8.3: Statistical indicators for first set of rules using "Find Laws" (AR=Active/Reflective; SI=Sensing/Intuitive; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

AR2 and SI2 were accurate with a standard error near to zero. AR2 was significant but not SI2, as its SIn was less than 3.

8.5.2. Second exploration

The dataset was transformed and enhanced to seek more accurate and significant rules. The "Average time on page", "average document length" and "average image area" were imported as integers in the previous exploration, and other attributes were imported as decimal numbers. This was incorrect because "average document length" and "average image area" contained decimals that were lost in the conversion to integer. All attributes were imported as decimal numbers for the second exploration.

A new attribute called "Average count of visited documents per domain" was added. It was expected that "Global" users navigated to many pages of different sites while they grasped general information about concepts, while "Sequential" users would navigate to more pages within a site, retrieving detailed information about a concept at a time. This would result in a lower count for "Global" users and higher for "Sequential" users.

"Classify" was used with "Linear Regression" to perform a preliminary exploration of the dataset. Results can be seen in Table 8.4.

	Classify			Linear Regression			
Rule	cp	ce	PVal	StdErr	RSq	StdDev	SIn
AR3	100%	100%	2.58E-05	0.2876	0.9173	0.1352	3.569
SI3	80%	60%	3.19E-01	0.8815	0.2229	0.4522	-0.9254
VV2	90%	60%	-4.90E-03	0.7761	0.3977	0.3448	0.09402
SG2	75%	38%	7.92E-06	0.9814	0.03685	0.4933	-1.359

Table 8.4: Statistical indicators for second set of rules using "Classify" and "Linear Regression" (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

A general improvement could be seen in classification probability, efficiency and significance for AR3, SI3 and VV2, although SI3 and VV2 were still not effective or significant enough. SG2 statistical indicators remained as in the previous exploration.

"Classify" was run with "Find Laws" over the dataset to seek more accurate and significant rules. As it can be seen in Table 8.5, AR4 showed no improvement with respect to AR2 in Table 8.3. SI4 showed a similar significance index but worse standard error, r-squared and standard deviation with respect to SI2 (Table 8.3). Neither SI2 nor SI4 are significant enough and could be due to random fluctuations, so the lack of improvement was not due to a decline in data quality.

	Classify			Find Laws			
Rule	cp	ce	PVal	StdErr	RSq	StdDev	SIn
AR4	100%	100%	2.58E-05	1.00E-05	1	4.58E-06	> 100
SI4	80%	60%	3.19E-01	0.7367	0.4573	0.3683	2.636

Table 8.5: Statistical indicators for second set of rules using "Find Laws" (AR=Active/Reflective; SI=Sensing/Intuitive; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

8.5.3. Third exploration

The dataset was enhanced with information derived from attributes in the database to seek more accurate and significant rules. "Average document length" and "average image area" were removed because they were not believed to provide useful information to predict user dimensions of learning style as users did not have any control over them. Attributes to model differences in the behaviour of users depending on the length and images of documents were generated by measuring and averaging ratios between user activity attributes, document length and image area. The following attributes were added:

- Average of image area to time on page
- Average of document length to time on page
- Average of image area to mouse distance
- Average of document length to mouse distance
- Average of image area to scroll distance
- Average of document length to scroll distance
- Average of image area to scroll peaks
- Average of document length to scroll peaks

Also, "Average of scroll peaks to time on page" was added to model the relationship between the changes in the direction of scrolling and the time spent in a document. "Average count of visited documents per domain" was removed from the dataset because it did not prove to be relevant to find rules for the "Sequential/Global" dimension of learning style, as SG2's statistical indicators (Table 8.4) did not improve over SG1 (Table 8.2).

"Classify" was run with "Linear Regression" to perform a preliminary exploration of the dataset. Results can be seen in Table 8.6.

	Classify			Linear Regression			
Rule	**cp**	**ce**	**PVal**	**StdErr**	**RSq**	**StdDev**	**SIn**
AR5	100%	100%	2.58E-05	0.2614	0.9317	0.1229	0.3293
SI5	80%	60%	3.19E-01	0.8289	0.3129	0.4252	-0.9782
VV3	100%	100%	6.44E-05	0.4291	0.8159	0.1906	0.4304
SG3	70%	25%	7.43E-01	0.9095	0.1728	0.4572	-1.261

Table 8.6: Statistical indicators for third set of rules using "Classify" and "Linear Regression" (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

There was a drop in the significance index of AR5: SIn for AR5 was 0.3293 compared with 3.569 for AR3 (Table 8.4) or 3.379 for AR1 (Table 8.2). Classification statistical indicators remained the same as in previous explorations, but there was an improvement in the linear regression statistical indicators: Standard error was 0.2614 for AR5, 0.2876 for AR3 (Table 8.4) and 0.4038 for AR1 (Table 8.2). This explained the drop in SIn: The introduction of new attributes enabled the finding of a more accurate rule for AR, but this resulted in over fitting, and while AR5 was more accurate than AR3 or AR1, it represent a less generic model. The same issue occurs in VV3: "Classify" reports an accurate rule, with 100% classification probability and efficiency, but not significant enough (SIn = 0.4304) due to over fitting. SI5 and SG3 showed no improvement compared to previous rules.

"Classify" was run with "Find Laws" over the dataset to seek more accurate and significant rules. Rules for Active/Reflective and Visual/Verbal were found. Results can be seen in Table 8.7.

	Classify			Find Laws			
Rule	**cp**	**ce**	**PVal**	**StdErr**	**RSq**	**StdDev**	**SIn**
AR6	100%	100%	2.58E-05	3.78E-05	1	1.73E-05	6.915
VV4	100%	100%	6.44E-05	3.56E-04	1	1.54E-04	4.891

Table 8.7: Statistical indicators for second set of rules using "Find Laws" (AR=Active/Reflective; VV=Visual/Verbal; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

As in the rules found using "Classify" and "Linear Regression", there was a significant drop in the Significance index of AR6 (SIn = 6.915) compared with AR2 (Table 8.3) (SIn >100) and AR4 (Table 8.5) (SIn >100) due to the reasons described above although it was significant. No significant rule was found for Sensing/Intuitive, but an accurate and significant rule was found to determine the Visual/Verbal dimension of learning style, which was not achieved in previous explorations. As it can be seen in Appendix F, the rule was based entirely on the derived attributes introduced in this exploration. This was the reason why previous explorations failed to find rules for this dimension.

8.5.4. Fourth exploration

A new exploration was performed including derived attributes discussed above as well as the attributes removed in the third exploration: "average document length", "average image area" and "average count of visited documents per domain". "Classify" was run with "Linear Regression" to perform a preliminary exploration of the dataset. Results can be seen in Table 8.8.

The accuracy of AR7 and VV5 improved with respect to AR5 and VV3 (both in Table 8.6) and remained constant for SI6 and SG4. Significance indexes increased compared with the previous exploration, but rules were still over fitted to the data.

	Classify			Linear Regression			
Rule	**cp**	**ce**	**PVal**	**StdErr**	**RSq**	**StdDev**	**SIn**
AR7	100%	100%	2.58E-05	0.2614	0.9317	0.1229	0.3293
SI6	80%	60%	3.19E-01	0.8289	0.3129	0.4252	-0.9782
VV5	100%	100%	6.44E-05	0.4291	0.8159	0.1906	0.4304
SG4	70%	25%	7.43E-01	0.9095	0.1728	0.4572	-1.261

Table 8.8: Statistical indicators for fourth set of rules using "Classify" and "Linear Regression" (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

"Classify" was run with "Find Laws" over the dataset to search for more accurate and significant rules. Rules were sought using the attributes selected by "Classify" and "Linear Regression" instead of the whole set of attributes, in order to optimise the computing time used for the search. Accurate and significant rules for Active/Reflective and Visual/Verbal were found. Results can be seen in Table 8.9.

	Classify			Find Laws			
Rule	cp	ce	PVal	StdErr	RSq	StdDev	SIn
AR8	100%	100%	2.58E-05	8.22E-06	1	3.77E-06	> 100
VV6	100%	100%	6.44E-05	4.74E-03	1	2.05E-03	6.489

Table 8.9: Statistical indicators for second set of rules using "Find Laws" (AR=Active/Reflective; VV=Visual/Verbal; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

Using only attributes found relevant by "Linear Regression" as input for "Find Laws" enabled the finding of AR8, the most accurate and significant rule for Active/Reflective so far. VV6 was less accurate than VV4 (Table 8.7), but more significant.

8.5.5. Further data cleaning and enrichment

The research moved on to analyse the data collected by the agent and see if more data cleaning and transformation could be performed.

DataObjectAnalysis

The DataObjectAnalysis table was discarded because no attributes that helped to determine user learning style were selected by previous explorations from the data contained in the table.

DocumentAnalysis

Data about the number of Web page elements such as images and tables and their position within the page was stored as three values, indicating the number of elements in the top, middle and bottom thirds of each page. It was thought that such detail would make it difficult for PolyAnalyst to find useful patterns. Top, middle and bottom fields were consolidated in a single field that provided information about the number of elements in the page.

UserActivityAnalysis

In previous data cleaning, user activity entries that contained zero mouse distance or time spent on page were removed. This approach was not correct because analysis of data and video feeds showed many instances in which users spent large amounts of time in a page without moving the mouse, for example, by using the "back" or "forward" buttons to navigate to a page. Entries corresponding to user activity that lasted less than ten seconds were removed instead. This was done because in many cases users utilised the back button to navigate to a page, spend a few seconds identifying it and then navigated again away from the page. These interactions were not considered to be relevant and were discarded.

The way that the time spent by users viewing pages was measured did not take into account that users could use more than one Internet Explorer window at the same time. If users navigated to a page and then minimised the window where the page was displayed, the system measured the time spent in the page regardless of the fact that users might not be viewing it. In order to minimise the bias produced by this, the average time spent in viewing pages was calculated for each user, and then the time spent on each page was divided by this average. In this way the information provided about the time spent in each page was relative to the average time spent and minimised the effect of having several windows open at the same time: when users navigated to a page and stayed briefly in it, the time was less than average and therefore the relative time spent in the page was less than 1. When users spent a long time in a page the time spent was more than average and therefore the relative time spent in the page was more than 1. If users opened several windows the average time spent viewing pages increased, so the relative time spent was high as well but in line with the rest of relative times. A new attribute "Average of relative time on page" was added.

There were cases in which users opened a page in a new window and did not close it until the end of the session. These pages were identified with pop-up advertising windows or Google listings and were removed from the database.

There was an error calculating ratios derived from scroll distance, such as "Ratio of document length by scroll distance". In previous explorations, only entries whose scroll distance was more than zero were taken into account to avoid "divided by zero" errors. Other entries were not taken into account when calculating the averages. For example, if five out of ten entries contained scrolling information, the average was calculated dividing the sum of data by five, instead of ten. Averages collected in this way were biased as they did not take into account situations in which users did not scroll, regardless of the length of the page. This was corrected by using the total amount of entries in the average.

Two users spent a larger amount of time than allowed navigating the Internet. Video footage and questioning showed that they were comparatively tired and bored after the first fifteen minutes using the Internet and their user interface activity was reduced. Entry time stamps for these users were examined and entries created after more than 15 minutes were deleted.

Data enrichment

Data was enriched with attributes not used in previous explorations as well as new attributes derived from the attributes recorded by BUCAgent.

a) Document attributes

Document attributes were not included in previous explorations because it was believed that document attributes were not relevant to determine user dimensions of learning style as users did not have control over the layout and contents of the page that they visited. It was thought that while this premise was true, document attributes could provide information that could be compared with other attributes derived from document and user attributes such as “Average of image area to time on page” or “Average of document length to Mouse distance” when the data mining engine sought for rules. The following document attributes were included:

- Average of number of images
- Average of number of tables
- Average of number of lists
- Average of number of objects

b) Document ratios

It was thought that useful information could be found not only in the number of elements in a document, but also in the ratio of appearance depending on the document length. The following ratios were added:

- Average of area of images to document length
- Average of number of images to document length
- Average of number of tables to document length
- Average of number of lists to document length
- Average of number of objects to document length

c) *Ratios to user attributes*

Only the ratios of the document attributes "Average of document length" and "Average of images area" to user activity attributes were included in previous explorations to see if they provided relevant information to generate rules. As these ratios proved to be relevant, it was decided to enrich the data with similar ratios using other document attributes. The following types of ratio between document and user activity attributes were added, and can be seen in Appendix F:

- Ratios to time on page
- Ratios to mouse distance
- Ratios to mouse speed
- Ratios to mouse movement in the X axis
- Ratios to mouse movement in the Y axis
- Ratios to scroll distance
- Ratios to scroll speed
- Ratios to number of scroll peaks

8.5.6. Fifth exploration

"Classify" was used with "Linear Regression" to find new rules that could predict the learning style of new users accurately. PolyAnalyst was used to specify the minimum F-Ratio, called the "critical F-Ratio" of the attributes used to create the regression model. F-Ratios, as described in Section 8.4.3, were used for measuring the importance of including attributes into a model. Attributes that influenced the target variable strongly had higher F-ratio values. Setting a high Critical F-Ratio resulted in more significant but less accurate rules. Critical F-Ratios were set to include only significant attributes into any generated rule and prevent over fitting. A number of critical F- Ratios were tested for each rule to find which ones provided accurate rules with maximum significance index. Optimal critical F-Ratios for each rule can be seen in Table 8.10.

Rule	AR9	SI7	VV7	SG5
Critical F-R	14	5	3	1

Table 8.10: Optimal minimum F-Ratios (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global)

Table 8.11 shows the statistical indicators for the rules found using "Classify" with "Linear Regression" and optimal critical F-Values.

	Classify			Linear Regression			
Rule	**cp**	**ce**	**PVal**	**StdErr**	**RSq**	**StdDev**	**SIn**
AR9	100%	100%	6.44E-05	0.4992	0.7508	2.22E-01	12.27
SI7	100%	100%	7.92E-06	0.2973	0.9116	1.49E-01	5.107
VV7	100%	100%	2.06E-04	7.54E-07	1	3.09E-07	1.58
SG5	100%	100%	7.92E-06	1.45E-06	1	7.28E-07	0

Table 8.11: Statistical indicators for fifth set of rules using "Find Laws" (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

Accurate rules were found for all the dimensions of learning style, but only AR9 and SI7 were significant enough. "Classify" was run with "Find Laws" using only the attributes selected by "Linear Regression", but no significant rules were found for any of the dimensions of learning style.

8.5.7. Visualisation of rules

Scatter graphs were plotted to visualise users clustered by their Active/Reflective dimension of learning style using the three attributes that compose AR9: Amount of mouse movement in the Y axis; ratio of document length to time spent on page; and ratio of images area to document length and scroll distance. Figure 8.4 shows a 3-D scatter graph showing user data points against the three attributes used by AR9.

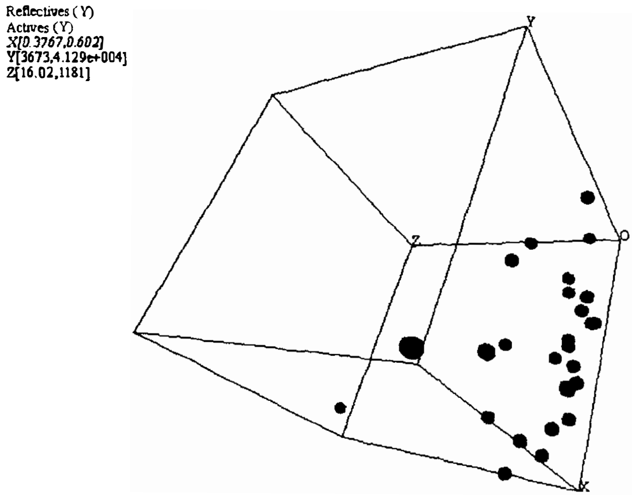

Figure 8.4: Clusters of Active (red) and Reflective (blue) users visualised by plotting data points against "amount of mouse movement in the Y axis" (X), "ratio of document length to time spent on page" (Y); and "ratio of images area to document length and scroll distance" (Z) as used by AR9 (Table 8.11)

Figure 8.5, Figure 8.6 and Figure 8.7 show projections of the 3-D scatter graph as 2-D scatter graphs using two attributes.

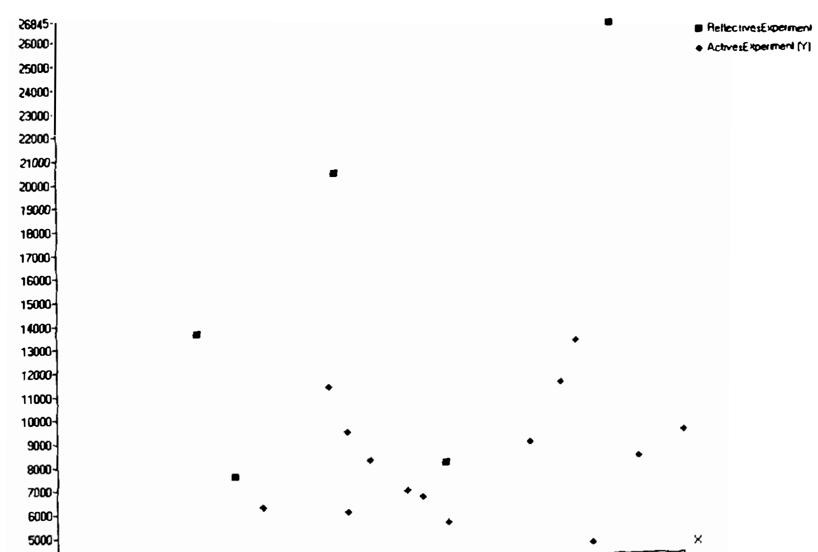

Figure 8.5: Clusters of Active (red) and Reflective (blue) users visualised by plotting data points against "Amount of mouse movement in the Y axis" (X) and "ratio of document length to time spent on page" (Y) as used by AR9 (Table 8.11)

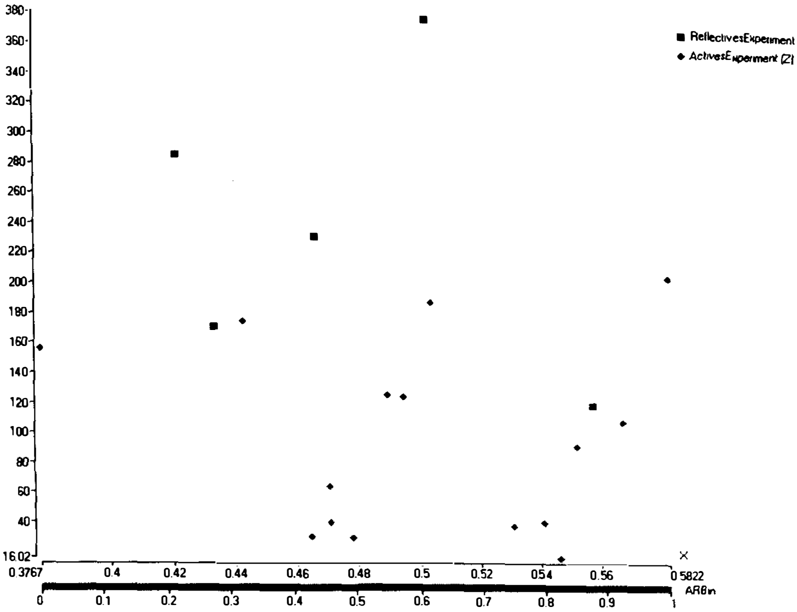

Figure 8.6: Clusters of Active (red) and Reflective (blue) users visualised by plotting data points against "Amount of mouse movement in the Y axis" (X) and "ratio of images area to document length and scroll distance" (Y) as used by AR9 (Table 8.11)

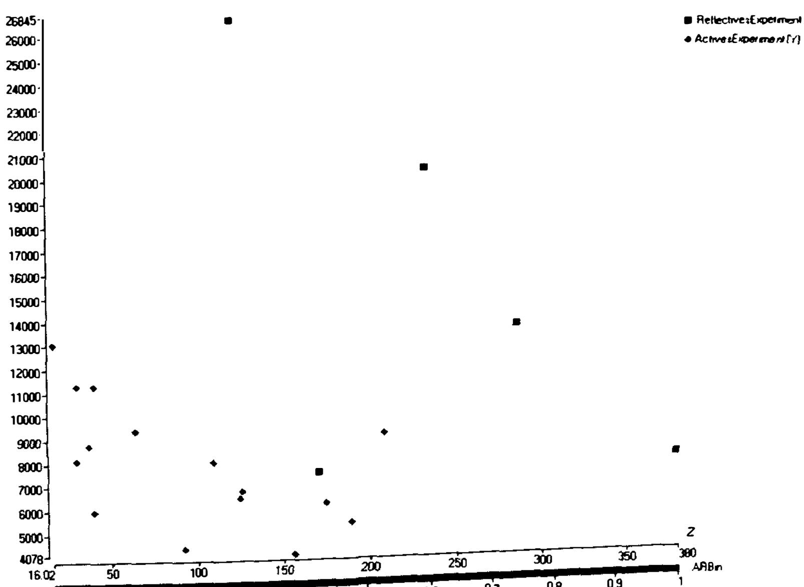

Figure 8.7: Clusters of Active (red) and Reflective (blue) users visualised by plotting data points against "ratio of document length to time spent on page" (X) and "ratio of images area to document length and scroll distance" (Y) as used by AR9 (Table 8.11)

Figure 8.8 shows a 3-D scatter graph showing user data points against the three attributes used by AR9.

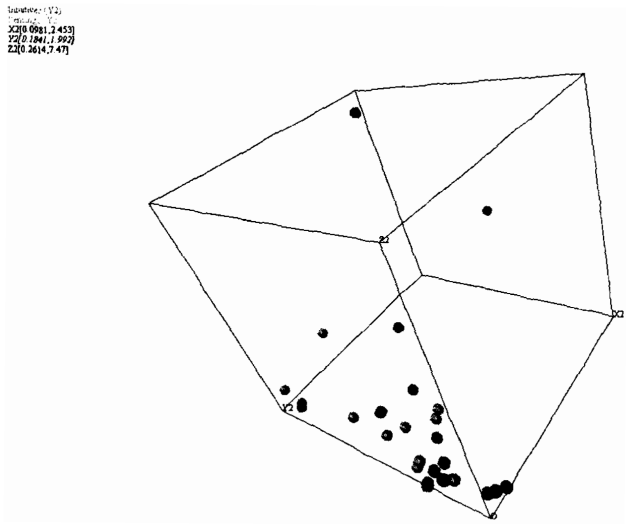

Figure 8.8: Clusters of Sensing (orange) and Intuitive (green) users visualised by plotting data points against "average of time spent on page" (X), "average of scroll speed" (Y); and "ratio of images area to time spent on page" (Z) as used by SI7 (Table 8.11)

Figure 8.9, Figure 8.10 and Figure 8.11show projections of the 3-D scatter graph as 2-D scatter graphs using two attributes.

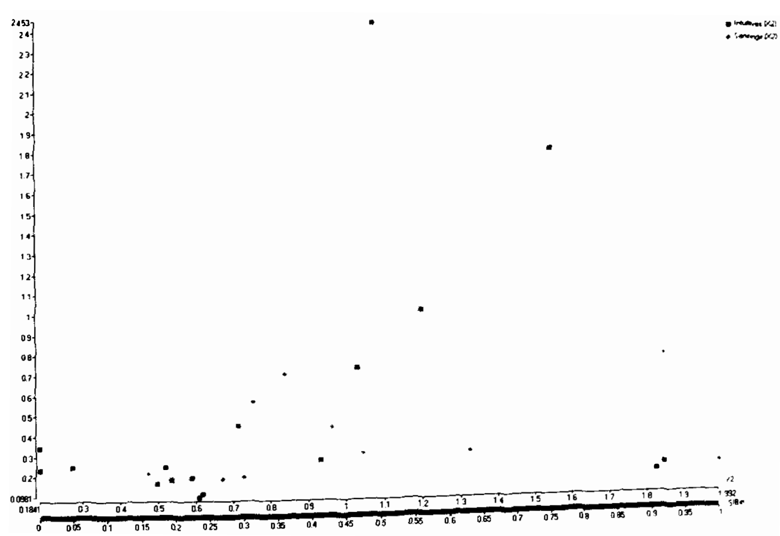

Figure 8.9: Clusters of Sensing (orange) and Intuitive (green) users visualised by plotting data points against "average of time spent on page" (X) and "average of scroll speed" (Y) as used by SI7 (Table 8.11)

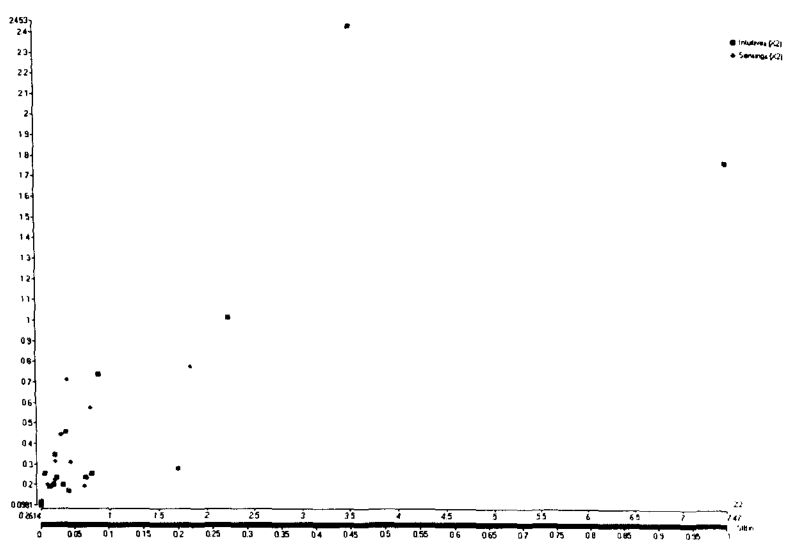

Figure 8.10: Clusters of Sensing (orange) and Intuitive (green) users visualised by plotting data points against "average of time spent on page" (X) and "ratio of images area to time spent on page" (Y) as used by SI7 (Table 8.11)

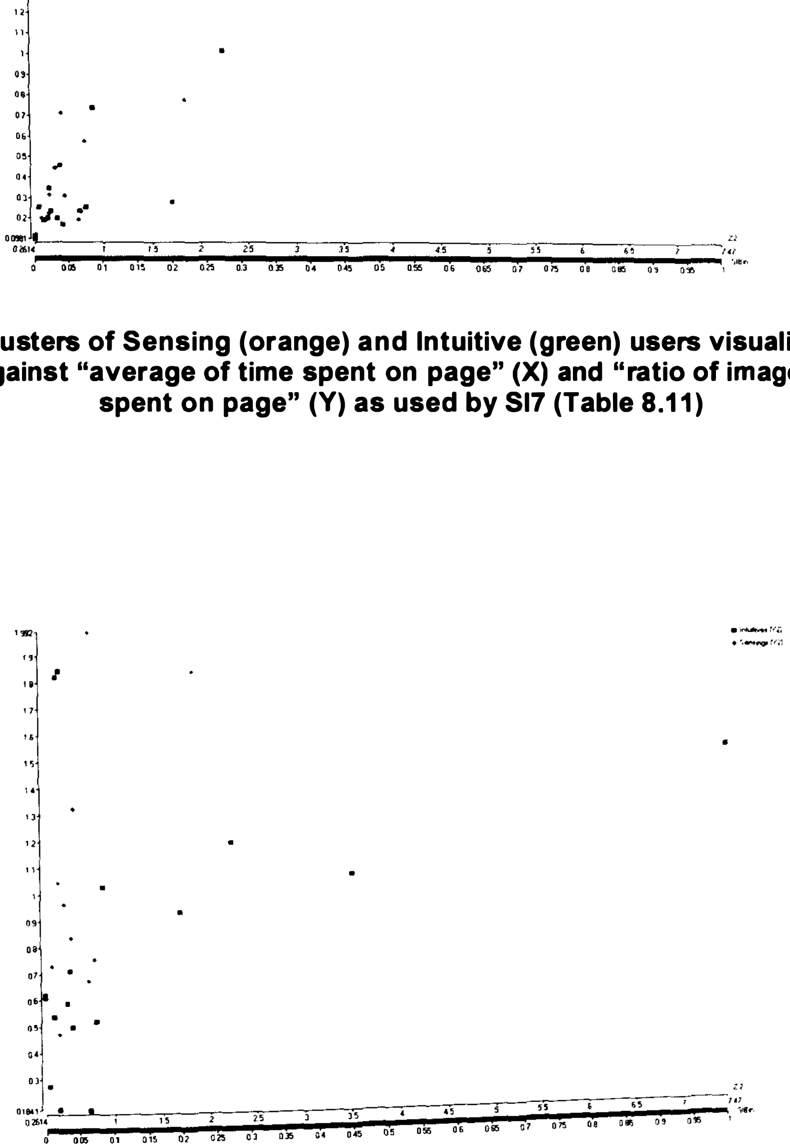

Figure 8.11: Clusters of Sensing (orange) and Intuitive (green) users visualised by plotting data points against "average of scroll speed" (X); and "ratio of images area to time spent on page" (Y) as used by SI7 (Table 8.11)

8.5.8. Sixth exploration

After observing scatter graphs created by plotting user data points against the attributes used by rules to predict user learning style, it was found that simple rules could be generated by observing the maximum and minimum value of each attribute for each dimension of learning style. For example, in Figure 8.12 two thresholds, A and B, could be defined in the X axis, corresponding to "ratio of document length to time spent on page". All user data points with a ratio less than A were Active; all user data points with a ratio more than B were Reflective; Six Active data points between A and B were Active and two Reflective. A probabilistic rule could be inferred from this observation: New data points with a ratio of document length to time spent on page less than A have a probability of being Active equal to 1. If the ratio is more than B the probability was equal to 0, and if the ratio was between A and B the probability was 6/8.

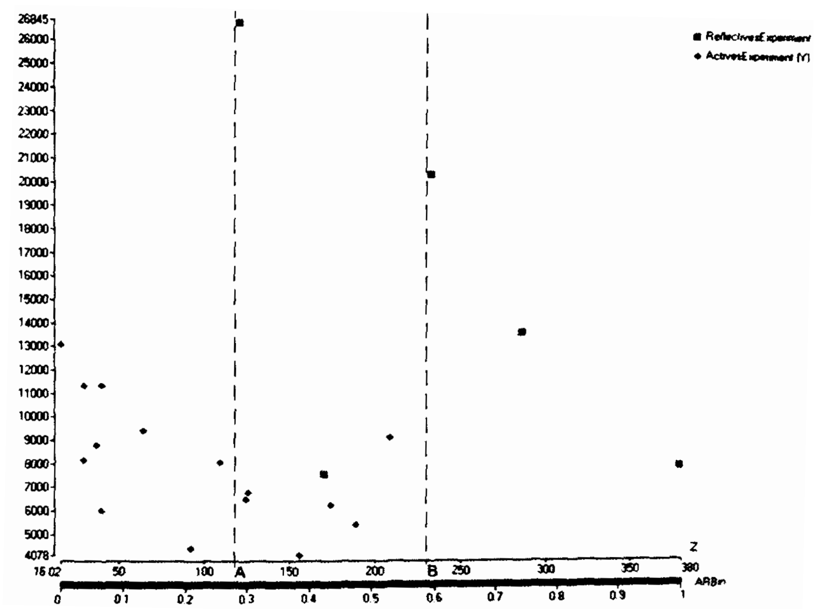

Figure 8.12: Thresholds in the X axis (ratio of document length to time spent on page) to create a simple rule to predict Active/Reflective users

PolyAnalyst was used to run "Linear Regression" to find the most significant attributes. Two linear regressions were run for each dimension of learning style: One using a Boolean value as target variable (True as Active and False as Receptive) and another using a continuous value (1 as an extreme Active and 0 as an extreme Reflective) as a target variable. The selected attributes for the first linear regression were attributes that were significant to determine whether a user belonged to one dimension of learning style or another, while the second set of attributes were significant to determine the users' degree of belonging to a dimension of learning style and could be compared with the ILS questionnaire scores. Both sets of attributes could be used to create probabilistic models and compare their accuracy.

The most significant parameters for each dimension (the attributes selected by PolyAnalyst in the linear regression) were used to create a probability model for each dimension of learning style that could predict the dimensions of learning style of users, by averaging the probability returned from each of the thresholds. Microsoft Excel was used to automatically calculate the thresholds and probabilities for each attribute and dimension of learning style and generate rules that returned a value between 0 and 1 that indicated the average probability of belonging to a dimension of learning style. A threshold of 0.5 was set to create a second group of rules that returned a Boolean value that represented whether users belonged to a dimension of learning style. Finally, two new sets of rules were created from the previous sets by weighing each parameter by their F-ratio. Rule names and their description can be seen in Table 8.12.

Rule names	Abbreviation	Description
PAR1, PSI1, PVV1, PSG1	PXX1	Rules that return a continuous value between 0 and 1 using attributes from the linear regression that returned a continuous value, without weighing.
PAR1W, PSI1W, PVV1W, PSG1W	PXX1W	Rules that return a continuous value between 0 and 1 using attributes from the linear regression that returned a continuous value, weighed by F-ratio.
PAR1B, PSI1B, PVV1B, PSG1B	PXX1B	Rules that return a Boolean value using attributes from the linear regression that returned a continuous value, without weighing.
PAR1WB, PSI1WB, PVV1WB, PSG1WB	PXX1WB	Rules that return a Boolean value using attributes from the linear regression that returned a continuous value, weighed by F-ratio.
PAR2, PSI2, PVV2, PSG2	PXX2	Rules that return a continuous value between 0 and 1 using attributes from the linear regression that returned a Boolean value, without weighing.
PAR2W, PSI2W, PVV2W, PSG2W	PXX2W	Rules that return a continuous value between 0 and 1 using attributes from the linear regression that returned a Boolean value, weighed by F-ratio.
PAR2B, PSI2B, PVV2B, PSG2B	PXX2B	Rules that return a Boolean value using attributes from the linear regression that returned a Boolean value, without weighing.
PAR2WB, PSI2WB, PVV2WB, PSG2WB	PXX2WB	Rules that return a Boolean value using attributes from the linear regression that returned a Boolean value, weighed by F-ratio.

Table 8.12: Rule names and description

As it can be seen in Table 8.13, none of the PXX1 and PXX1W rules are accurate. This is because these rules return a continuous value that can be compared to the exact value of the user's dimensions of learning style. It is not possible to find rules that predict the exact value of users' dimensions of learning style because the ILS questionnaire results used as training data represent a tendency to one of the extremes of each dimension of learning style. ILS questionnaire results do not represent an absolute and definitive measure of the exact value of the dimensions of learning style for each user.

	PXX1	PXX1W	PXX1B		PXX1WB	
	stderr	stderr	cp	ce	cp	ce
AR	68.96%	66.47%	85%	57.14%	80%	42.86%
SI	97.77%	99.12%	65%	0%	65%	0%
VV	101.28%	110.61%	80%	20%	75%	0%
SG	108.70%	183.30%	80%	55.56%	50%	-11.11%

Table 8.13: Statistical indicators for probabilistic rules using attributes from a linear regression that returned continuous values, using data from 20 volunteers (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; StdErr=Standard Error)

PXX1B and PXX1WB present better results, with cp ranging from 85% (PAR1B) to 50% (PSG1WB), but their ce is not high enough. It must be observed that the best rules in these two groups belong to the AR dimension of learning style, in line with previous findings. It can also be noted that weighing the attributes used to generate the prediction using their F-Ratio did not improve the rules, as PXX1 rules were more accurate than PXX1W and PXX1B rules were more accurate than PXX1WB.

PXX2 and PXX2W had a high standard error (see Table 8.14) because of the reasons described for PXX1 and PXX1W. The cp of PXX2B and PXX2WB was generally less than PXX1B and PXX1WB, but their ce improved with respect to previous groups. This means that rules were less accurate but more significant. PAR2B has a cp = 90% and ce = 71.43%, which made this rule accurate and significant enough, as its ce was more than the minimum required based on the naïve prediction for AR. These groups of rules follow the same trends as the rest of rules: rules to predict the AR dimension of learning style are the most accurate; and weighing attributes by their F-Ratio does not improve the accuracy of rules.

	PXX2	PXX2W	PXX2B		PXX2WB	
	stderr	stderr	cp	ce	cp	ce
AR	68.22%	114.72%	90%	71.43%	80%	42.86%
SI	98.27%	107.81%	55%	-28.57%	60%	-14.29%
VV	101.23%	106.76%	85%	40%	80%	20%
SG	127.64%	158.50%	50%	-11.11%	60%	11%

Table 8.14: Statistical indicators for probabilistic rules using attributes from linear regression that returned Boolean values, using data from 20 volunteers (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; StdErr=Standard Error)

8.5.9. Further data acquisition and cleaning

20 records were used to create the rules described previously. In order to improve the statistical significance and accuracy of the rules, a second round of experiments took place in the University of Portsmouth and at the Director of Studies' house. The research laptop used in previous experiments was set up in one room, and two desktop computers were set up in separate rooms. 33 new volunteers completed the ILS questionnaire and carried out the same experiment task. The distribution of dimensions of learning style from the ILS questionnaire, incorporating the new volunteers, can be seen in Table 8.15.

Data recorded by the user agent while volunteers carried out the experiment task was imported into a database along data recorded from users in previous stages and cleaned as described in Sections 8.4.2 and 8.5.5.

Dimension	This study (20 volunteers)	This study (53 volunteers)	Other Studies
Active	**57%**	**59%**	**60%**
Reflective	43%	41%	40%
Sensor	**52%**	**56%**	**65%**
Intuitive	48%	44%	35%
Visual	**76%**	**77%**	**77%**
Verbal	24%	23%	23%
Sequential	34%	40%	**60%**
Global	**66%**	**60%**	40%

Table 8.15: Distribution of dimensions of learning style over sample population, coompared with previous sample and other studies.

8.5.10. Seventh exploration

Cleaned data was imported into PolyAnalyst to find accurate and significant rules to predict user learning style. "Classify" was used with "Linear Regression" to find significant rules that could accurately predict the learning style of new users. Although accurate rules were found, they were not significant enough, as it can be seen in Table 8.16. The best critical F-Ratio was sought for each rule in order to increase their significance, but no significant increase was achieved by modifying the critical F-Ratio.

	Classify			Linear Regression			
Rule	**cp**	**ce**	**PVal**	**StdErr**	**RSq**	**StdDev**	**SIn**
AR10	96.2%	88.2%	1.88E-11	0.5601	0.6863	0.264	0.3522
SI8	73.6%	43.2%	0.3641	0.8737	0.2367	0.4409	-1.109
VV8	98.1%	91.7%	1.84E-09	0.5156	0.7341	0.2179	0.1123
SG6	94.3%	87.5%	8.90E-13	0.5415	0.7068	0.2721	1.003

Table 8.16: Statistical indicators for seventh set of rules using "Classify" and "Linear Regression" (AR=Active/Reflective; SI=Sensing/Intuitive; VV=Visual/Verbal; SG=Sequential/Global; cp=Classification Probability; ce=Classification Efficiency; PVal=P-Value; StdErr=Standard Error; RSq=R-Squared; StdDev=Standard Deviation; SIn= Significance Index)

"Classify" was used with "Find Laws" to find non-linear rules for Active/Reflective. No significant rules were found for any of the dimensions of learning style.

A number of attributes that appeared in AR10 also appeared in AR9 and other AR rules, which implied that these attributes might be indicative of the dimension of learning style of the volunteers, as they continued to appear even when the number of volunteers had grown. These attributes were:

- Average of scroll speed
- Average of number of images to mouse speed
- Average of document length to scroll distance
- Average of number of images to scroll distance
- Average of document length to scroll speed

Probabilistic rules were created as described in section 8.5.8. The rules were named following the scheme described previously. Statistical indicators of accuracy can be seen in Table 8.17and Table 8.18.

	PXX3	PXX3W	PXX3B		PXX3WB	
	stderr	stderr	cp	ce	cp	ce
AR	146.40%	145.21%	75.47%	23.53%	81.13	41.18%
SI	132.11%	132.18%	52.83%	3.85%	54.72%	7.69%
VV	161.93%	160.54%	81.13%	16.67%	83.02%	25%
SG	118.79%	119.78%	58.49%	8.33%	56.60%	4.17%

Table 8.17: Statistical indicators for probabilistic rules using attributes from a linear regression that returned continuous values, using data from 50 volunteers

PXX3, PXX3W, PXX4 and PXX4W were not accurate because of the same reasons described for PXX1, PXX1W, PXX2 and PXX2W above. Also, although some of the PXX3B, PXX3WB, PXX4B and PXX4WB rules were accurate, none of the rules had good classification efficiency.

	PXX4	PXX4W	PXX4B		PXX4WB	
	stderr	stderr	cp	ce	cp	ce
AR	139.11%	135.62%	67%	0%	71.70%	11.76%
SI	169.3%	195.6%	54.72%	7.69%	60.38%	19.23%
VV	156.9%	152.8%	79.25%	8.33%	67.92%	-41.67%
SG	114.8%	114.3%	54.72%	0%	50.94%	-8.33%

Table 8.18: Statistical indicators for probabilistic rules using attributes from linear regression that returned Boolean values, using data from 53 volunteers

Probabilistic rules created using attributes from a linear regression that returned continuous values (PXX4B and PXX4WB) were more accurate and efficient than probabilistic rules created using attributes from a linear regression that returned Boolean values (PXX3B and PXX3WB). This is a different case than the previous exploration, in which probabilistic rules created using attributes from a linear regression that returned Boolean values had better cp and ce.

8.6. *Chapter discussion*

An experiment was designed using the intelligent agent system described in Chapter 6. The aim of the experiment was to collect data from users and analyse it to find rules that enabled a prediction of user dimensions of learning style from recorded UI activity, as well as to rate the suitability of Web pages for each dimension of learning style.

Data from 20 volunteers was collected and analysed. The analysis yielded significant results and rules to determine the Active/Reflective, Sensing/Intuitive and Visual/Verbal dimensions of learning style, but further analysis using data collected from 50 users were not more significant. It was found that certain parameters remained as part of the best rules found using 20 and then 50 users. In particular, "Average of scroll speed", "Average of number of images to mouse speed", "Average of document length to scroll distance", "Average of number of images to scroll distance" and "Average of document length to scroll speed" were found in the most significant and accurate rules created to determine whether users were Active or Reflective.

The way that the time spent by users on documents was measured did not take into account whether users were viewing the document or if the document window was minimised or hidden under other windows. Although an attempt was made to correct this issue by calculating a "relative time" based on the average time that users spent viewing documents (see Section 8.5.5), it is thought that ratios where time on page was used are biased by this flaw. That said, most of the volunteers recorded on video used a single window to carry out the task.

Some of the second round of experiments was performed in the Director of Studies' house, as described in Section 8.5.9. Two of the sites where computers were installed to perform the experiment were not isolated from the rest of the house and were noisy, so several volunteers were distracted while performing the experiment. This could have led to biased data for these volunteers. More volunteers need to perform the experiment in a controlled environment, ideally in a dedicated room with a researcher observing them and taking notes on their behaviour, or alternatively being recorded with a digital video camera.

More volunteers were also needed to validate the rules. When a model was built from training data, the error on the training data was an optimistic estimate of the error rates the model achieved on new data [Han & Kamber (2001)]. If significant rules were found, they need validation using the holdout method: volunteer records split in two datasets. One dataset can be used to generate rules and the other dataset can be used to validate the accuracy of the rules on new volunteers.

Some volunteers were surprised that questions about the investigated subject were not asked at the end of the activity. Questions were not asked because the outcome of the experiment was not to measure the volunteer's knowledge gain, but the way the knowledge had been acquired. Several volunteers stated that if they had been warned that questions would be asked after the investigation, the overall motivation of the volunteers might have improved and been made more homogeneous. Some volunteers stated that they got bored while investigating.

It was described in Section 8.4.3 that "Classify" calculated a threshold value for the output using a genetic algorithm, so that output from algorithms that returned a numerical value could be transformed into rules to split a dataset in two groups, such as "Active" and "Reflective". Output of probabilistic rules described in

Sections 8.5.8 and 8.5.10 was used in a similar way, splitting users into two groups using a threshold of 0.5 because the output of the rules was a value between 0 and 1. Genetic algorithms such as the one used by "Classify" could be used to find thresholds that make the probabilistic rules most accurate and significant.

Rules to determine which document attributes were more appropriate for each dimension of learning style could not be found because only 30% of the pages visited were rated by at least one user. The experiment should have been split into two separate experiments: an experiment similar to the one described in this Chapter, without asking volunteers to rate Web pages and a second experiment where volunteers were asked to rate how easy to understand a set of predefined Web pages were. These pages could be live samples from the Internet, or pages constructed using the same contents but different layouts. All pages could be related to the same subject.

The fact that certain parameters appeared constantly throughout the different sets of rules for each dimension of learning style demonstrated the fact that user interaction with User Interfaces could be used to classify users in a number of behavioural groups, such as the dimensions of learning style used in this research or other learning style or larger scale psychological models. This could help to create systems that assist users in a number of tasks such as retrieving information from the WWW in the way that suits more their learning style, or in a bigger scale, their thinking style.

CHAPTER NINE
DISCUSSION AND CONCLUSION

This chapter describes the conclusions and recommendations resulting from the research presented in this thesis.

Existing Web-Based Teaching (WBT) systems provide tools to develop Web-based courses; deliver them on the Web; test user knowledge; track user activity; filter access to the Internet; and allow collaboration between peers. WBT systems provided limited functionality from the client side, so students could lose concentration and navigate to unrelated Web sites. They did not provide intelligent advice on potential sites, consider student activity or provide content-specific filtering of Web pages. Most of these systems were designed for distance learning, and not to use the Internet as an education tool within classrooms.

9.1. The first prototype filter

A system called "Caught In The Act" (CITA) was designed to overcome these limitations. Specifications were defined after researching existing systems and gathering information from teachers and the marketing department at the collaborating company. CITA was divided between a server and a client. The server side, called CITA server, consisted of a Web server that stored and delivered Web lessons to clients and a proxy server that filtered client requests depending on the lesson being taught at the client location. Lessons could be accessed using a standard Web browser and filtering was done by the server depending on the computer location. The client side, called CITA client, was a single window proprietary application where Web pages were displayed in the same way as a standard Web browser. This also enabled teachers to edit lesson Web pages within the browsing area; grant access to areas of the Internet; publish lessons on a Web server; and monitor student activity.

The CITA server prototype consisted of a client request filter that was created using ISAPI filters and extensions for Microsoft Proxy Server 2.0. This enabled the reuse of an existing proxy server. Internet permissions were stored in a Microsoft Access database. This allowed the use of the prototype CITA server as a test bed for testing filtering methods. A CITA client prototype received student activity notifications from the server. After the prototype passed unit tests carried out by the author, it was installed on a test network in the collaborating company and tested by staff and teachers. Testers accessed the Internet using standard Web browsers and the CITA server prototype filtered client access using a number of filtering methods and blocked the Internet access when necessary.

Four filtering methods were considered for the client request filter: URL filtering; full text filtering; feature-based filtering; and URL filtering combined with full text filtering. Feature based filtering was not tested because it required testers to extract document features manually and it could only be applied to reduced sets of documents. Full text filtering proved to be effective when blocking access to clearly unrelated Web pages but unrelated pages could be allowed and related pages could be blocked if keywords were not selected carefully. URL filtering proved to be easy to use and enabled teachers to define access for areas of the Internet. The CITA client prototype successfully notified teachers when students tried to access blocked areas of the internet, but it flooded the client with alerts of access attempts to blocked pages.

A mock version of the CITA client was designed to look similar to standard Web browsers and use locally stored Web page templates to display information. However, redeveloping existing technology in a proprietary software package was an ineffective way of developing the CITA client. Also, a limitation of using template Web pages to display information was that information to populate the templates was pulled from the CITA server when the templates were loaded. Templates could not be used to notify teachers in real time when students did not behave according to the lesson. Java applets or ActiveX components were required to receive real time information from the CITA server and display it from template Web pages.

The methodology was proven although at this stage filtering was not enforced depending on computer location. Permissions were manually stored in a Microsoft Access Database, there were no tools to edit lesson Web pages, to save them into single files or to publish them on a Web server. Management of users, classrooms or computers were not provided. Functions were not provided to add, modify or delete teacher log in information. Also, the CITA server prototype ran from a Web server and a proxy server, which involved the need to establish and maintain a network infrastructure that was not available in many schools and colleges. The knowledge gained from the feedback received from the CITA design and from testing the CITA prototype suggested a need for another type of software tool that provided structured, focused and controlled access to the Internet in an intuitive and non-intrusive way, relying on a minimal network infrastructure. The implementation of CITA did not proceed any further as it was not considered the best design to achieve the goals and the research moved on to create a system called iLessons, which achieved the goals set for CITA.

9.2. *iLessons*

A novel set of tools called iLessons was created to overcome the limitations of the CITA design. iLessons provided tools that enabled teachers to: gather resources from the Internet such as text or images (resource collection); create lesson Web pages (lesson editing); define student access to zones of the Internet (navigation zone); and load lesson Web pages into student computers and enforce access restrictions to defined zones of the Internet (lesson implementation). iLessons also provided students with tools to create resource collections and create coursework using collected resources (coursework editing). The iLessons User Interface (UI) was created within Microsoft Internet Explorer (IE) using Explorer Extensions. Interaction with users was achieved by using Dynamic HTML (DHTML) pages that provided dynamic, adaptive and attractive UIs. Drag and drop was available to manage resources collections and edit lesson Web pages. Drag and drop eliminated the need for menus and was quicker than a copy/paste sequence. Teachers and students considered iLessons to be intuitive and easy to use because it was embedded into IE, a standard Web browser that they were familiar with. IE was selected because it was widely used in educational establishments and its continuity and backward-compatibility was ensured. Versions of iLessons for other Web browsers such as Netscape or Firefox could be also created.

iLessons enabled teachers to load lessons remotely onto computers grouped by classroom, making lesson Web pages available to students and restricting Internet access. iLessons did not rely on a server to provide lesson implementation. Lessons were copied to network folders with the same name as the classrooms where computers were located, and the student computers loaded the correct lesson at start-up.

Teachers and students used iLessons to reuse Internet resources such as images, text, hyperlinks and HTML content. Testers claimed that collecting resources by using drag and drop was effective and easy to use, but using drag and drop to reuse resources while editing lesson pages was slow and ineffective. This was because users had to constantly switch between the resource collection and the lesson views in the infoPad and the infoPad sometimes limited the editing area. Buttons were added to the edit toolbar UI to enable teachers to use resources in lesson Web pages without having to display the infoPad.

Web page editing was implemented by reusing the editing features available in IE. Standard editing functions were applied by executing standard commands, such as "Bold" or "Italic". Editing functions that were not standard were created. Internet Web pages were imported using a third-party component.

The navigation zone defined Internet pages, directories and domains that students were allowed to access. The navigation zone was part of the lesson and was saved in the same file. Three kinds of permissions were available to define navigation zones: "allowed", "denied" and "trusted". Trusting a Web page granted students access to the page and to any other page linked to the trusted Web page to a specified level. This enabled teachers to create complex navigation zone structures. URL filtering was selected for iLessons because it was a fast, simple and accurate filtering method. The iLessons filter monitored every request made from IE and granted access to pages or page elements as specified in the navigation zone. Filtering was mainly performed by monitoring IE navigation events but raw HTTP requests were also monitored to update trusting information and filter Web page element requests. When users navigated to a page inside a frameset, the main frame URL remained the same. Not having individual URLs for each set of frames could lead to an allowed frame within a frameset being unreachable if other pages in the same frame preceding the allowed frame were not allowed as well. Teachers were advised to allow the directories where frames were stored or to use trusting to grant access to frames within a frameset.

9.3. The new intelligent agent systems

Research moved on to provide less restrictive filtering so that the Internet could be used by students as a research tool while restricting access to a subject area. Content-based document filtering could be used to grant access to documents classified as relevant to a subject, rather than to a list of URLs created by the teacher. Teachers provided training Web pages related to a subject. Terms from these pages were extracted using a feature extraction algorithm and a document classification algorithm generated a classification pattern from the training set. When students requested Web pages, the feature extraction algorithm extracted page terms and the document classification algorithm returned the likelihood that the page belonged to a subject. Access was granted to pages likely to belong to a certain subject within a specified threshold.

Other research work utilised content-based document filtering methods to assess the suitability and relevance of Web pages and to recommend new pages. Intelligent document filtering algorithms and feature extraction algorithms were investigated. After considering assessments made by other researchers, Document Frequency and k-Nearest Neighbour were selected as the feature extraction algorithm and the document classification algorithm for the model of a new intelligent system. New enhanced models of intelligent document classification algorithms were created to assist users in researching using the Internet. The models were created by combining intelligent document classification algorithms with URL filtering, semantic networks and collaborative agents: URL filtering was combined with document classification to store the score of retrieved documents given by the document classification algorithm in a URL database, enhancing the performance of the algorithm. Semantic Networks of related documents were used to recommend related pages to users. These two enhancements were combined in a new model of a system of collaborative agents that received new URL database entries or semantic network updates from other users and recommended related pages found by peers.

Subject-specific filtering using document categorisation was flexible enough to enable students to use the Internet as a research tool while keeping them focused on a subject, but the model lacked adaptability to meet student learning styles and did not provide any collaboration facilities. A number of researchers examined and developed adaptive computer-based educational environments that utilised learning styles to model users and adapted educational content to match user learning style. Existing systems provided intelligent content adaptation based on learning style and previous knowledge. These systems worked with Web-based adaptive material created with proprietary tools, but none of these systems used Web pages readily available on the Internet, or inferred students' learning styles by analysing the way users navigate and interact with standard Web browsers. The research moved on to the creation of a new model of a collaborative agent system that filtered and recommended Web pages to students based on three different dimensions: page relevancy, based on contents; page layout based on student learning style; and user activity (active or inactive). The new model enabled students to use the Internet to freely investigate a subject using intelligent document classification to filter irrelevant Web pages. A UI agent determined user learning style and activity by monitoring the way in which the user interacted with Web pages. To encourage users to join the learning experience after periods of inactivity, pages found by other students that suited their learning style were recommended to them by a recommender agent. Four models of learning style were considered: Field dependency [Messick (1976)]; Felder and Silverman [Felder & Silverman (1988)]; Honey and Mumford [Honey & Mumford (1986)]; and Dunn and Dunn [Dunn (2000)]. The Felder-Silverman dimensions of learning style model was a well-accepted model and it was selected because it provided four dimensions of learning style that might be measured from data obtained from the user interaction with the computer.

In order to automatically determine the learning style of students, patterns needed to be found in the way users with different learning styles interacted with a standard Web browser. It was also necessary to find patterns in the layout and elements of Web pages that were easier to understand by students depending on their learning style. These patterns could also be used to enhance distance-learning WBT systems described in Chapter 2. Two new intelligent agent systems were created to record Web page structure and user activity while using Web browsers: Solstice and BUCAgent. Recorded data was then analysed to create rules that could infer user learning styles from the way users utilised the Web browser, and the suitability of pages for each dimension of learning style could be found. Solstice was a first prototype created to test the ability to retrieve user activity and document layout information from a standard Web browser such as IE. This used the same technology as iLessons so that it could be fully integrated with it. Information about Web pages and user activity was shown in a dynamically generated Web page within IE. BUCAgent (Browser User and Contents Agent) was then created to integrate with iLessons and record UI activity information that could be used to find rules that helped to infer the users' dimensions of learning style, as well as document structure features that could be used to infer the suitability of documents for each learning style. BUCAgent was successfully implemented as a multi-agent system comprising two types of agent: IE agents monitored IE events, retrieving page and user activity data while a single user agent per system kept the user's dimensions of learning style and stored user activity information and document contents analysis from IE agents. User agents were saved into a file and imported into a Microsoft Access database to be combined with data from other users.

9.4. Experiment and results

BUCAgent was utilised in a controlled environment to retrieve UI activity and document structure data while volunteers completed a research task. Collected data was analysed using a data mining engine to find rules to predict user dimensions of learning style and the suitability of Web pages for each dimension of learning style.

An experiment was designed in three stages to retrieve user dimensions of learning style, UI activity data and Web page structure data. During Stage I, volunteers completed the Index of Learning Styles (ILS) questionnaire [Felder & Spurlin (2005)] so that their dimensions of learning style were known. During Stage II, volunteers investigated "Plate tectonics: What they are, different types and their effects on the landscape" for 15 minutes using IE and BUCAgent embedded within the browser and optionally rated Web pages. During Stage III, data from volunteers was imported into a database, cleaned and used in a data mining engine to identify rules that can be used to automatically determine the learning style of users by the way they interacted with standard Web browsers. Patterns were also searched in the layout and contents of Web pages and the ratings given by volunteers of each dimension of learning style so that Web pages with the most suitable layout for each dimension of learning style could be recommended to students based on their learning style.

The ILS questionnaire was sent by email to Ninety one potential volunteers. Sixty seven volunteers completed the questionnaire and twenty completed the research task. The distribution of dimensions of learning styles in the volunteer population was similar to findings of other studies, apart from the "Sequential/Global" dimension of learning style. For this reason "Sequential/Global" was not considered further.

Data was imported into a data mining engine called "PolyAnalyst" to find rules to predict user learning style from the way users with different learning styles interacted with a standard Web browser, as well as rules to predict the suitability of pages to each learning style from the layout and elements of Web pages. Two algorithms were selected: "Linear Regression" and "Find Laws". The output of these algorithms was a human-readable model that could be used to predict a continuous target variable from a set of input attributes. Also, the "Classify" tool could be used to transform algorithm output into rules to split a dataset in two groups, such as "Active" and "Reflective". Four explorations were performed using these algorithms in an iterative way, fine tuning the data and adding and removing attributes in order to find progressively accurate and significant rules. Accurate and significant rules were found for the "Active/Reflective" and the "Visual/Verbal" dimensions of learning style.

Data was analysed and further cleaning and transformation was performed. Data tables found irrelevant in previous explorations were removed and document structure data was transformed to provide more meaningful attributes. Also, the measurement of time was transformed to correct bias produced by volunteers using more than one IE window at the same time. Ratios where time on page was used were biased by this flaw, although most volunteers used a single window. A new exploration was performed and accurate and significant rules were found for the "Active/Reflective" and "Sensing/Intuitive" dimensions of learning style.

After plotting scatter graphs using the most significant attributes found in each rule, it was found that simple rules could be generated by observing the maximum and minimum value of each attribute for each dimension of learning style. Microsoft Excel was used to automatically calculate sets of rules that returned a value between 0 and 1 that indicated the average probability of belonging to a dimension of learning style and rules that returned a Boolean value that represented whether users belonged to a dimension of learning style. None of the rules that returned average probabilities were accurate because it was not possible to find rules that predicted the exact value of users' dimensions of learning style, as ILS questionnaire results did not represent an absolute and definitive measure of the exact value of the dimensions of learning style for each user. Rules that returned Boolean values presented more accurate results, and an accurate and significant rule to determine "Active/Reflective" was found.

In order to improve the statistical significance and accuracy of the rules, a second round of experiments was performed. Data from 53 volunteers was utilised to find accurate and significant rules to predict user learning style. A number of attributes that appeared in previous Active/Reflective rules also appeared in this exploration, which implied that these attributes may be indicative of the dimension of learning style of the volunteers, as they continue to appear even when the number of volunteers grows. This proved that there were parameters in the way that users interacted with the Internet that could be measured to classify users in a number of behavioural groups, such as different learning style models or larger scale psychological models. Systems could then adapt their behaviour to suit the behavioural traits of the user.

9.5. Resolution of Research Aims and Objectives

a) Investigate existing Web Based Teaching (WBT) systems.

Commercial WBT systems were investigated and reviewed in Chapter 2. New intelligent agent systems that provided adaptive content depending on student learning style were reviewed in Chapter 6. Related technologies were reviewed in

Chapter 2, including computer hardware, computer networks, operating systems, proxy servers and Web browsers.

b) *Design and implement new User Interfaces to assist teachers.*

UI strategies were investigated and new UIs were created to assist teachers and students taking into account the limitations of existing systems and feedback from teachers. The UIs were embedded into a standard Web browser and used DHTML and drag & drop technology, which made them intuitive and easy to use.

c) *Create a novel WBT system.*

The CITA server prototype described in Chapter 3 consisted of a client request for Microsoft Proxy Server 2.0. Areas of the Internet allowed during lessons were stored in a Microsoft Access database. This allowed using the prototype CITA server as a test bed to test filtering methods. The CITA client prototype received student activity notifications from the server.

iLessons was described in Chapter 4 and enabled teachers to collect resources from the Internet and reuse them in Web-based lessons using drag & drop; to define access to zones of the Internet by navigating to selected sites; and to load lessons and filter relevant Web pages in student computers grouped by classroom. It enabled students to create coursework using resources collected from the Internet.

d) *Investigate filtering methods and intelligent document classification.*

Models of existing filtering methods were created in Chapter 2. Models of new intelligent filtering methods using supervised machine learning algorithms were defined in Chapter 6 and enhanced using existing filtering methods. Document filtering based on learning styles was investigated.

e) *Investigate learning style models.*

Models of learning style were identified and investigated in Chapter 6. WBT systems that took into account learning styles to adapt their behaviour to users were investigated and it was found that none of these used intelligent methods to automatically determine users learning style.

f) Define user behaviour and document parameters to determine user learning style.

User behaviour parameters that could help to determine user learning styles were identified. Some parameters could be recorded using different methods. Methods were investigated and the most appropriate methods were identified.

g) Design and implement a new and intelligent student agent.

Solstice and BUCAgent were described in Chapter 6. Solstice was a first prototype created to test the ability to retrieve user activity and document layout information from a standard Web browser such as IE using the same technology as iLessons. BUCAgent was created to integrate with iLessons and record UI activity information that could be used by to find rules that helped to infer users' dimensions of learning style, as well as document structure features that could be used to infer the suitability of documents for each learning style.

h) Find ways to infer student learning style from student behaviour

Data mining algorithms were applied to data recorded by the new intelligent student agent to find rules to infer student learning style. Results were compared to find the most accurate and significant rules. A new method based on probabilities and thresholds was created and rules were created using this method.

9.6. *Key research successes and contribution*

Research into WBT and learning styles has been undertaken. A WBT system that could be used for further research and development was created. The research work brought the following successes:

Main systems created:

- CITA prototype: A client/server system used for testing filtering methods and UI designs.
- iLessons: A Web browser-based system that enabled teachers to focus, structure and control the use of the Internet from a standard Web browser.

- Solstice: A prototype of an intelligent agent system that recorded user activity and page layout data while users browsed the World Wide Web (WWW).

- BUCAgent: An intelligent agent system that recorded user activity and page layout data while users browsed the WWW. Data was used for creating rules to infer user learning style and suitable pages from their behaviour.

New methods:

- Resource collection from the Web browser enabled users to compile and share resources from the WWW using drag & drop from a standard Web browser.

- Page editing from the Web browser enabled teachers to create and share lesson Web pages and use collected resources from a standard Web browser.

- Page filtering from the Web browser enabled teachers to focus and control the use of the Internet by students from a standard Web browser without the need of server software.

- New and enhanced Web page filtering models to enable students to use the Internet as a research tool while keeping them focused into a subject and to assist them by sharing the most suitable pages found by other students based on learning style.

- Methods to capture user behaviour learning styles to create a database that could be mined to find relationship between user behaviour and learning style.

- Rules to infer student learning style from student behaviour so that new systems could automatically detect users' learning style and react accordingly.

The key contribution to knowledge was the creation of a method to infer student learning styles from their behaviour while interacting with a standard Web browser and the WWW, and the rules and knowledge resulting from the application of this method.

9.7. Improvements to this research

Some experiments during the second experiment row were performed in a house and two of the sites where computers were installed were noisy and several volunteers were distracted while performing the experiment. This could have led to biased data for these volunteers. Volunteers were needed to perform the experiment in a controlled environment. A second group of volunteers was also needed to validate the rules using the holdout method by splitting data from volunteers in a generation dataset and a validation dataset.

Using an extended sample population would enable more accurate and significant rules to be found for the visual/verbal dimension of learning style. Other research programmes being undertaken at the University of Portsmouth use incentives such as prize draws to attract volunteers. This approach could have been used to obtain volunteers for this research but it was not possible due to funding and time constraints.

Rules to determine which document attributes were more appropriate for each dimension of learning style could not be found because rating pages was a secondary requirement in the experiment task and only 30% of the pages visited were rated by at least one user. A second experiment was needed where volunteers were asked to rate a set of predefined Web pages on how easy they were to understand. These pages could be live samples from the Internet, or pages constructed using identical contents displayed using different layouts.

"Classify" calculated a threshold value for the output using a genetic algorithm, so that output from algorithms that returned a numerical value could be transformed into rules to split a dataset in two groups, such as "Active" and "Reflective". Output of probabilistic rules was used in a similar way, splitting users into two groups using a threshold of 0.5 because the output of the rules was a value between 0 and 1. Genetic algorithms such as the one used by "Classify" could be used to find thresholds that make the probabilistic rules most accurate and significant.

9.8. *Suggestions for future work*

User navigation plots could be recorded from volunteers and patterns could be found to determine the sequential/global dimension of learning style.

A new experiment could be designed to find the characteristics of documents that make them suitable for each learning style. Volunteers could navigate a series of prearranged Web pages containing the same information, but displayed in different ways. Ratings for these pages could be obtained from the volunteers and rules could be inferred to rate the suitability of new pages for each learning style.

The experiment described in Chapter 8 to record user interface activity data and to create rules to infer user dimensions of learning style from the collected data could be extended to include other models such as Honey and Mumford, described in Chapter 6. Comparative analysis could then be carried out between different learning style models.

9.9. *Thesis Conclusion*

Research was undertaken in the area of WBT to create new and intelligent software tools and methods to assist teachers and students in using the Internet. New WBT systems were developed as a result of this research, and iLessons is being marketed as a commercial product. New intelligent agent systems were created. Data collected by a new intelligent agent system was analysed and rules were created from it to predict the Active/Reflective, Sensing/Intuitive and Visual/Verbal dimensions of learning style. The new WBT systems were designed in collaboration with Counterpoint MTC Ltd, who now markets the new systems. BUCAgent could be marketed as part of iLessons if further research on suitability of documents for each dimension of learning style was undertaken.

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APPENDIX A

iLESSONS USER INTERFACE SOFTWARE DESIGN

iLessons User Interface (UI) classes were loaded by Internet Explorer to display the iLessons UI. UIs were displayed as HTML pages embedded within the iLessons toolbar and the infoPad.

iLessons UI classes were organised hierarchically and common functionality was implemented in parent classes (Figure A.1). The generic functionality necessary to implement an Explorer Extension was implemented in CCoBrowserExtension. CCoToolband implemented functionality specific to the iLessons toolbar and CCoInfoPad implemented functionality specific to the iLessons infoPad.

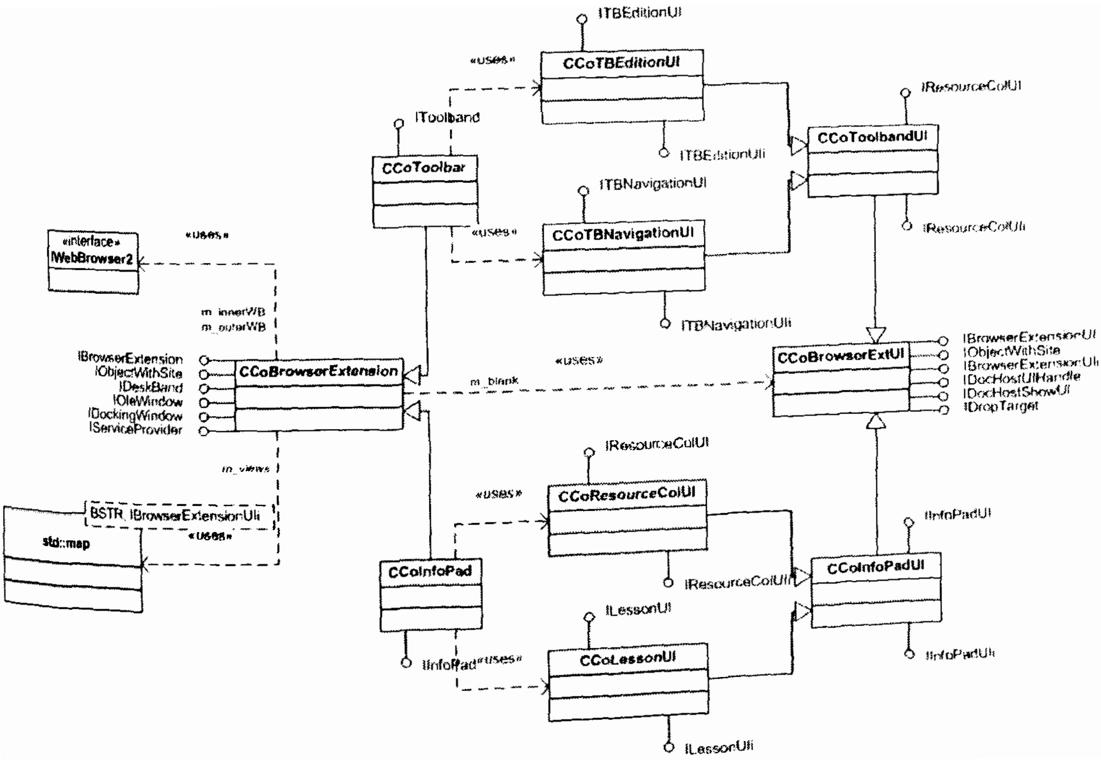

Figure A.1: UI class diagram

CCoBrowserExtension, CCoToolband and CCoInfoPad stored pointers to classes that implemented InfoPad or toolbar UI views: CCoResourceColUI for the resource collection; CCoLessonUI for the lesson view; CCoTBNavigationUI for the teacher/student toolbar; and CCoTBEditionUI for the edition toolbar.

Functionality was exposed to the UI by classes named with the "UI" suffix so that different UI views could be added to the same extension without overloading the extension class with methods. UI classes followed the same hierarchy structure than extension classes (Figure A.2). Generic functionality was implemented by CCoBrowserExtUI. CCoToolbandUI and CCoInfoPadUI provided specialised functionality and the UI classes added specific functionality to each view. The left branch of Figure A.2 shows interfaces implemented by the extension classes. The right branch shows UI classes. Interfaces with the UI suffix were accessed by the HTML UI. Interfaces with the UIi suffix were accessed by extension classes to control the HTML UIs.

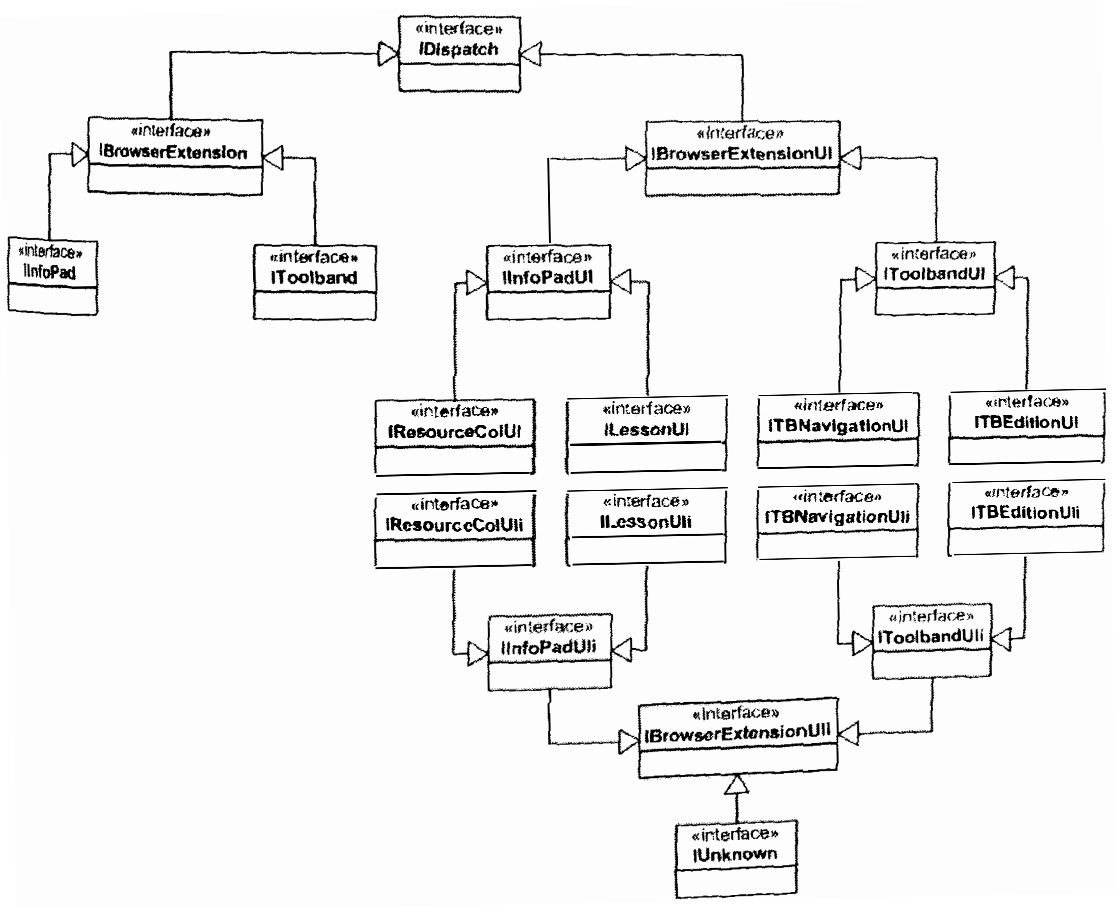

Figure A.2: Interface hierarchy

APPENDIX B

ILESSONS USER FEEDBACK QUESTIONNAIRE

1. **Did you experience any problems with the iLessons download?**
   - ☐ Yes
   - ☐ No

   If Yes, what problems?

2. **Have you installed iLessons since downloading the software?**
   - ☐ Yes
   - ☐ No

   If No, why not?

3. **Have you used iLessons?**
   - ☐ Yes
   - ☐ No

   If Yes, which features have you used:
   - ☐ Allow or deny web pages
   - ☐ Collect resources
   - ☐ Building a lesson web page
   - ☐ Implement a lesson
   - ☐ Preview a lesson as a student

   If No, why not?

4. **In overall, how easy did you find iLessons to use?**
   - ☐ very easy
   - ☐ easy
   - ☐ quite difficult
   - ☐ difficult

   If you found iLessons quite difficult or difficult to use, why?.

5. **Would you consider buying iLessons?**
   - ☐ Yes
   - ☐ No

   If No, why not?

6. **Did you use the tutorials?**
   - ☐ Yes
   - ☐ No

   If No, any particular reason why not?

   If yes, how helpful did you find the tutorials?
   - ☐ not helpful
   - ☐ slightly helpful
   - ☐ helpful
   - ☐ very helpful

   If you found the tutorials not helpful or only slightly helpful, why?

APPENDIX C

EXPERIMENTAL SYSTEM DATABASE DESIGN

Table definitions

Users table

userGUID	Number
username	Text
activeReflective	Number
sensitiveIntuitive	Number
visualVerbal	Number
sequentialGlobal	Number

UserRatings table

userID	Number
documented	Number
rating	Yes/No

UserActivityAnalysis table

analysisID	AutoNumber
userID	Number
dataObjectID	Number
documented	Number
timestamp	Number
timespent	Number
mouseDistance	Number
mouseSpeed	Number
mouseXFactor	Number
mouseYFactor	Number
scrollYDistance	Number
scrollYSpeed	Number
scrollYPeaks	Number
navigationIn	Number
navigationOut	Number

DocumentAnalysis table

documented	AutoNumber
url	Memo
documentLength	Number
imagesArea	Number
imagesTop	Number
imagesMiddle	Number
imagesBottom	Number
tablesTop	Number
TablesMiddle	Number
tablesBottom	Number
bulletListsTop	Number
bulletListsMiddle	Number
bulletListsBottom	Number
numberListsTop	Number
numberListsMiddle	Number
numberListsBottom	Number
objectsTop	Number
objectsMiddle	Number
objectsBottom	Number
countQuestionMarks	Number
countExclamationMarks	Number
countExample	Number
countFigure	Number
countQuestion	Number
countDiagram	Number
countFact	Number
countPrevious	Number
countNext	Number

DataObjectAnalysis table

dataObjectID	AutoNumber
textLenght	Number
numCopies	Number
numDragDrops	Number
countImages	Number
countTables	Number
countBulletLists	Number
countNumberLists	Number
countObjects	Number
countQuestionMarks	Number
countExclamationMarks	Number
countExample	Number
countFigure	Number
countQuestion	Number
countDiagram	Number
countFact	Number
countPrevious	Number
countNext	Number

Table relationships

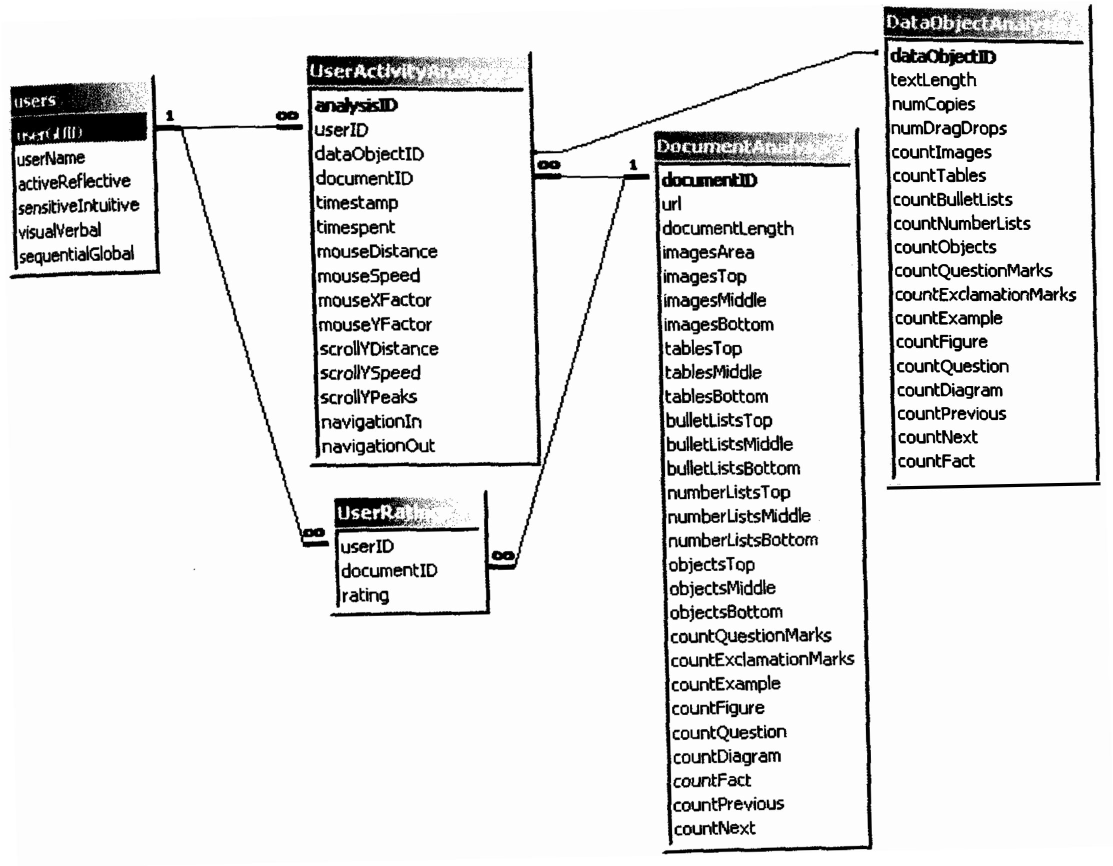

Figure B.1: Table relationships

APPENDIX D

VOLUNTEER TASK FOR EXPERIMENT STAGE II

Task title: Gain knowledge on plate tectonics

Time to complete the task: 15 minutes.

Objectives:

To gain knowledge on plate tectonics – What they are, different types, their effects on the landscape.

Description:

Use the World Wide Web to learn about plate tectonics. After you complete this task, you should have a good knowledge on:

- What plate tectonics are.
- The different layers of the Earth.
- The major plates and how they are distributed.
- The different kinds of plate boundaries.
- The different kinds of plate motion.
- The impact of plate tectonics on the landscape.

You may use the search engines of your choice to find the resources to complete this task.

There are two buttons on the top right corner of Internet Explorer, showing two light bulbs, switched on and off. If you find a page particularly easy to understand, you may click on the switched on bulb. If you find a page particularly difficult to understand, you may click on the switched off bulb.

Please note that by clicking on the light bulbs you are expressing how easy to understand is the page for you, not the relevance of the contents to the subject.

Also, using the light bulbs is not part of the main task and no special effort should be put in rating a particular page.

Thank you very much for your collaboration!!!

APPENDIX E

INDEX OF LEARNING STYLES QUESTIONNAIRE

Barbara A. Soloman
First-Year College
North Carolina State University
Raleigh, North Carolina 27695

Richard M. Felder
Department of Chemical Engineering
North Carolina State University
Raleigh, NC 27695-7905

Directions

Circle "a" or "b" to indicate your answer to every question. Please choose only one answer for each question. If both "a" and "b" seem to apply to you, choose the one that applies more frequently.

1. I understand something better after I
(a) try it out.
(b) think it through.

2. I would rather be considered
(a) realistic.
(b) innovative.

3. When I think about what I did yesterday, I am most likely to get
(a) a picture.
(b) words.

4. I tend to
(a) understand details of a subject but may be fuzzy about its overall structure.
(b) understand the overall structure but may be fuzzy about details.

5. When I am learning something new, it helps me to
(a) talk about it.
(b) think about it.

6. If I were a teacher, I would rather teach a course
(a) that deals with facts and real life situations.
(b) that deals with ideas and theories.

7. I prefer to get new information in
(a) pictures, diagrams, graphs, or maps.
(b) written directions or verbal information.

8. Once I understand
(a) all the parts, I understand the whole thing.
(b) the whole thing, I see how the parts fit.

9. In a study group working on difficult material, I am more likely to
(a) jump in and contribute ideas.
(b) sit back and listen.

10. I find it easier
(a) to learn facts.
(b) to learn concepts.

11. In a book with lots of pictures and charts, I am likely to
(a) look over the pictures and charts carefully.
(b) focus on the written text.

12. When I solve math problems
(a) I usually work my way to the solutions one step at a time.
(b) I often just see the solutions but then have to struggle to figure out the steps to get to them.

13. In classes I have taken
(a) I have usually gotten to know many of the students.
(b) I have rarely gotten to know many of the students.

14. In reading nonfiction, I prefer
(a) something that teaches me new facts or tells me how to do something.
(b) something that gives me new ideas to think about.

15. I like teachers
(a) who put a lot of diagrams on the board.
(b) who spend a lot of time explaining.

16. When I'm analyzing a story or a novel
(a) I think of the incidents and try to put them together to figure out the themes.
(b) I just know what the themes are when I finish reading and then I have to go back and find the incidents that demonstrate them.

17. When I start a homework problem, I am more likely to
(a) start working on the solution immediately.
(b) try to fully understand the problem first.

18. I prefer the idea of
(a) certainty.
(b) theory.

19. I remember best
(a) what I see.
(b) what I hear.

20. It is more important to me that an instructor
(a) lay out the material in clear sequential steps.
(b) give me an overall picture and relate the material to other subjects.

21. I prefer to study
(a) in a study group.
(b) alone.

22. I am more likely to be considered

(a) careful about the details of my work.
(b) creative about how to do my work.

23. When I get directions to a new place, I prefer

(a) a map.
(b) written instructions.

24. I learn

(a) at a fairly regular pace. If I study hard, I'll "get it."
(b) in fits and starts. I'll be totally confused and then suddenly it all "clicks."

25. I would rather first

(a) try things out.
(b) think about how I'm going to do it.

26. When I am reading for enjoyment, I like writers to

(a) clearly say what they mean.
(b) say things in creative, interesting ways.

27. When I see a diagram or sketch, I am most likely to remember

(a) the picture.
(b) what the instructor said about it.

28. When considering a body of information, I am more likely to

(a) focus on details and miss the big picture.
(b) try to understand the big picture before getting into the details.

29. I more easily remember

(a) something I have done.
(b) something I have thought a lot about.

30. When I have to perform a task, I prefer to

(a) master one way of doing it.
(b) come up with new ways of doing it.

31. When someone is showing me data, I prefer

(a) charts or graphs.
(b) text summarizing the results.

32. When writing a paper, I am more likely to

(a) work on (think about or write) the beginning of the paper and progress forward.
(b) work on (think about or write) different parts of the paper and then order them.

33. When I have to work on a group project, I first want to

(a) have "group brainstorming" where everyone contributes ideas.
(b) brainstorm individually and then come together as a group to compare ideas.

34. I consider it higher praise to call someone

(a) sensible.
(b) imaginative.

35. When I meet people at a party, I am more likely to remember
(a) what they looked like.
(b) what they said about themselves.

36. When I am learning a new subject, I prefer to
(a) stay focused on that subject, learning as much about it as I can.
(b) try to make connections between that subject and related subjects.

37. I am more likely to be considered
(a) outgoing.
(b) reserved.

38. I prefer courses that emphasize
(a) concrete material (facts, dat(a).
(b) abstract material (concepts, theories).

39. For entertainment, I would rather
(a) watch television.
(b) read a book.

40. Some teachers start their lectures with an outline of what they will cover. Such outlines are
(a) somewhat helpful to me.
(b) very helpful to me.

41. The idea of doing homework in groups, with one grade for the group,
(a) appeals to me.
(b) does not appeal to me.

42. When I am doing long calculations,
(a) I tend to repeat all my steps and check my work carefully.
(b) I find checking my work tiresome and have to force myself to do it.

43. I tend to picture places I have been
(a) easily and fairly accurately.
(b) with difficulty and without much detail.

44. When solving problems in a group, I would be more likely to
(a) think of the steps in the solution process.
(b) think of possible consequences or applications of the solution in a wide range of areas.

ILS scoring sheet

1. Put "1"s in the appropriate spaces in the table below (e.g. if you answered "a" to Question 3, put a "1" in Column A by Question 3).

2. Total the columns and write the totals in the indicated spaces.

3. For each of the four scales, subtract the smaller total from the larger one. Write the difference (1 to 11) and the letter (a or b) for which the total was larger on the bottom line. For example, if under "ACT/REF" you had 4 "a" and 7 "b" responses, you would write "3b" on the bottom line under that heading..

4. On the next page, mark "X"s above your scores on each of the four scales.

ACT/REF			SNS/INT			VIS/VRB			SEQ/GLO		
Q	a	b	Q	a	b	Q	a	b	Q	a	b
1			2			3			4		
5			6			7			8		
9			10			11			12		
13			14			15			16		
17			18			19			20		
21			22			23			24		
25			26			27			28		
29			30			31			32		
33			34			35			36		
37			38			39			40		
41			42			43			44		
Total (sum X's in each column)											
ACT/REF			**SNS/INT**			**VIS/VRB**			**SEQ/GLO**		
	a	b		a	b		a	b		a	b
(Larger – Smaller) + Letter of Larger (see below*)											

**Example:* If you totaled 3 for a and 8 for b, you would enter 5b in the space below. Transfer your scores to the ILS report form by placing X's at the appropriate locations on the four scales.

ILS report form

ACT											REF
11a	9a	7a	5a	3a	1a	1b	3b	5b	7b	9b	11b
SEN											INT
11a	9a	7a	5a	3a	1a	1b	3b	5b	7b	9b	11b
VIS											VRB
11a	9a	7a	5a	3a	1a	1b	3b	5b	7b	9b	11b
SEQ											GLO
11a	9a	7a	5a	3a	1a	1b	3b	5b	7b	9b	11b

If your score on a scale is 1-3, you are fairly well balanced on the two dimensions of that scale.

If your score on a scale is 5 or 7, you have a moderate preference for one dimension of the scale and will learn more easily in a teaching environment which favors that dimension.

If your score on a scale is 9 or 11, you have a very strong preference for one dimension of the scale. You may have real difficulty learning in an environment which does not support that preference.

See "Learning Styles and Strategies" by Richard Felder and Barbara Soloman for explanations of your preferences on the individual scales.

APPENDIX F

RULES TO INFER STUDENT LEARNING STYLE

Attributes

User activity attributes

Attribute	Abbreviation
Average time on page	AvgOftimespent
Average relative time on page	AvgOfrelativeTimeSpent
Average mouse distance	AvgOfmouseDistance
Average mouse speed	AvgOfmouseSpeec
Average mouse movement in the X axis	AvgOfmouseXFactor
Average mouse movement in the Y axis	AvgOfmouseYFactor
Average scroll distance	AvgOfscrollDistance
Average scroll speed	AvgOfscrollSpeed
Average number of changes in scroll direction	AvgOfscrollYPeaks
Average count of visited documents per domain	nPagesVisited

Document layout attributes

Attribute	Abbreviation
Average document length	AvgOfdocumentLength
Average image area	AvgOfimagesArea
Average of number of images	AvgOfnImages
Average of number of tables	AvgOfnTables
Average of number of lists	AvgOfnLists
Average of number of objects	AvgOfnObjects

Ratios to document length

Attribute	Abbreviation
Average of area of images to document length	AvgOfimagesArea2DocumentLength
Average of number of images to document length	AvgOfnImages2DocumentLength
Average of number of tables to document length	AvgOfnTables2DocumentLength
Average of number of lists to document length	AvgOfnLists2DocumentLength
Average of number of objects to document length	AvgOfnObjects2DocumentLength

Ratios to time on page

Attribute	Abbreviation
Average of image area to time on page	imagesArea2TimeSpent
Average of document length to time on page	documentLenght2TimeSpent
Average of number of images to time on page	nImages2TimeSpent
Average of number of tables to time on page	nTables2TimeSpent
Average of number of lists to time on page	nLists2TimeSpent
Average of number of objects to time on page	nObjects2TimeSpent
Average of area of images to document length to time on page	imagesArea2documentLenght2TimeSpent
Average of number of images to document length to time on page	nImages2documentLenght2TimeSpent

Average of number of tables to document length to time on page	nTables2documentLenght2TimeSpent
Average of number of lists to document length to time on page	nLists2documentLenght2TimeSpent
Average of number of objects to document length to time on page	nObjects2documentLenght2TimeSpent
Average of scroll peaks to time on page	scrollYPeaks2TimeSpent

Ratios to mouse distance

Attribute	Abbreviation
Average of image area to mouse distance	imagesArea2mouseDistance
Average of document length to mouse distance	documentLenght2mouseDistance
Average of number of images to mouse distance	nImages2mouseDistance
Average of number of tables to mouse distance	nTables2mouseDistance
Average of number of lists to mouse distance	nLists2mouseDistance
Average of number of objects to mouse distance	nObjects2mouseDistance
Average of area of images to document length to mouse distance	imagesArea2documentLenght2mouseDistance
Average of number of images to document length to mouse distance	nImages2documentLenght2mouseDistance
Average of number of tables to document length to mouse distance	nTables2documentLenght2mouseDistance
Average of number of lists to document length to mouse distance	nLists2documentLenght2mouseDistance
Average of number of objects to document length to mouse distance	nObjects2documentLenght2mouseDistance

Ratios to mouse speed

Attribute	Abbreviation
Average of document length to mouse speed	documentLenght2mouseSpeed
Average of image area to mouse speed	imagesArea2mouseSpeed
Average of number of images to mouse speed	nImages2mouseSpeed
Average of number of tables to mouse speed	nTables2mouseSpeed
Average of number of lists to mouse speed	nLists2mouseSpeed
Average of number of objects to mouse speed	nObjects2mouseSpeed
Average of area of images to document length to mouse speed	imagesArea2documentLenght2mouseSpeed
Average of number of images to document length to mouse speed	nImages2documentLenght2mouseSpeed
Average of number of tables to document length to mouse speed	nTables2documentLenght2mouseSpeed
Average of number of lists to document length to mouse speed	nLists2documentLenght2mouseSpeed
Average of number of objects to document length to mouse speed	nObjects2documentLenght2mouseSpeed

Ratios to mouse movement in the X axis

Attribute	Abbreviation
Average of document length to mouse movement in the X axis	documentLenght2mouseXFactor
Average of image area to mouse movement in the X axis	imagesArea2mouseXFactor
Average of number of images to mouse movement in the X axis	nImages2mouseXFactor
Average of number of tables to mouse movement in the X axis	nTables2mouseXFactor
Average of number of lists to mouse movement in the X axis	nLists2mouseXFactor
Average of number of objects to mouse movement in the X axis	nObjects2mouseXFactor
Average of area of images to document length to mouse movement in the X axis	imagesArea2documentLenght2mouseXFactor
Average of number of images to document length to mouse movement in the X axis	nImages2documentLenght2mouseXFactor

Average of number of tables to document length to mouse movement in the X axis nTables2documentLenght2mouseXFactor
Average of number of lists to document length to mouse movement in the X axis nLists2documentLenght2mouseXFactor
Average of number of objects to document length to mouse movement in the X axis nObjects2documentLenght2mouseXFactor

Ratios to mouse movement in the Y axis

Attribute **Abbreviation**

Average of document length to mouse movement in the Y axis documentLenght2mouseYFactor
Average of image area to mouse movement in the Y axis............ imagesArea2mouseYFactor
Average of number of images to mouse movement in the Y axis.......nImages2mouseYFactor
Average of number of tables to mouse movement in the Y axis..........nTables2mouseYFactor
Average of number of lists to mouse movement in the Y axis nLists2mouseYFactor
Average of number of objects to mouse movement in the Y axis...... nObjects2mouseYFactor
Average of area of images to document length to mouse movement in the Y axis imagesArea2documentLenght2mouseYFactor
Average of number of images to document length to mouse movement in the Y axis nImages2documentLenght2mouseYFactor
Average of number of tables to document length to mouse movement in the Y axis nTables2documentLenght2mouseYFactor
Average of number of lists to document length to mouse movement in the Y axis nLists2documentLenght2mouseYFactor
Average of number of objects to document length to mouse movement in the Y axis nObjects2documentLenght2mouseYFactor

Ratios to scroll distance

Attribute **Abbreviation**

Average of image area to scroll distance imagesArea2scrollDistance
Average of document length to scroll distance documentLenght2scrollDistance
Average of number of images to scroll distance nImages2scrollDistance
Average of number of tables to scroll distance nTables2scrollDistance
Average of number of lists to scroll distance... nLists2scrollDistance
Average of number of objects to scroll distance nObjects2scrollDistance
Average of area of images to document length to scroll distance imagesArea2documentLenght2scrollDistance
Average of number of images to document length to scroll distance nImages2documentLenght2scrollDistance
Average of number of tables to document length to scroll distance nTables2documentLenght2scrollDistance
Average of number of lists to document length to scroll distance nLists2documentLenght2scrollDistance
Average of number of objects to document length to scroll distance nObjects2documentLenght2scrollDistance

Ratios to scroll speed

Attribute **Abbreviation**

Average of document length to scroll speed documentLenght2scrollSpeed
Average of image area to scroll speed..imagesArea2scrollSpeed
Average of number of images to scroll speed.. nImages2scrollSpeed
Average of number of tables to scroll speed... nTables2scrollSpeed
Average of number of lists to scroll speed nLists2scrollSpeed
Average of number of objects to scroll speed nObjects2scrollSpeed
Average of area of images to document length to scroll speed imagesArea2documentLenght2scrollSpeed
Average of number of images to document length to scroll speed nImages2documentLenght2scrollSpeed

Average of number of tables to document length to scroll speed nTables2documentLenght2scrollSpeed
Average of number of lists to document length to scroll speed nLists2documentLenght2scrollSpeed
Average of number of objects to document length to scroll speed nObjects2documentLenght2scrollSpeed

Ratios to number of scroll peaks

Attribute **Abbreviation**
Average of image area to scroll peaks imagesArea2scrollYPeaks
Average of document length to scroll peaks documentLenght2scrollYPeaks
Average of number of images to scroll peaks nImages2scrollYPeaks
Average of number of tables to scroll peaks nTables2scrollYPeaks
Average of number of lists to scroll peaks...nLists2scrollYPeaks
Average of number of objects to scroll peaks nObjects2scrollYPeaks
Average of area of images to document length to scroll peaks imagesArea2documentLenght2scrollYPeaks
Average of number of images to document length to scroll peaks nImages2documentLenght2scrollYPeaks
Average of number of tables to document length to scroll peaks nTables2documentLenght2scrollYPeaks
Average of number of lists to document length to scroll peaks..nLists2documentLenght2scrollYPeaks
Average of number of objects to document length to scroll peaks nObjects2documentLenght2scrollYPeaks

Rules

First exploration

Rule name	**AR1**	**Dimension of learning style**	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.5405 < (-0.0466779*AvgOfmouseDistance +2.77642*AvgOfmouseYFactor -0.481459*AvgOfscrollYSpeed -0.166629*AvgOfscrollYPeaks)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseDistance		1.694
	AvgOfmouseYFactor		185.2
	AvgOfscrollYSpeed		43.22
	AvgOfscrollYPeaks		1.576
Classification probability	100%	**Standard deviation**	0.1898
Classification efficiency	100%	**Standard error**	0.4038
P-value	2.575E-5	**R-squared**	0.837
Significance Index	3.379		

Rule name	**SI1**	**Dimension of learning style**	Sensing / Intuitive
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.4027 < (-0.152604*AvgOfmouseSpeed +1.31869*AvgOfmouseYFactor)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseSpeed		1.371
	AvgOfmouseYFactor		14.17
Classification probability	65%	**Standard deviation**	0.4805
Classification efficiency	30%	**Standard error**	0.9367
P-value	9.80E-01	**R-squared**	0.1225
Significance Index	-1.167		

Rule name	VV1	Dimension of learning style	Visual / Verbal
Output	Boolean: TRUE if Visual, FALSE if Verbal		
Rule Expression	0.426 < (+0.831203 -0.330758*AvgOfscrollYPeaks)		
Terms	Term name		F-Ratio
	AvgOfscrollYPeaks		1.706
Classification probability	80%	Standard deviation	0.4246
Classification efficiency	20%	Standard error	0.9557
P-value	8.06E-01	R-squared	0.08657
Significance Index	-1.01		

Rule name	SG1	Dimension of learning style	Sequential / Global
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.4572 < (+0.794524*AvgOfmouseYFactor)		
Terms	Term name		F-Ratio
	AvgOfmouseYFactor		13.88
Classification probability	75%	Standard deviation	0.4933
Classification efficiency	38%	Standard error	0.9814
P-value	7.92E-06	R-squared	0.03685
Significance Index	-1.28		

Rule name	AR2	Dimension of learning style	Active/Reflective
Output	Continuous value: 1 if Active, 0 if Reflective		
Rule Expression	1 *if(-0.0561185 <= 1*AvgOfscrollYSpeed and 1*AvgOfscrollYSpeed < -0.0561185 + 2.97228*AvgOfmouseYFactor,1 ,1.44321e-006)		
Terms	Term name		F-Ratio
	AvgOfscrollYSpeed		N/A
	AvgOfmouseYFactor		N/A
Classification probability	N/A	Standard deviation	4.583E-6
Classification efficiency	N/A	Standard error	1E-5
P-value	N/A	R-squared	1
Significance Index	> 100		

Rule name	SI2	Dimension of learning style	Sensing / Intuitive
Output	Continuous value: 1 if Sensing, 0 if Intuitive		
Rule Expression	1.0001 *AvgOfscrollYSpeed*AvgOfscrollYSpeed*AvgOfscrollYSpeed-20.0508)/(AvgOfscrollYSpeed*AvgOfscrollYSpeed*AvgOfscrollYSpeed*if(-0.490882*AvgOfscrollYDistance <= 1*AvgOfmouseSpeed and 1*AvgOfmouseSpeed < -0.490882*AvgOfscrollYDistance + 1.80487*AvgOfscrollYSpeed,1 ,1.43766*AvgOftimespent)-20.0536 +0.00373225 *AvgOfmouseSpeed		
Terms	Term name		F-Ratio
	AvgOfscrollYSpeed		N/A
	AvgOfscrollYDistance		N/A
	AvgOfmouseSpeed		N/A
	AvgOftimespent		N/A
Classification probability	N/A	Standard deviation	2.75E-5
Classification efficiency	N/A	Standard error	5.49E-5
P-value	N/A	R-squared	1
Significance Index	2.612		

Second exploration

Rule name	AR3	Dimension of learning style	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.4245 < (+3.52420 -2.49796e-010*AvgOftimespent -0.167342*AvgOfmouseDistance -1.65235*AvgOfmouseXFactor +0.0754695*AvgOfscrollYDistance -0.257725*AvgOfscrollYSpeed -0.000101858*AvgOfdocumentLength -0.0752309*AvgOfCountOfdocumentID)		
Terms	**Term name**		**F-Ratio**
	AvgOftimespent		6.276
	AvgOfmouseDistance		17
	AvgOfmouseXFactor		4.768
	AvgOfscrollYDistance		3.108
	AvgOfscrollYSpeed		34.97
	AvgOfdocumentLength		12.44
	AvgOfCountOfdocumentID		10.93
Classification probability	100%	**Standard deviation**	0.1352
Classification efficiency	100%	**Standard error**	0.2876
P-value	2.575E-5	**R-squared**	0.9173
Significance Index	3.569		

Rule name	SI3	Dimension of learning style	Sensing / Intuitive
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.4656 < (+1.75259*AvgOfmouseYFactor -0.0765132*AvgOfCountOfdocumentID)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		16.23
	AvgOfCountOfdocumentID		3.872
Classification probability	80 %	**Standard deviation**	0.4522
Classification efficiency	60 %	**Standard error**	0.8815
P-value	0.3187	**R-squared**	0.2229
Significance Index	-0.9254		

Rule name	VV2	Dimension of learning style	Visual / Verbal
Output	Boolean: TRUE if Visual, FALSE if Verbal		
Rule Expression	0.5898 < (+2.69835 -2.87084*AvgOfmouseYFactor +0.119905*AvgOfscrollYDistance -0.253936*AvgOfscrollYPeaks -3.34205e-006*AvgOfimagesArea)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		2.7
	AvgOfscrollYDistance		2.535
	AvgOfscrollYPeaks		0.1509
	AvgOfimagesArea		6.965
Classification probability	90 %	**Standard deviation**	0.3448
Classification efficiency	60 %	**Standard error**	0.7761
P-value	0.004897	**R-squared**	0.3977
Significance Index	0.09402		

Rule name	**SG2**	**Dimension of learning style**	Sequential / Global
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.4572 < (+0.794524*AvgOfmouseYFactor)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		13.88
Classification probability	75%	**Standard deviation**	0.4933
Classification efficiency	38%	**Standard error**	0.9814
P-value	7.92E-06	**R-squared**	0.03685
Significance Index	-1.28		

Rule name	**AR4**	**Dimension of learning style**	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.4998 < ((1.00078 *AvgOfscrollYSpeed*AvgOfscrollYSpeed-4.60118 *AvgOfscrollYSpeed+0.00574098 *if(1.01019 *AvgOfmouseXFactor <= 0.729478 and 0.729478 < 1.01019 *AvgOfmouseXFactor + 1.01019 *AvgOfmouseYFactor,1 ,884.89)-0.00460499)/(AvgOfscrollYSpeed*AvgOfscrollYSpeed*if(1.01019 *AvgOfmouseXFactor <= 0.729478 and 0.729478 < 1.01019 *AvgOfmouseXFactor + 1.01019 *AvgOfmouseYFactor,1 ,884.89)-4.59889 *AvgOfscrollYSpeed))		
Terms	**Term name**		**F-Ratio**
	AvgOfscrollYSpeed		N/A
	AvgOfmouseXFactor		N/A
	AvgOfmouseYFactor		N/A
	AvgOfscrollYSpeed		N/A
Classification probability	100 %	**Standard deviation**	4.58E-06
Classification efficiency	100 %	**Standard error**	1.00E-05
P-value	2.575E-5	**R-squared**	1
Significance Index	> 100		

Rule name	**SI4**	**Dimension of learning style**	Sensing / Intuitive
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.3586 < (0.714281 *if(0.0113714 *AvgOfCountOfdocumentID+0.430699 <= 1 *AvgOfmouseYFactor and 1 *AvgOfmouseYFactor < 0.0113714 *AvgOfCountOfdocumentID+0.430699 + 2.42875 ,1 ,0.00395698))		
Terms	**Term name**		**F-Ratio**
	AvgOfCountOfdocumentID		N/A
	AvgOfmouseYFactor		N/A
Classification probability	80 %	**Standard deviation**	0.3683
Classification efficiency	60 %	**Standard error**	0.7367
P-value	0.3187	**R-squared**	0.4573
Significance Index	2.636		

Third exploration

Rule name	AR5	Dimension of learning style	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.4088 < (+1.16567 -0.122474*AvgOfmouseDistance +1.89403*AvgOfmouseYFactor -0.221499*AvgOfscrollYSpeed - 0.0861639*AvgOfscrollYPeaks -1.21102e-006*AvgOfimgsAreaToScrollDist - 5.41779e-005*AvgOfdocLenToScrollYPeaks)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseDistance		14.72
	AvgOfmouseYFactor		6.848
	AvgOfscrollYSpeed		40.31
	AvgOfscrollYPeaks		2.466
	AvgOfimgsAreaToScrollDist		16.47
	AvgOfdocLenToScrollYPeaks		11.29
Classification probability	100%	**Standard deviation**	0.1229
Classification efficiency	100%	**Standard error**	0.2614
P-value	2.575E-5	**R-squared**	0.9317
Significance Index	0.3293		

Rule name	SI5	Dimension of learning style	Sensing / Intuitive
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.4231 < (+1.32827*AvgOfmouseYFactor +0.126146*AvgOfscrollYSpeed - 118.317*AvgOfimgsAreaToTimespent -1.11946e-006*AvgOfimgsAreaToScrollDist)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		4.794
	AvgOfscrollYSpeed		1.399
	AvgOfimgsAreaToTimespent		1.779
	AvgOfimgsAreaToScrollDist		1.367
Classification probability	80 %	**Standard deviation**	0.4252
Classification efficiency	60 %	**Standard error**	0.8289
P-value	0.3187	**R-squared**	0.3129
Significance Index	-0.9782		

Rule name	VV3	Dimension of learning style	Visual / Verbal
Output	Boolean: TRUE if Visual, FALSE if Verbal		
Rule Expression	0.4813 < (+2.98146 -2.52268*AvgOfmouseYFactor +0.131770*AvgOfscrollYSpeed -0.148819*AvgOfscrollYPeaks +145.483*AvgOfimgsAreaToTimespent -3.22031e-006*AvgOfimgsAreaToScrollDist -0.000115188*AvgOfdocLenToScrollYPeaks)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		2.7
	AvgOfscrollYDistance		2.535
	AvgOfscrollYPeaks		0.1509
	AvgOfimagesArea		6.965
Classification probability	100 %	**Standard deviation**	0.1906
Classification efficiency	100 %	**Standard error**	0.4291
P-value	6.441E-5	**R-squared**	0.8159
Significance Index	0.4304		

Rule name	SG3	**Dimension of learning style**		Sequential / Global	
Output	Boolean: TRUE if Sensing, FALSE if Intuitive				
Rule Expression	0.4813 < (+2.98146 -2.52268*AvgOfmouseYFactor +0.131770*AvgOfscrollYSpeed -0.148819*AvgOfscrollYPeaks +145.483*AvgOfimgsAreaToTimespent -3.22031e-006*AvgOfimgsAreaToScrollDist -0.000115188*AvgOfdocLenToScrollYPeaks)				
Terms	**Term name**				**F-Ratio**
	AvgOfmouseYFactor				13.88
Classification probability		100 %	**Standard deviation**		0.1906
Classification efficiency		100 %	**Standard error**		0.4291
P-value		6.441E-5	**R-squared**		0.8159
Significance Index		0.4304			

Rule name	AR6	**Dimension of learning style**		Active/Reflective	
Output	Boolean: TRUE if Active, FALSE if Reflective				
Rule Expression	0.6646 < ((1.15188 -7.14852e-012 *AvgOfimgsAreaToScrollDist*AvgOfimgsAreaToScrollDist)/ (AvgOfmouseDistance-1.21027e-006* AvgOfimgsAreaToScrollDist* AvgOfmouseDistance* AvgOfmouseDistance))				
Terms	**Term name**				**F-Ratio**
	AvgOfimgsAreaToScrollDist				N/A
	AvgOfmouseDistance				N/A
Classification probability		100 %	**Standard deviation**		1.732E-5
Classification efficiency		100 %	**Standard error**		3.78E-5
P-value		2.575E-5	**R-squared**		1
Significance Index		6.915			

Rule name	VV4	**Dimension of learning style**		Visual / Verbal	
Output	Boolean: TRUE if Visual, FALSE if Verbal				
Rule Expression	0.5029 < ((0.999043 *AvgOfmouseYFactor*if(0.00148037*AvgOfimgsAreaToScrollDist <= 603.18 and 603.18 < 0.00148037*AvgOfimgsAreaToScrollDist + 55.2539*AvgOfimgsAreaToScrollDist,1 ,7.14312e-005)-0.611447 *if(0.00148037*AvgOfimgsAreaToScrollDist <= 603.18 and 603.18 < 0.00148037*AvgOfimgsAreaToScrollDist + 55.2539*AvgOfimgsAreaToScrollDist,1 ,7.14312e-005))/(AvgOfmouseYFactor-0.612891 +0.000932765 *if(0.00148037*AvgOfimgsAreaToScrollDist <= 603.18 and 603.18 < 0.00148037*AvgOfimgsAreaToScrollDist + 55.2539*AvgOfimgsAreaToScrollDist,1 ,7.14312e-005)*if(0.00148037*AvgOfimgsAreaToScrollDist <= 603.18 and 603.18 < 0.00148037*AvgOfimgsAreaToScrollDist + 55.2539*AvgOfimgsAreaToScrollDist,1 ,7.14312e-005)))				
Terms	**Term name**				**F-Ratio**
	AvgOfmouseYFactor				N/A
	AvgOfimgsAreaToScrollDist				N/A
Classification probability		100 %	**Standard deviation**		1.541E-4
Classification efficiency		100 %	**Standard error**		3.558E-4
P-value		6.441E-5	**R-squared**		1
Significance Index		4.891			

Fourth exploration

Rule name	AR7	Dimension of learning style	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.4299 < (+0.924947 -0.0719723*AvgOfmouseDistance +2.31372*AvgOfmouseYFactor -0.201854*AvgOfscrollYSpeed - 0.000100890*AvgOfdocumentLength +0.00200758*AvgOfdocLenToTimespent -1.35637e-006*AvgOfimgsAreaToScrollDist - 3.54662E+7*AvgOfScrollYPeaksToTimespent - 0.0501277*AvgOfscrollPeakDistance)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseDistance		3.733
	AvgOfmouseYFactor		14.25
	AvgOfscrollYSpeed		46.72
	AvgOfdocumentLength		23.1
	AvgOfdocLenToTimespent		7.313
	AvgOfimgsAreaToScrollDist		22.84
	AvgOfScrollYPeaksToTimespent		5.289
	AvgOfscrollPeakDistance		1
Classification probability	100%	Standard deviation	0.0922
Classification efficiency	100%	Standard error	0.1961
P-value	2.575E-5	R-squared	0.9615
Significance Index	0.5626		

Rule name	SI6	Dimension of learning style	Sensing / Intuitive
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.4231 < (+1.32827*AvgOfmouseYFactor +0.126146*AvgOfscrollYSpeed - 118.317*AvgOfimgsAreaToTimespent -1.11946e-006*AvgOfimgsAreaToScrollDist)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		4.794
	AvgOfscrollYSpeed		1.399
	AvgOfimgsAreaToTimespent		1.779
	AvgOfimgsAreaToScrollDist		1.367
Classification probability	80 %	Standard deviation	0.4252
Classification efficiency	60 %	Standard error	0.8289
P-value	0.3187	R-squared	0.3129
Significance Index	-0.8491		

Rule name	**VV5**	**Dimension of learning style**	Visual / Verbal
Output	Boolean: TRUE if Visual, FALSE if Verbal		
Rule Expression	0.4624 < (+4.25279 -0.103700*AvgOfmouseSpeed -2.99759*AvgOfmouseYFactor -0.629890*AvgOfscrollYPeaks +5.63635e-006*AvgOfimagesArea +3.61444e-005*AvgOfimgsAreaToTimespent -3.44388e-005*AvgOfdocLenToMouseDist -2.58056e-006*AvgOfimgsAreaToScrollDist -5.42149e-006*AvgOfimgsAreaToScrollYPeaks -0.000161363*AvgOfdocLenToScrollYPeaks +4.57876E+7*AvgOfScrollYPeaksToTimespent)		

Terms	Term name	F-Ratio
	AvgOfmouseSpeed	2.606
	AvgOfmouseYFactor	9.736
	AvgOfscrollYPeaks	18.78
	AvgOfimagesArea	10.59
	AvgOfimgsAreaToTimespent	6.624
	AvgOfdocLenToMouseDist	4.82
	AvgOfimgsAreaToScrollDist	35.06
	AvgOfimgsAreaToScrollYPeaks	16.48
	AvgOfdocLenToScrollYPeaks	19.02
	AvgOfScrollYPeaksToTimespent	5.583

Classification probability	100 %	**Standard deviation**	0.1221
Classification efficiency	100 %	**Standard error**	0.2748
P-value	6.441E-5	**R-squared**	0.9245
Significance Index	0.6342		

Rule name	**SG4**	**Dimension of learning style**	Sequential / Global
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.4364 < (-0.0889428*AvgOfmouseDistance +1.56193*AvgOfmouseYFactor -4.07380e-005*AvgOfdocLenToMouseDist)		

Terms	Term name	F-Ratio
	AvgOfmouseDistance	1.441
	AvgOfmouseYFactor	9.364
	AvgOfdocLenToMouseDist	1.945

Classification probability	70 %	**Standard deviation**	0.4572
Classification efficiency	25 %	**Standard error**	0.9095
P-value	0.7429	**R-squared**	0.1728
Significance Index	-0.9074		

Rule name	AR8	Dimension of learning style	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.5115 < ((-16680.8 *if(0.229582/AvgOfmouseYFactor <= 1/AvgOfscrollYSpeed and 1/AvgOfscrollYSpeed < 0.229582/AvgOfmouseYFactor + 1.89818 ,1 ,5541.74)+3.00936 *if(0.229582/AvgOfmouseYFactor <= 1/AvgOfscrollYSpeed and 1/AvgOfscrollYSpeed < 0.229582/AvgOfmouseYFactor + 1.89818 ,1 ,5541.74)*if(0.229582/AvgOfmouseYFactor <= 1/AvgOfscrollYSpeed and 1/AvgOfscrollYSpeed < 0.229582/AvgOfmouseYFactor + 1.89818 ,1 ,5541.74))/(if(0.229582/AvgOfmouseYFactor <= 1/AvgOfscrollYSpeed and 1/AvgOfscrollYSpeed < 0.229582/AvgOfmouseYFactor + 1.89818 ,1 ,5541.74)*if(0.229582/AvgOfmouseYFactor <= 1/AvgOfscrollYSpeed and 1/AvgOfscrollYSpeed < 0.229582/AvgOfmouseYFactor + 1.89818 ,1 ,5541.74)-359.969 *AvgOfmouseDistance*if(0.229582/AvgOfmouseYFactor <= 1/AvgOfscrollYSpeed and 1/AvgOfscrollYSpeed < 0.229582/AvgOfmouseYFactor + 1.89818 ,1 ,5541.74)-5020.96 *if(0.229582/AvgOfmouseYFactor <= 1/AvgOfscrollYSpeed and 1/AvgOfscrollYSpeed < 0.229582/AvgOfmouseYFactor + 1.89818 ,1 ,5541.74)-10961.1))		
Terms	Term name		F-Ratio
	AvgOfmouseYFactor		N/A
	AvgOfscrollYSpeed		N/A
	AvgOfmouseDistance		N/A
Classification probability	100 %	Standard deviation	3.766E-6
Classification efficiency	100 %	Standard error	8.219E-6
P-value	2.575E-5	R-squared	1
Significance Index	>100		

Rule name	VV6	Dimension of learning style	Visual / Verbal
Output	Boolean: TRUE if Visual, FALSE if Verbal		
Rule Expression	0.5257 < ((0.99296 *AvgOfimagesArea*if(0.0118017 <= 1*AvgOfimgsAreaToScrollDist and 1*AvgOfimgsAreaToScrollDist < 0.0118017 + 81.4492*AvgOfdocLenToMouseDist,1 ,-0.0287374)-160896 *if(0.0118017 <= 1*AvgOfimgsAreaToScrollDist and 1*AvgOfimgsAreaToScrollDist < 0.0118017 + 81.4492*AvgOfdocLenToMouseDist,1 ,-0.0287374)-401.28)/(AvgOfimagesArea-161927))		
Terms	Term name		F-Ratio
	AvgOfimagesArea		N/A
	AvgOfimgsAreaToScrollDist		N/A
	AvgOfdocLenToMouseDist		N/A
Classification probability	100 %	Standard deviation	2.051E-4
Classification efficiency	100 %	Standard error	4.736E-4
P-value	6.441E-5	R-squared	1
Significance Index	6.489		

Fifth exploration

Rule name	**AR9**	**Dimension of learning style**	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.5842 < (+3.10657*AvgOfmouseYFactor -4.95907e-005*documentLength2timespent - 0.00236782*imagesArea2documentLength2scrollYDistance)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		150.4
	documentLength2timespent		24.47
	imagesArea2documentLength2scrollYDistance		19.25
Classification probability	100%	**Standard deviation**	0.2218
Classification efficiency	100%	**Standard error**	0.4992
P-value	6.441E-5	**R-squared**	0.7508
Significance Index	12.27		

Rule name	**SI7**	**Dimension of learning style**	Sensing / Intuitive
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.3857 < (+1.00457e-009*AvgOftimespent +0.648043*AvgOfscrollYSpeed - 2.02203e-006*imagesArea2timespent +6.95122e-007*imagesArea2mouseYFactor -1.45478e-006*imagesArea2scrollYDistance -1.97550*nObjects2scrollYSpeed)		
Terms	**Term name**		**F-Ratio**
	AvgOftimespent		27.59
	AvgOfscrollYSpeed		139.2
	imagesArea2timespent		43.92
	imagesArea2mouseYFactor		15.68
	imagesArea2scrollYDistance		8.637
	nObjects2scrollYSpeed		29.93
Classification probability	100 %	**Standard deviation**	0.1494
Classification efficiency	100 %	**Standard error**	0.2973
P-value	7.916E-6	**R-squared**	0.9116
Significance Index	5.107		

Rule name	VV7	Dimension of learning style	Visual / Verbal
Output	Boolean: TRUE if Visual, FALSE if Verbal		
Rule Expression	0.4624 < (+4.25279 -0.103700*AvgOfmouseSpeed -2.99759*AvgOfmouseYFactor -0.629890*AvgOfscrollYPeaks +5.63635e-006*AvgOfimagesArea +3.61444e-005*AvgOfimgsAreaToTimespent -3.44388e-005*AvgOfdocLenToMouseDist -2.58056e-006*AvgOfimgsAreaToScrollDist -5.42149e-006*AvgOfimgsAreaToScrollYPeaks -0.000161363*AvgOfdocLenToScrollYPeaks +4.57876E+7*AvgOfScrollYPeaksToTimespent)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseYFactor		1.429E+11
	AvgOfdocumentLength		3.075E+10
	AvgOfimagesArea		4.023E+6
	AvgOfnObjects		1.367E+11
	AvgOfimagesArea2documentLength		1.999E+10
	AvgOfcountExclamationMarks2documentLength		7.713E+9
	AvgOfcountDiagram2documentLength		6.463E+10
	documentLength2timespent		2.621E+9
	nImages2mouseDistance		6.04E+9
	nTables2mouseDistance		1.013E+11
	nObjects2mouseDistance		1.671E+9
	nImages2documentLength2mouseDistance		2.838E+8
	documentLength2mouseSpeed		5.812E+7
	imagesArea2documentLength2mouseSpeed		3008
	nImages2documentLength2mouseXFactor		8.137E+8
	imagesArea2documentLength2scrollYDistance		4.735E+10
	nTables2documentLength2scrollYDistance		1.363E+8
	nObjects2documentLength2scrollYSpeed		5.264E+7
	documentLength2mouseXFactor		6.795E+9
Classification probability	100 %	**Standard deviation**	3.094E-7
Classification efficiency	100 %	**Standard error**	7.539E-7
P-value	2.062E-4	**R-squared**	1
Significance Index	1.58		

Rule name	SG5	Dimension of learning style	Sequential / Global
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.5 < (+2.41269e-009*AvgOftimespent +0.222233*AvgOfscrollYDistance +3019.10*AvgOfcountExclamationMarks2documentLength +13.9946*AvgOfcountQuestion2documentLength -3.30583e-006*imagesArea2timespent +3.23098*nObjects2timespent -152.522*nTables2documentLength2timespent -38.1120*nImages2documentLength2mouseDistance +2179.42*nLists2documentLength2mouseDistance -0.822809*nLists2mouseSpeed -19.7345*nObjects2mouseSpeed -4.36224*nImages2documentLength2mouseSpeed +8.09948e-005*documentLength2mouseYFactor +5.28087e-007*imagesArea2mouseYFactor +0.872196*nLists2scrollYDistance +19.0814*nImages2documentLength2scrollYDistance -4.52701e-005*documentLength2scrollYSpeed +326.253*nLists2documentLength2scrollYSpeed -6.47540e-006*documentLength2scrollYPeaks)		
Terms	**Term name**		**F-Ratio**
	AvgOftimespent		1.437e+10
	AvgOfscrollYDistance		6.536E+9
	AvgOfcountExclamationMarks2documentLength		4.392e+010
	AvgOfcountQuestion2documentLength		7.158E+4
	imagesArea2timespent		2.333e+10
	nObjects2timespent		5.473e+10
	nTables2documentLength2timespent		1.167e+10
	nImages2documentLength2mouseDistance		3.318E+9
	nLists2documentLength2mouseDistance		1.098e+10
	nLists2mouseSpeed		1.102e+10
	nObjects2mouseSpeed		8.621e+10
	nImages2documentLength2mouseSpeed		3.547E+7
	documentLength2mouseYFactor		8.012E+9
	imagesArea2mouseYFactor		5.137E+9
	nLists2scrollYDistance		2.636e+10
	nImages2documentLength2scrollYDistance		1.925e+10
	nLists2documentLength2scrollYSpeed		1.299E+8
	documentLength2scrollYPeaks		7.213E+6
	documentLength2scrollYSpeed		3.345E+8
Classification probability	70 %	**Standard deviation**	7.284E-7
Classification efficiency	25 %	**Standard error**	1.449E-6
P-value	7.916E-6	**R-squared**	1
Significance Index	0		

Sixth exploration

Rule name	PAR1	Dimension of learning style		Active/Reflective	
Std. error	68.96%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ if (AvgOftimespent<182995000,1,if (AvgOftimespent>769424000,0,0.48))
+ if (AvgOfrelativeTimeSpent<1.10185,1,if (AvgOfrelativeTimeSpent>1.24734,1,0.347826087))
+ if (AvgOfimagesAverageArea<28939.8,1,if
(AvgOfimagesAverageArea>58823.9,0,0.363636364))
+ if (imagesArea2timespent<176602,1,if (imagesArea2timespent>912391,0,0.48))
+ if (nObjects2timespent<0,0,if (nObjects2timespent>0.857677,1,0.482758621))
+ if (imagesArea2documentLength2timespent<74.5553,1,if
(imagesArea2documentLength2timespent>343.999,0,0.5))
+ if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0236,1,0.52))
+ if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.0939798,1,0.464285714))
+ if (nTables2documentLength2mouseDistance<0.00140822,1,if
(nTables2documentLength2mouseDistance>0.00334805,1,0.166666667))
+ if (nLists2documentLength2mouseDistance<1.19789E-05,1,if
(nLists2documentLength2mouseDistance>0.00035356,1,0.444444444))
+ if (imagesArea2mouseSpeed<193412,1,if
(imagesArea2mouseSpeed>547021,1,0.318181818))
+ if (imagesArea2documentLength2mouseXFactor<94.5044,1,if
(imagesArea2documentLength2mouseXFactor>183.425,1,0.285714286))
+ if (nImages2mouseYFactor<18.6658,1,if (nImages2mouseYFactor>65.672,0,0.461538462))
+ if (documentLength2scrollYDistance<3576.44,1,if
(documentLength2scrollYDistance>7719.66,1,0.423076923))
+ if (imagesArea2documentLength2scrollYDistance<120.239,1,if
(imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ if (documentLength2scrollYSpeed<1676.81,0,if
(documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ if (imagesArea2documentLength2scrollYPeaks<31.4118,0,if
(imagesArea2documentLength2scrollYPeaks>123.973,0,0.576923077))) / 17.57692308

Terms	Term name	F-ratio
	nPagesVisited	2.894e+010
	AvgOftimespent	1.288e+011
	AvgOfrelativeTimeSpent	1.506e+010
	AvgOfimagesAverageArea	1.642e+004
	imagesArea2timespent	9.324e+010
	nObjects2timespent	5.631e+010
	imagesArea2documentLength2timespent	1.256e+011
	nTables2mouseDistance	6.404e+009
	nObjects2mouseDistance	8.686e+010
	nTables2documentLength2mouseDistance	1.031e+009
	nLists2documentLength2mouseDistance	1.038e+011
	imagesArea2mouseSpeed	2.465e+010
	imagesArea2documentLength2mouseXFactor	1.236e+007
	nImages2mouseYFactor	1.183e+011
	documentLength2scrollYDistance	6.227e+010
	imagesArea2documentLength2scrollYDistance	1.218e+011
	documentLength2scrollYSpeed	4.26e+008
	imagesArea2documentLength2scrollYPeaks	1.425e+011

Rule name	PSI1	Dimension of learning style			Sensing/Intuitive
Std. error	97.77%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfmouseSpeed<0.679655,1,if (AvgOfmouseSpeed>1.41877,0,0.444444444))
+ if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714))
+ if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.230769,0,0.571428571))
+ if (AvgOfcountExclamationMarks2documentLength<0.000101669,1,if
(AvgOfcountExclamationMarks2documentLength>0.0006161,0,0.461538462))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if
(AvgOfcountExample2documentLength>0.000246011,0,0.5))
+ if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if
(AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667))
+ if (AvgOfcountPrevious2documentLength<0,0,if
(AvgOfcountPrevious2documentLength>9.54004E-05,0,0.666666667))
+ if (AvgOfcountNext2documentLength<8.69095E-05,0,if
(AvgOfcountNext2documentLength>0.000250706,0,0.727272727))
+ if (nTables2documentLength2timespent<0.00257035,0,if
(nTables2documentLength2timespent>0.0129168,0,0.6))
+ if (nObjects2documentLength2timespent<0,0,if
(nObjects2documentLength2timespent>0.00146276,0,0.533333333))
+ if (imagesArea2mouseDistance<61820.8,0,if
(imagesArea2mouseDistance>255500,0,0.648648649))
+ if (nTables2documentLength2mouseDistance<0.00140822,1,if
(nTables2documentLength2mouseDistance>0.00541111,0,0.7))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615))
+ if (imagesArea2documentLength2mouseSpeed<65.7492,0,if
(imagesArea2documentLength2mouseSpeed>217.122,0,0.827586207))
+ if (nImages2mouseYFactor<16.7638,1,if (nImages2mouseYFactor>41.3627,0,0.545454545))
+ if (nLists2documentLength2mouseYFactor<0.000222495,0,if
(nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286))
+ if (documentLength2scrollYDistance<3050.9,1,if
(documentLength2scrollYDistance>7719.66,0,0.5))
+ if (documentLength2scrollYSpeed<2235.71,1,if
(documentLength2scrollYSpeed>3191.54,0,0.666666667))) / 14.87603506

Terms	Term name	F-ratio
	AvgOfmouseSpeed	1.947e+007
	AvgOfscrollYSpeed	8.745e+006
	AvgOfnObjects	6.497e+005
	AvgOfcountExclamationMarks2documentLength	7.352e+005
	AvgOfcountExample2documentLength	1.347e+005
	AvgOfcountQuestion2documentLength	3.528e+007
	AvgOfcountPrevious2documentLength	2.508e+006
	AvgOfcountNext2documentLength	9.59e+006
	nTables2documentLength2timespent	9.235e+006
	nObjects2documentLength2timespent	1.014e+007
	imagesArea2mouseDistance	2.915e+006
	nTables2documentLength2mouseDistance	1.4e+007
	nObjects2mouseSpeed	1.673e+004
	imagesArea2documentLength2mouseSpeed	9.467e+005
	nImages2mouseYFactor	324.2
	nLists2documentLength2mouseYFactor	6.606e+005
	documentLength2scrollYDistance	7.241e+007
	documentLength2scrollYSpeed	4.493e+006

Rule name	PVV1	Dimension of learning style		Visual/Verbal	
Std. error	101.28%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (nPagesVisited<20,1,if (nPagesVisited>54,1,0.384615385))
+ if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.567134,1,0.466666667))
+ if (AvgOfdocumentLength<4817.63,1,if (AvgOfdocumentLength>7970.65,0,0.210526316))
+ if (AvgOfcountQuestion2documentLength<9.55737E-06,1,if (AvgOfcountQuestion2documentLength>2.72986E-05,1,0.272727273))
+ if (nImages2timespent<17.3894,1,if (nImages2timespent>63.2741,0,0.423076923))
+ if (imagesArea2documentLength2timespent<74.5553,1,if (imagesArea2documentLength2timespent>389.307,0,0.464285714))
+ if (nImages2documentLength2timespent<0.00475117,1,if (nImages2documentLength2timespent>0.0228699,1,0.384615385))
+ if (nTables2documentLength2mouseDistance<0.00149485,1,if (nTables2documentLength2mouseDistance>0.00639048,1,0.384615385))
+ if (nTables2mouseSpeed<5.15177,0,if (nTables2mouseSpeed>18.5058,1,0.652173913))
+ if (nTables2mouseYFactor<7.03919,0,if (nTables2mouseYFactor>31.5493,0,0.592592593))
+ if (nTables2documentLength2mouseYFactor<0.00217229,0,if (nTables2documentLength2mouseYFactor>0.0127791,1,0.538461538))
+ if (nLists2documentLength2mouseYFactor<0.000101106,0,if (nLists2documentLength2mouseYFactor>0.000288549,1,0.428571429))
+ if (documentLength2scrollYDistance<4866.04,1,if (documentLength2scrollYDistance>7719.66,0,0.25))
+ if (imagesArea2documentLength2scrollYDistance<108.712,1,if (imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826))
+ if (nObjects2documentLength2scrollYDistance<0,0,if (nObjects2documentLength2scrollYDistance>0.000222829,0,0.516129032))
+ if (nImages2scrollYSpeed<5.31189,1,if (nImages2scrollYSpeed>18.9242,0,0.444444444))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.185507,1,0.466666667))
+ if (imagesArea2scrollYPeaks<123012,1,if (imagesArea2scrollYPeaks>433558,0,0.4))) / 17.10872162

Terms	Term name	F-ratio
	nPagesVisited	3.448e+008
	AvgOfmouseYFactor	1.943e+008
	AvgOfdocumentLength	5.696e+006
	AvgOfcountQuestion2documentLength	4.667e+008
	nImages2timespent	3.498e+006
	imagesArea2documentLength2timespent	1.585e+006
	nImages2documentLength2timespent	2.245e+008
	nTables2documentLength2mouseDistance	4.805e+009
	nTables2mouseSpeed	5.047e+007
	nTables2mouseYFactor	1.992e+006
	nTables2documentLength2mouseYFactor	9.571e+006
	nLists2documentLength2mouseYFactor	5.344e+007
	documentLength2scrollYDistance	4.51e+009
	imagesArea2documentLength2scrollYDistance	1.199e+006
	nObjects2documentLength2scrollYDistance	1.598e+007
	nImages2scrollYSpeed	8.659e+004
	nObjects2scrollYSpeed	9.325e+007

Rule name	PSG1	Dimension of learning style		Sequential/Global	
Std. error	108.70%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfscrollYDistance<0.790629,1,if (AvgOfscrollYDistance>3.64042,0,0.447761194))
+ if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>1.45833,0,0.555555556))
+ if (AvgOfdocumentLength<2730.64,0,if (AvgOfdocumentLength>7970.65,1,0.476190476))
+ if (AvgOfimagesAverageArea<15503.6,0,if (AvgOfimagesAverageArea>52644.8,0,0.583941606))
+ if (AvgOfimagesArea2documentLength<45.5953,1,if (AvgOfimagesArea2documentLength>123.973,1,0.416666667))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000195526,0,0.614035088))
+ if (AvgOfcountNext2documentLength<8.05629E-05,1,if (AvgOfcountNext2documentLength>0.000247635,0,0.576923077))
+ if (documentLength2timespent<6483.93,0,if (documentLength2timespent>13662.4,0,0.733944954))
+ if (imagesArea2documentLength2timespent<69.2824,1,if (imagesArea2documentLength2timespent>359.302,0,0.52238806))
+ if (imagesArea2mouseDistance<63988.7,0,if (imagesArea2mouseDistance>242455,0,0.727272727))
+ if (nTables2mouseDistance<2.22275,1,if (nTables2mouseDistance>16.0976,1,0.416666667))
+ if (nTables2documentLength2mouseSpeed<0.0014146,1,if (nTables2documentLength2mouseSpeed>0.00773544,1,0.416666667))
+ if (imagesArea2mouseXFactor<171223,1,if (imagesArea2mouseXFactor>658493,0,0.52238806))
+ if (nImages2documentLength2mouseXFactor<0.00309131,0,if (nImages2documentLength2mouseXFactor>0.0158329,0,0.583941606))
+ if (imagesArea2documentLength2scrollYDistance<29.4085,1,if (imagesArea2documentLength2scrollYDistance>232.112,1,0.373134328))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.302637,0,0.519480519))
+ if (nLists2documentLength2scrollYSpeed<1.66472E-05,0,if (nLists2documentLength2scrollYSpeed>0.000388615,1,0.476190476))
+ if (documentLength2scrollYPeaks<2514.77,1,if (documentLength2scrollYPeaks>5539.75,1,0.416666667))
+ if (imagesArea2documentLength2scrollYPeaks<35.1047,0,if (imagesArea2documentLength2scrollYPeaks>123.973,1,0.5))) / 16.70413697

Terms	Term name	F-ratio
	AvgOfscrollYDistance	1.771e+008
	AvgOfscrollYPeaks	3.245e+004
	AvgOfdocumentLength	2.882e+005
	AvgOfimagesAverageArea	6.104e+004
	AvgOfimagesArea2documentLength	1.917e+007
	AvgOfcountExample2documentLength	5.391e+007
	AvgOfcountNext2documentLength	832.2
	documentLength2timespent	3.041e+007
	imagesArea2documentLength2timespent	3.216e+006
	imagesArea2mouseDistance	2.615e+007
	nTables2mouseDistance	8.261e+008
	nTables2documentLength2mouseSpeed	8.396e+006
	imagesArea2mouseXFactor	4.926e+006
	nImages2documentLength2mouseXFactor	1.127e+009
	imagesArea2documentLength2scrollYDistance	3.273e+008
	nObjects2scrollYSpeed	7.267e+005
	nLists2documentLength2scrollYSpeed	1.226e+007
	documentLength2scrollYPeaks	1825
	imagesArea2documentLength2scrollYPeaks	3.054e+007

Rule name	PAR1W	Dimension of learning style		Active/Reflective	
Std. error	66.47%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(2.89E+10* if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ 1.29E+11* if (AvgOftimespent<182995000,1,if (AvgOftimespent>769424000,0,0.48))
+ 1.1E+10* if (AvgOfrelativeTimeSpent<1.10185,1,if (AvgOfrelativeTimeSpent>1.24734,1,0.347826087))
+ 1.64E+04* if (AvgOfimagesAverageArea<28939.8,1,if (AvgOfimagesAverageArea>58823.9,0,0.363636364))
+ 9.32E+10* if (imagesArea2timespent<176602,1,if (imagesArea2timespent>912391,0,0.48))
+ 5.63E+10* if (nObjects2timespent<0,0,if (nObjects2timespent>0.857677,1,0.482758621))
+ 1.26E+11* if (imagesArea2documentLength2timespent<74.5553,1,if (imagesArea2documentLength2timespent>343.999,0,0.5))
+ 6.40E+09* if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0236,1,0.52))
+ 8.69E+10* if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.0939798,1,0.464285714))
+ 1.03E+09* if (nTables2documentLength2mouseDistance<0.00140822,1,if (nTables2documentLength2mouseDistance>0.00334805,1,0.166666667))
+ 1.04E+11* if (nLists2documentLength2mouseDistance<1.19789E-05,1,if (nLists2documentLength2mouseDistance>0.00035356,1,0.444444444))
+ 2.47E+10* if (imagesArea2mouseSpeed<193412,1,if (imagesArea2mouseSpeed>547021,1,0.318181818))
+ 1.24E+07* if (imagesArea2documentLength2mouseXFactor<94.5044,1,if (imagesArea2documentLength2mouseXFactor>183.425,1,0.285714286))
+ 1.18E+11* if (nImages2mouseYFactor<18.6658,1,if (nImages2mouseYFactor>65.672,0,0.461538462))
+ 6.23E+10* if (documentLength2scrollYDistance<3576.44,1,if (documentLength2scrollYDistance>7719.66,1,0.423076923))
+ 1.22E+11* if (imagesArea2documentLength2scrollYDistance<120.239,1,if (imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ 4.26E+08* if (documentLength2scrollYSpeed<1676.81,0,if (documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ 1.43E+11* if (imagesArea2documentLength2scrollYPeaks<31.4118,0,if (imagesArea2documentLength2scrollYPeaks>123.973,0,0.576923077))) / 1.06E+12

Terms	Term name	F-ratio
	nPagesVisited	2.894e+010
	AvgOftimespent	1.288e+011
	AvgOfrelativeTimeSpent	1.506e+010
	AvgOfimagesAverageArea	1.642e+004
	imagesArea2timespent	9.324e+010
	nObjects2timespent	5.631e+010
	imagesArea2documentLength2timespent	1.256e+011
	nTables2mouseDistance	6.404e+009
	nObjects2mouseDistance	8.686e+010
	nTables2documentLength2mouseDistance	1.031e+009
	nLists2documentLength2mouseDistance	1.038e+011
	imagesArea2mouseSpeed	2.465e+010
	imagesArea2documentLength2mouseXFactor	1.236e+007
	nImages2mouseYFactor	1.183e+011
	documentLength2scrollYDistance	6.227e+010
	imagesArea2documentLength2scrollYDistance	1.218e+011
	documentLength2scrollYSpeed	4.26e+008
	imagesArea2documentLength2scrollYPeaks	1.425e+011

Rule name	PSI1W	Dimension of learning style		Sensing/Intuitive	
Std. error	99.12%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(1.95E+07* if (AvgOfmouseSpeed<0.679655,1,if (AvgOfmouseSpeed>1.41877,0,0.444444444)) +
8.75E+06* if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714)) +
6.50E+05* if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.230769,0,0.571428571)) +
7.35E+05* if (AvgOfcountExclamationMarks2documentLength<0.000101669,1,if (AvgOfcountExclamationMarks2documentLength>0.0006161,0,0.461538462)) +
1.35E+05* if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000246011,0,0.5)) +
3.53E+07* if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if (AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667)) +
2.51E+06* if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>9.54004E-05,0,0.666666667)) +
9.59E+06* if (AvgOfcountNext2documentLength<8.69095E-05,0,if (AvgOfcountNext2documentLength>0.000250706,0,0.727272727)) +
9.24E+06* if (nTables2documentLength2timespent<0.00257035,0,if (nTables2documentLength2timespent>0.0129168,0,0.6)) +
1.01E+07* if (nObjects2documentLength2timespent<0,0,if (nObjects2documentLength2timespent>0.00146276,0,0.533333333)) +
2.92E+06* if (imagesArea2mouseDistance<61820.8,0,if (imagesArea2mouseDistance>255500,0,0.648648649)) +
1.40E+07* if (nTables2documentLength2mouseDistance<0.00140822,1,if (nTables2documentLength2mouseDistance>0.00541111,0,0.7)) +
1.67E+04* if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615)) +
9.47E+05* if (imagesArea2documentLength2mouseSpeed<65.7492,0,if (imagesArea2documentLength2mouseSpeed>217.122,0,0.827586207)) +
3.24E+02* if (nImages2mouseYFactor<16.7638,1,if (nImages2mouseYFactor>41.3627,0,0.545454545)) +
6.61E+05* if (nLists2documentLength2mouseYFactor<0.000222495,0,if (nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286)) +
7.24E+07* if (documentLength2scrollYDistance<3050.9,1,if (documentLength2scrollYDistance>7719.66,0,0.5)) +
4.49E+06* if (documentLength2scrollYSpeed<2235.71,1,if (documentLength2scrollYSpeed>3191.54,0,0.666666667))) / 1.78E+08

Terms	Term name	F-ratio
	AvgOfmouseSpeed	1.947e+007
	AvgOfscrollYSpeed	8.745e+006
	AvgOfnObjects	6.497e+005
	AvgOfcountExclamationMarks2documentLength	7.352e+005
	AvgOfcountExample2documentLength	1.347e+005
	AvgOfcountQuestion2documentLength	3.528e+007
	AvgOfcountPrevious2documentLength	2.508e+006
	AvgOfcountNext2documentLength	9.59e+006
	nTables2documentLength2timespent	9.235e+006
	nObjects2documentLength2timespent	1.014e+007
	imagesArea2mouseDistance	2.915e+006
	nTables2documentLength2mouseDistance	1.4e+007
	nObjects2mouseSpeed	1.673e+004
	imagesArea2documentLength2mouseSpeed	9.467e+005
	nImages2mouseYFactor	324.2
	nLists2documentLength2mouseYFactor	6.606e+005
	documentLength2scrollYDistance	7.241e+007
	documentLength2scrollYSpeed	4.493e+006

Rule name	PVV1W	Dimension of learning style		Visual/Verbal	
Std. error	110.61%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(3.45E+08* if (nPagesVisited<20,1,if (nPagesVisited>54,1,0.384615385)) +
1.94E+08* if (AvgOfmouseYFactor<0.421104,1,if
(AvgOfmouseYFactor>0.567134,1,0.466666667)) +
5.70E+06* if (AvgOfdocumentLength<4817.63,1,if
(AvgOfdocumentLength>7970.65,0,0.210526316)) +
4.67E+08* if (AvgOfcountQuestion2documentLength<9.55737E-06,1,if
(AvgOfcountQuestion2documentLength>2.72986E-05,1,0.272727273)) +
3.50E+06* if (nImages2timespent<17.3894,1,if (nImages2timespent>63.2741,0,0.423076923)) +
1.59E+06* if (imagesArea2documentLength2timespent<74.5553,1,if
(imagesArea2documentLength2timespent>389.307,0,0.464285714)) +
2.25E+08* if (nImages2documentLength2timespent<0.00475117,1,if
(nImages2documentLength2timespent>0.0228699,1,0.384615385)) +
4.81E+09* if (nTables2documentLength2mouseDistance<0.00149485,1,if
(nTables2documentLength2mouseDistance>0.00639048,1,0.384615385)) +
5.05E+07* if (nTables2mouseSpeed<5.15177,0,if
(nTables2mouseSpeed>18.5058,1,0.652173913)) +
1.99E+06* if (nTables2mouseYFactor<7.03919,0,if
(nTables2mouseYFactor>31.5493,0,0.592592593)) +
9.57E+06* if (nTables2documentLength2mouseYFactor<0.00217229,0,if
(nTables2documentLength2mouseYFactor>0.0127791,1,0.538461538)) +
5.34E+07* if (nLists2documentLength2mouseYFactor<0.000101106,0,if
(nLists2documentLength2mouseYFactor>0.000288549,1,0.428571429)) +
4.51E+09* if (documentLength2scrollYDistance<4866.04,1,if
(documentLength2scrollYDistance>7719.66,0,0.25)) +
1.20E+06* if (imagesArea2documentLength2scrollYDistance<108.712,1,if
(imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826)) +
1.60E+07* if (nObjects2documentLength2scrollYDistance<0,0,if
(nObjects2documentLength2scrollYDistance>0.000222829,0,0.516129032)) +
8.66E+04* if (nImages2scrollYSpeed<5.31189,1,if
(nImages2scrollYSpeed>18.9242,0,0.444444444)) +
9.33E+07* if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.185507,1,0.466666667))
+
9.10E+06* if (imagesArea2scrollYPeaks<123012,1,if
(imagesArea2scrollYPeaks>433558,0,0.4))) / 1.08E+10

Terms	Term name	F-ratio
	nPagesVisited	3.448e+008
	AvgOfmouseYFactor	1.943e+008
	AvgOfdocumentLength	5.696e+006
	AvgOfcountQuestion2documentLength	4.667e+008
	nImages2timespent	3.498e+006
	imagesArea2documentLength2timespent	1.585e+006
	nImages2documentLength2timespent	2.245e+008
	nTables2documentLength2mouseDistance	4.805e+009
	nTables2mouseSpeed	5.047e+007
	nTables2mouseYFactor	1.992e+006
	nTables2documentLength2mouseYFactor	9.571e+006
	nLists2documentLength2mouseYFactor	5.344e+007
	documentLength2scrollYDistance	4.51e+009
	imagesArea2documentLength2scrollYDistance	1.199e+006
	nObjects2documentLength2scrollYDistance	1.598e+007
	nImages2scrollYSpeed	8.659e+004
	nObjects2scrollYSpeed	9.325e+007

Rule name	PSG1W	Dimension of learning style		Sequential/Global	
Std. error	183.30%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(1.77E+08* if (AvgOfscrollYDistance<0.790629,1,if (AvgOfscrollYDistance>3.64042,0,0.447761194)) +
3.25E+04* if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>1.45833,0,0.555555556)) +
2.88E+05* if (AvgOfdocumentLength<2730.64,0,if (AvgOfdocumentLength>7970.65,1,0.476190476)) +
6.10E+04* if (AvgOfimagesAverageArea<15503.6,0,if
(AvgOfimagesAverageArea>52644.8,0,0.583941606)) +
1.92E+07* if (AvgOfimagesArea2documentLength<45.5953,1,if
(AvgOfimagesArea2documentLength>123.973,1,0.416666667)) +
5.39E+07* if (AvgOfcountExample2documentLength<4.09929E-05,1,if
(AvgOfcountExample2documentLength>0.000195526,0,0.614035088)) +
8.32E+02* if (AvgOfcountNext2documentLength<8.05629E-05,1,if
(AvgOfcountNext2documentLength>0.000247635,0,0.576923077)) +
3.04E+07* if (documentLength2timespent<6483.93,0,if
(documentLength2timespent>13662.4,0,0.733944954)) +
3.22E+06* if (imagesArea2documentLength2timespent<69.2824,1,if
(imagesArea2documentLength2timespent>359.302,0,0.52238806)) +
2.62E+07* if (imagesArea2mouseDistance<63988.7,0,if
(imagesArea2mouseDistance>242455,0,0.727272727)) +
8.26E+08* if (nTables2mouseDistance<2.22275,1,if (nTables2mouseDistance>16.0976,1,0.416666667)) +
8.40E+06* if (nTables2documentLength2mouseSpeed<0.0014146,1,if
(nTables2documentLength2mouseSpeed>0.00773544,1,0.416666667)) +
4.93E+06* if (imagesArea2mouseXFactor<171223,1,if
(imagesArea2mouseXFactor>658493,0,0.52238806)) +
1.13E+09* if (nImages2documentLength2mouseXFactor<0.00309131,0,if
(nImages2documentLength2mouseXFactor>0.0158329,0,0.583941606)) +
3.27E+08* if (imagesArea2documentLength2scrollYDistance<29.4085,1,if
(imagesArea2documentLength2scrollYDistance>232.112,1,0.373134328)) +
7.27E+05* if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.302637,0,0.519480519)) +
1.23E+07* if (nLists2documentLength2scrollYSpeed<1.66472E-05,0,if
(nLists2documentLength2scrollYSpeed>0.000388615,1,0.476190476)) +
1.83E+03* if (documentLength2scrollYPeaks<2514.77,1,if
(documentLength2scrollYPeaks>5539.75,1,0.416666667)) +
3.05E+07* if (imagesArea2documentLength2scrollYPeaks<35.1047,0,if
(imagesArea2documentLength2scrollYPeaks>123.973,1,0.5))) / 2.16E+09

Terms	Term name	F-ratio
	AvgOfscrollYDistance	1.771e+008
	AvgOfscrollYPeaks	3.245e+004
	AvgOfdocumentLength	2.882e+005
	AvgOfimagesAverageArea	6.104e+004
	AvgOfimagesArea2documentLength	1.917e+007
	AvgOfcountExample2documentLength	5.391e+007
	AvgOfcountNext2documentLength	832.2
	documentLength2timespent	3.041e+007
	imagesArea2documentLength2timespent	3.216e+006
	imagesArea2mouseDistance	2.615e+007
	nTables2mouseDistance	8.261e+008
	nTables2documentLength2mouseSpeed	8.396e+006
	imagesArea2mouseXFactor	4.926e+006
	nImages2documentLength2mouseXFactor	1.127e+009
	imagesArea2documentLength2scrollYDistance	3.273e+008
	nObjects2scrollYSpeed	7.267e+005
	nLists2documentLength2scrollYSpeed	1.226e+007
	documentLength2scrollYPeaks	1825
	imagesArea2documentLength2scrollYPeaks	3.054e+007

Rule name	PAR1B	Dimension of learning style		Active/Reflective	
Std. error	N/A	**Class. Prob.**	85%	**Class. Eff.**	57.14%

Rule Expression

((if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ if (AvgOftimespent<182995000,1,if (AvgOftimespent>769424000,0,0.48))
+ if (AvgOfrelativeTimeSpent<1.10185,1,if (AvgOfrelativeTimeSpent>1.24734,1,0.347826087))
+ if (AvgOfimagesAverageArea<28939.8,1,if (AvgOfimagesAverageArea>58823.9,0,0.363636364))
+ if (imagesArea2timespent<176602,1,if (imagesArea2timespent>912391,0,0.48))
+ if (nObjects2timespent<0,0,if (nObjects2timespent>0.857677,1,0.482758621))
+ if (imagesArea2documentLength2timespent<74.5553,1,if (imagesArea2documentLength2timespent>343.999,0,0.5))
+ if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0236,1,0.52))
+ if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.0939798,1,0.464285714))
+ if (nTables2documentLength2mouseDistance<0.00140822,1,if (nTables2documentLength2mouseDistance>0.00334805,1,0.166666667))
+ if (nLists2documentLength2mouseDistance<1.19789E-05,1,if (nLists2documentLength2mouseDistance>0.00035356,1,0.444444444))
+ if (imagesArea2mouseSpeed<193412,1,if (imagesArea2mouseSpeed>547021,1,0.318181818))
+ if (imagesArea2documentLength2mouseXFactor<94.5044,1,if (imagesArea2documentLength2mouseXFactor>183.425,1,0.285714286))
+ if (nImages2mouseYFactor<18.6658,1,if (nImages2mouseYFactor>65.672,0,0.461538462))
+ if (documentLength2scrollYDistance<3576.44,1,if (documentLength2scrollYDistance>7719.66,1,0.423076923))
+ if (imagesArea2documentLength2scrollYDistance<120.239,1,if (imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ if (documentLength2scrollYSpeed<1676.81,0,if (documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ if (imagesArea2documentLength2scrollYPeaks<31.4118,0,if (imagesArea2documentLength2scrollYPeaks>123.973,0,0.576923077))) / 17.57692308) >= 0.5

Terms	Term name	F-ratio
	nPagesVisited	2.894e+010
	AvgOftimespent	1.288e+011
	AvgOfrelativeTimeSpent	1.506e+010
	AvgOfimagesAverageArea	1.642e+004
	imagesArea2timespent	9.324e+010
	nObjects2timespent	5.631e+010
	imagesArea2documentLength2timespent	1.256e+011
	nTables2mouseDistance	6.404e+009
	nObjects2mouseDistance	8.686e+010
	nTables2documentLength2mouseDistance	1.031e+009
	nLists2documentLength2mouseDistance	1.038e+011
	imagesArea2mouseSpeed	2.465e+010
	imagesArea2documentLength2mouseXFactor	1.236e+007
	nImages2mouseYFactor	1.183e+011
	documentLength2scrollYDistance	6.227e+010
	imagesArea2documentLength2scrollYDistance	1.218e+011
	documentLength2scrollYSpeed	4.26e+008
	imagesArea2documentLength2scrollYPeaks	1.425e+011

Rule name	**PSI1B**	**Dimension of learning style**		Sensing/Intuitive	
Std. error	N/A	**Class. Prob.**	65%	**Class. Eff.**	0%

Rule Expression

((if (AvgOfmouseSpeed<0.679655,1,if (AvgOfmouseSpeed>1.41877,0,0.444444444))
+ if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714))
+ if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.230769,0,0.571428571))
+ if (AvgOfcountExclamationMarks2documentLength<0.000101669,1,if (AvgOfcountExclamationMarks2documentLength>0.0006161,0,0.461538462))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000246011,0,0.5))
+ if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if (AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667))
+ if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>9.54004E-05,0,0.666666667))
+ if (AvgOfcountNext2documentLength<8.69095E-05,0,if (AvgOfcountNext2documentLength>0.000250706,0,0.727272727))
+ if (nTables2documentLength2timespent<0.00257035,0,if (nTables2documentLength2timespent>0.0129168,0,0.6))
+ if (nObjects2documentLength2timespent<0,0,if (nObjects2documentLength2timespent>0.00146276,0,0.533333333))
+ if (imagesArea2mouseDistance<61820.8,0,if (imagesArea2mouseDistance>255500,0,0.648648649))
+ if (nTables2documentLength2mouseDistance<0.00140822,1,if (nTables2documentLength2mouseDistance>0.00541111,0,0.7))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615))
+ if (imagesArea2documentLength2mouseSpeed<65.7492,0,if (imagesArea2documentLength2mouseSpeed>217.122,0,0.827586207))
+ if (nImages2mouseYFactor<16.7638,1,if (nImages2mouseYFactor>41.3627,0,0.545454545))
+ if (nLists2documentLength2mouseYFactor<0.000222495,0,if (nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286))
+ if (documentLength2scrollYDistance<3050.9,1,if (documentLength2scrollYDistance>7719.66,0,0.5))
+ if (documentLength2scrollYSpeed<2235.71,1,if (documentLength2scrollYSpeed>3191.54,0,0.666666667))) / 14.87603506) >= 0.5

Terms	**Term name**	**F-ratio**
	AvgOfmouseSpeed	1.947e+007
	AvgOfscrollYSpeed	8.745e+006
	AvgOfnObjects	6.497e+005
	AvgOfcountExclamationMarks2documentLength	7.352e+005
	AvgOfcountExample2documentLength	1.347e+005
	AvgOfcountQuestion2documentLength	3.528e+007
	AvgOfcountPrevious2documentLength	2.508e+006
	AvgOfcountNext2documentLength	9.59e+006
	nTables2documentLength2timespent	9.235e+006
	nObjects2documentLength2timespent	1.014e+007
	imagesArea2mouseDistance	2.915e+006
	nTables2documentLength2mouseDistance	1.4e+007
	nObjects2mouseSpeed	1.673e+004
	imagesArea2documentLength2mouseSpeed	9.467e+005
	nImages2mouseYFactor	324.2
	nLists2documentLength2mouseYFactor	6.606e+005
	documentLength2scrollYDistance	7.241e+007
	documentLength2scrollYSpeed	4.493e+006

Rule name	PVV1B	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	80%	Class. Eff.	20%

Rule Expression

((if (nPagesVisited<20,1,if (nPagesVisited>54,1,0.384615385))
+ if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.567134,1,0.466666667))
+ if (AvgOfdocumentLength<4817.63,1,if (AvgOfdocumentLength>7970.65,0,0.210526316))
+ if (AvgOfcountQuestion2documentLength<9.55737E-06,1,if (AvgOfcountQuestion2documentLength>2.72986E-05,1,0.272727273))
+ if (nImages2timespent<17.3894,1,if (nImages2timespent>63.2741,0,0.423076923))
+ if (imagesArea2documentLength2timespent<74.5553,1,if (imagesArea2documentLength2timespent>389.307,0,0.464285714))
+ if (nImages2documentLength2timespent<0.00475117,1,if (nImages2documentLength2timespent>0.0228699,1,0.384615385))
+ if (nTables2documentLength2mouseDistance<0.00149485,1,if (nTables2documentLength2mouseDistance>0.00639048,1,0.384615385))
+ if (nTables2mouseSpeed<5.15177,0,if (nTables2mouseSpeed>18.5058,1,0.652173913))
+ if (nTables2mouseYFactor<7.03919,0,if (nTables2mouseYFactor>31.5493,0,0.592592593))
+ if (nTables2documentLength2mouseYFactor<0.00217229,0,if (nTables2documentLength2mouseYFactor>0.0127791,1,0.538461538))
+ if (nLists2documentLength2mouseYFactor<0.000101106,0,if (nLists2documentLength2mouseYFactor>0.000288549,1,0.428571429))
+ if (documentLength2scrollYDistance<4866.04,1,if (documentLength2scrollYDistance>7719.66,0,0.25))
+ if (imagesArea2documentLength2scrollYDistance<108.712,1,if (imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826))
+ if (nObjects2documentLength2scrollYDistance<0,0,if (nObjects2documentLength2scrollYDistance>0.000222829,0,0.516129032))
+ if (nImages2scrollYSpeed<5.31189,1,if (nImages2scrollYSpeed>18.9242,0,0.444444444))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.185507,1,0.466666667))
+ if (imagesArea2scrollYPeaks<123012,1,if (imagesArea2scrollYPeaks>433558,0,0.4))) / 17.10872162) >=0.5

Terms	Term name	F-ratio
	nPagesVisited	3.448e+008
	AvgOfmouseYFactor	1.943e+008
	AvgOfdocumentLength	5.696e+006
	AvgOfcountQuestion2documentLength	4.667e+008
	nImages2timespent	3.498e+006
	imagesArea2documentLength2timespent	1.585e+006
	nImages2documentLength2timespent	2.245e+008
	nTables2documentLength2mouseDistance	4.805e+009
	nTables2mouseSpeed	5.047e+007
	nTables2mouseYFactor	1.992e+006
	nTables2documentLength2mouseYFactor	9.571e+006
	nLists2documentLength2mouseYFactor	5.344e+007
	documentLength2scrollYDistance	4.51e+009
	imagesArea2documentLength2scrollYDistance	1.199e+006
	nObjects2documentLength2scrollYDistance	1.598e+007
	nImages2scrollYSpeed	8.659e+004
	nObjects2scrollYSpeed	9.325e+007

Rule name	PSG1B	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	80%	Class. Eff.	55.56%

Rule Expression

((if (AvgOfscrollYDistance<0.790629,1,if (AvgOfscrollYDistance>3.64042,0,0.447761194))
+ if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>1.45833,0,0.555555556))
+ if (AvgOfdocumentLength<2730.64,0,if (AvgOfdocumentLength>7970.65,1,0.476190476))
+ if (AvgOfimagesAverageArea<15503.6,0,if (AvgOfimagesAverageArea>52644.8,0,0.583941606))
+ if (AvgOfimagesArea2documentLength<45.5953,1,if (AvgOfimagesArea2documentLength>123.973,1,0.416666667))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000195526,0,0.614035088))
+ if (AvgOfcountNext2documentLength<8.05629E-05,1,if (AvgOfcountNext2documentLength>0.000247635,0,0.576923077))
+ if (documentLength2timespent<6483.93,0,if (documentLength2timespent>13662.4,0,0.733944954))
+ if (imagesArea2documentLength2timespent<69.2824,1,if (imagesArea2documentLength2timespent>359.302,0,0.52238806))
+ if (imagesArea2mouseDistance<63988.7,0,if (imagesArea2mouseDistance>242455,0,0.727272727))
+ if (nTables2mouseDistance<2.22275,1,if (nTables2mouseDistance>16.0976,1,0.416666667))
+ if (nTables2documentLength2mouseSpeed<0.0014146,1,if (nTables2documentLength2mouseSpeed>0.00773544,1,0.416666667))
+ if (imagesArea2mouseXFactor<171223,1,if (imagesArea2mouseXFactor>658493,0,0.52238806))
+ if (nImages2documentLength2mouseXFactor<0.00309131,0,if (nImages2documentLength2mouseXFactor>0.0158329,0,0.583941606))
+ if (imagesArea2documentLength2scrollYDistance<29.4085,1,if (imagesArea2documentLength2scrollYDistance>232.112,1,0.373134328))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.302637,0,0.519480519))
+ if (nLists2documentLength2scrollYSpeed<1.66472E-05,0,if (nLists2documentLength2scrollYSpeed>0.000388615,1,0.476190476))
+ if (documentLength2scrollYPeaks<2514.77,1,if (documentLength2scrollYPeaks>5539.75,1,0.416666667))
+ if (imagesArea2documentLength2scrollYPeaks<35.1047,0,if (imagesArea2documentLength2scrollYPeaks>123.973,1,0.5))) / 16.70413697) >= 0.5

Terms	Term name	F-ratio
	AvgOfscrollYDistance	1.771e+008
	AvgOfscrollYPeaks	3.245e+004
	AvgOfdocumentLength	2.882e+005
	AvgOfimagesAverageArea	6.104e+004
	AvgOfimagesArea2documentLength	1.917e+007
	AvgOfcountExample2documentLength	5.391e+007
	AvgOfcountNext2documentLength	832.2
	documentLength2timespent	3.041e+007
	imagesArea2documentLength2timespent	3.216e+006
	imagesArea2mouseDistance	2.615e+007
	nTables2mouseDistance	8.261e+008
	nTables2documentLength2mouseSpeed	8.396e+006
	imagesArea2mouseXFactor	4.926e+006
	nImages2documentLength2mouseXFactor	1.127e+009
	imagesArea2documentLength2scrollYDistance	3.273e+008
	nObjects2scrollYSpeed	7.267e+005
	nLists2documentLength2scrollYSpeed	1.226e+007
	documentLength2scrollYPeaks	1825
	imagesArea2documentLength2scrollYPeaks	3.054e+007

Rule name	PAR1WB	Dimension of learning style		Active/Reflective	
Std. error	N/A	Class. Prob.	80%	Class. Eff.	42.86%

Rule Expression

((2.89E+10* if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ 1.29E+11* if (AvgOftimespent<182995000,1,if (AvgOftimespent>769424000,0,0.48))
+ 1.1E+10* if (AvgOfrelativeTimeSpent<1.10185,1,if (AvgOfrelativeTimeSpent>1.24734,1,0.347826087))
+ 1.64E+04* if (AvgOfimagesAverageArea<28939.8,1,if (AvgOfimagesAverageArea>58823.9,0,0.363636364))
+ 9.32E+10* if (imagesArea2timespent<176602,1,if (imagesArea2timespent>912391,0,0.48))
+ 5.63E+10* if (nObjects2timespent<0,0,if (nObjects2timespent>0.857677,1,0.482758621))
+ 1.26E+11* if (imagesArea2documentLength2timespent<74.5553,1,if (imagesArea2documentLength2timespent>343.999,0,0.5))
+ 6.40E+09* if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0236,1,0.52))
+ 8.69E+10* if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.0939798,1,0.464285714))
+ 1.03E+09* if (nTables2documentLength2mouseDistance<0.00140822,1,if (nTables2documentLength2mouseDistance>0.00334805,1,0.166666667))
+ 1.04E+11* if (nLists2documentLength2mouseDistance<1.19789E-05,1,if (nLists2documentLength2mouseDistance>0.00035356,1,0.444444444))
+ 2.47E+10* if (imagesArea2mouseSpeed<193412,1,if (imagesArea2mouseSpeed>547021,1,0.318181818))
+ 1.24E+07* if (imagesArea2documentLength2mouseXFactor<94.5044,1,if (imagesArea2documentLength2mouseXFactor>183.425,1,0.285714286))
+ 1.18E+11* if (nImages2mouseYFactor<18.6658,1,if (nImages2mouseYFactor>65.672,0,0.461538462))
+ 6.23E+10* if (documentLength2scrollYDistance<3576.44,1,if (documentLength2scrollYDistance>7719.66,1,0.423076923))
+ 1.22E+11* if (imagesArea2documentLength2scrollYDistance<120.239,1,if (imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ 4.26E+08* if (documentLength2scrollYSpeed<1676.81,0,if (documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ 1.43E+11* if (imagesArea2documentLength2scrollYPeaks<31.4118,0,if (imagesArea2documentLength2scrollYPeaks>123.973,0,0.576923077))) / 1.06E+12) >= 0.5

Terms	Term name	F-ratio
	nPagesVisited	2.894e+010
	AvgOftimespent	1.288e+011
	AvgOfrelativeTimeSpent	1.506e+010
	AvgOfimagesAverageArea	1.642e+004
	imagesArea2timespent	9.324e+010
	nObjects2timespent	5.631e+010
	imagesArea2documentLength2timespent	1.256e+011
	nTables2mouseDistance	6.404e+009
	nObjects2mouseDistance	8.686e+010
	nTables2documentLength2mouseDistance	1.031e+009
	nLists2documentLength2mouseDistance	1.038e+011
	imagesArea2mouseSpeed	2.465e+010
	imagesArea2documentLength2mouseXFactor	1.236e+007
	nImages2mouseYFactor	1.183e+011
	documentLength2scrollYDistance	6.227e+010
	imagesArea2documentLength2scrollYDistance	1.218e+011
	documentLength2scrollYSpeed	4.26e+008
	imagesArea2documentLength2scrollYPeaks	1.425e+011

Rule name	PSI1WB	Dimension of learning style		Sensing/Intuitive	
Std. error	N/A	Class. Prob.	65%	Class. Eff.	0%

Rule Expression

((1.95E+07* if (AvgOfmouseSpeed<0.679655,1,if
(AvgOfmouseSpeed>1.41877,0,0.444444444)) +
8.75E+06* if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714)) +
6.50E+05* if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.230769,0,0.571428571)) +
7.35E+05* if (AvgOfcountExclamationMarks2documentLength<0.000101669,1,if
(AvgOfcountExclamationMarks2documentLength>0.0006161,0,0.461538462)) +
1.35E+05* if (AvgOfcountExample2documentLength<4.09929E-05,1,if
(AvgOfcountExample2documentLength>0.000246011,0,0.5)) +
3.53E+07* if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if
(AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667)) +
2.51E+06* if (AvgOfcountPrevious2documentLength<0,0,if
(AvgOfcountPrevious2documentLength>9.54004E-05,0,0.666666667)) +
9.59E+06* if (AvgOfcountNext2documentLength<8.69095E-05,0,if
(AvgOfcountNext2documentLength>0.000250706,0,0.727272727)) +
9.24E+06* if (nTables2documentLength2timespent<0.00257035,0,if
(nTables2documentLength2timespent>0.0129168,0,0.6)) +
1.01E+07* if (nObjects2documentLength2timespent<0,0,if
(nObjects2documentLength2timespent>0.00146276,0,0.533333333)) +
2.92E+06* if (imagesArea2mouseDistance<61820.8,0,if
(imagesArea2mouseDistance>255500,0,0.648648649)) +
1.40E+07* if (nTables2documentLength2mouseDistance<0.00140822,1,if
(nTables2documentLength2mouseDistance>0.00541111,0,0.7)) +
1.67E+04* if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615))
+
9.47E+05* if (imagesArea2documentLength2mouseSpeed<65.7492,0,if
(imagesArea2documentLength2mouseSpeed>217.122,0,0.827586207)) +
3.24E+02* if (nImages2mouseYFactor<16.7638,1,if
(nImages2mouseYFactor>41.3627,0,0.545454545)) +
6.61E+05* if (nLists2documentLength2mouseYFactor<0.000222495,0,if
(nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286)) +
7.24E+07* if (documentLength2scrollYDistance<3050.9,1,if
(documentLength2scrollYDistance>7719.66,0,0.5)) +
4.49E+06* if (documentLength2scrollYSpeed<2235.71,1,if
(documentLength2scrollYSpeed>3191.54,0,0.666666667))) / 1.78E+08) >= 0.5

Terms	Term name	F-ratio
	AvgOfmouseSpeed	1.947e+007
	AvgOfscrollYSpeed	8.745e+006
	AvgOfnObjects	6.497e+005
	AvgOfcountExclamationMarks2documentLength	7.352e+005
	AvgOfcountExample2documentLength	1.347e+005
	AvgOfcountQuestion2documentLength	3.528e+007
	AvgOfcountPrevious2documentLength	2.508e+006
	AvgOfcountNext2documentLength	9.59e+006
	nTables2documentLength2timespent	9.235e+006
	nObjects2documentLength2timespent	1.014e+007
	imagesArea2mouseDistance	2.915e+006
	nTables2documentLength2mouseDistance	1.4e+007
	nObjects2mouseSpeed	1.673e+004
	imagesArea2documentLength2mouseSpeed	9.467e+005
	nImages2mouseYFactor	324.2
	nLists2documentLength2mouseYFactor	6.606e+005
	documentLength2scrollYDistance	7.241e+007
	documentLength2scrollYSpeed	4.493e+006

Rule name	PVV1WB	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	75%	Class. Eff.	0%

Rule Expression

((3.45E+08* if (nPagesVisited<20,1,if (nPagesVisited>54,1,0.384615385)) +
1.94E+08* if (AvgOfmouseYFactor<0.421104,1,if
(AvgOfmouseYFactor>0.567134,1,0.466666667)) +
5.70E+06* if (AvgOfdocumentLength<4817.63,1,if
(AvgOfdocumentLength>7970.65,0,0.210526316)) +
4.67E+08* if (AvgOfcountQuestion2documentLength<9.55737E-06,1,if
(AvgOfcountQuestion2documentLength>2.72986E-05,1,0.272727273)) +
3.50E+06* if (nImages2timespent<17.3894,1,if (nImages2timespent>63.2741,0,0.423076923)) +
1.59E+06* if (imagesArea2documentLength2timespent<74.5553,1,if
(imagesArea2documentLength2timespent>389.307,0,0.464285714)) +
2.25E+08* if (nImages2documentLength2timespent<0.00475117,1,if
(nImages2documentLength2timespent>0.0228699,1,0.384615385)) +
4.81E+09* if (nTables2documentLength2mouseDistance<0.00149485,1,if
(nTables2documentLength2mouseDistance>0.00639048,1,0.384615385)) +
5.05E+07* if (nTables2mouseSpeed<5.15177,0,if
(nTables2mouseSpeed>18.5058,1,0.652173913)) +
1.99E+06* if (nTables2mouseYFactor<7.03919,0,if
(nTables2mouseYFactor>31.5493,0,0.592592593)) +
9.57E+06* if (nTables2documentLength2mouseYFactor<0.00217229,0,if
(nTables2documentLength2mouseYFactor>0.0127791,1,0.538461538)) +
5.34E+07* if (nLists2documentLength2mouseYFactor<0.000101106,0,if
(nLists2documentLength2mouseYFactor>0.000288549,1,0.428571429)) +
4.51E+09* if (documentLength2scrollYDistance<4866.04,1,if
(documentLength2scrollYDistance>7719.66,0,0.25)) +
1.20E+06* if (imagesArea2documentLength2scrollYDistance<108.712,1,if
(imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826)) +
1.60E+07* if (nObjects2documentLength2scrollYDistance<0,0,if
(nObjects2documentLength2scrollYDistance>0.000222829,0,0.516129032)) +
8.66E+04* if (nImages2scrollYSpeed<5.31189,1,if
(nImages2scrollYSpeed>18.9242,0,0.444444444)) +
9.33E+07* if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.185507,1,0.466666667))
+
9.10E+06* if (imagesArea2scrollYPeaks<123012,1,if
(imagesArea2scrollYPeaks>433558,0,0.4))) / 1.08E+10) >= 0.5

Terms	Term name	F-ratio
	nPagesVisited	3.448e+008
	AvgOfmouseYFactor	1.943e+008
	AvgOfdocumentLength	5.696e+006
	AvgOfcountQuestion2documentLength	4.667e+008
	nImages2timespent	3.498e+006
	imagesArea2documentLength2timespent	1.585e+006
	nImages2documentLength2timespent	2.245e+008
	nTables2documentLength2mouseDistance	4.805e+009
	nTables2mouseSpeed	5.047e+007
	nTables2mouseYFactor	1.992e+006
	nTables2documentLength2mouseYFactor	9.571e+006
	nLists2documentLength2mouseYFactor	5.344e+007
	documentLength2scrollYDistance	4.51e+009
	imagesArea2documentLength2scrollYDistance	1.199e+006
	nObjects2documentLength2scrollYDistance	1.598e+007
	nImages2scrollYSpeed	8.659e+004
	nObjects2scrollYSpeed	9.325e+007

Rule name	PSG1WB	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	50%	Class. Eff.	-11.11%

Rule Expression

((1.77E+08* if (AvgOfscrollYDistance<0.790629,1,if (AvgOfscrollYDistance>3.64042,0,0.447761194)) +
3.25E+04* if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>1.45833,0,0.555555556)) +
2.88E+05* if (AvgOfdocumentLength<2730.64,0,if (AvgOfdocumentLength>7970.65,1,0.476190476)) +
6.10E+04* if (AvgOfimagesAverageArea<15503.6,0,if (AvgOfimagesAverageArea>52644.8,0,0.583941606)) +
1.92E+07* if (AvgOfimagesArea2documentLength<45.5953,1,if (AvgOfimagesArea2documentLength>123.973,1,0.416666667)) +
5.39E+07* if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000195526,0,0.614035088)) +
8.32E+02* if (AvgOfcountNext2documentLength<8.05629E-05,1,if (AvgOfcountNext2documentLength>0.000247635,0,0.576923077)) +
3.04E+07* if (documentLength2timespent<6483.93,0,if (documentLength2timespent>13662.4,0,0.733944954)) +
3.22E+06* if (imagesArea2documentLength2timespent<69.2824,1,if (imagesArea2documentLength2timespent>359.302,0,0.52238806)) +
2.62E+07* if (imagesArea2mouseDistance<63988.7,0,if (imagesArea2mouseDistance>242455,0,0.727272727)) +
8.26E+08* if (nTables2mouseDistance<2.22275,1,if (nTables2mouseDistance>16.0976,1,0.416666667)) +
8.40E+06* if (nTables2documentLength2mouseSpeed<0.0014146,1,if (nTables2documentLength2mouseSpeed>0.00773544,1,0.416666667)) +
4.93E+06* if (imagesArea2mouseXFactor<171223,1,if (imagesArea2mouseXFactor>658493,0,0.52238806)) +
1.13E+09* if (nImages2documentLength2mouseXFactor<0.00309131,0,if (nImages2documentLength2mouseXFactor>0.0158329,0,0.583941606)) +
3.27E+08* if (imagesArea2documentLength2scrollYDistance<29.4085,1,if (imagesArea2documentLength2scrollYDistance>232.112,1,0.373134328)) +
7.27E+05* if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.302637,0,0.519480519)) +
1.23E+07* if (nLists2documentLength2scrollYSpeed<1.66472E-05,0,if (nLists2documentLength2scrollYSpeed>0.000388615,1,0.476190476)) +
1.83E+03* if (documentLength2scrollYPeaks<2514.77,1,if (documentLength2scrollYPeaks>5539.75,1,0.416666667)) +
3.05E+07* if (imagesArea2documentLength2scrollYPeaks<35.1047,0,if (imagesArea2documentLength2scrollYPeaks>123.973,1,0.5))) / 2.16E+09) >= 0.5

Terms	Term name	F-ratio
	AvgOfscrollYDistance	1.771e+008
	AvgOfscrollYPeaks	3.245e+004
	AvgOfdocumentLength	2.882e+005
	AvgOfimagesAverageArea	6.104e+004
	AvgOfimagesArea2documentLength	1.917e+007
	AvgOfcountExample2documentLength	5.391e+007
	AvgOfcountNext2documentLength	832.2
	documentLength2timespent	3.041e+007
	imagesArea2documentLength2timespent	3.216e+006
	imagesArea2mouseDistance	2.615e+007
	nTables2mouseDistance	8.261e+008
	nTables2documentLength2mouseSpeed	8.396e+006
	imagesArea2mouseXFactor	4.926e+006
	nImages2documentLength2mouseXFactor	1.127e+009
	imagesArea2documentLength2scrollYDistance	3.273e+008
	nObjects2scrollYSpeed	7.267e+005
	nLists2documentLength2scrollYSpeed	1.226e+007
	documentLength2scrollYPeaks	1825
	imagesArea2documentLength2scrollYPeaks	3.054e+007

Rule name	PAR2	Dimension of learning style		Active/Reflective	
Std. error	68.22%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ if (AvgOfmouseDistance<2.20644,1,if (AvgOfmouseDistance>3.37677,0,0.277777778))
+ if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.557359,1,0.444444444))
+ if (AvgOfscrollYDistance<0.773601,1,if (AvgOfscrollYDistance>3.64042,0,0.5))
+ if (AvgOfscrollYSpeed<0.82605,1,if (AvgOfscrollYSpeed>2.83884,0,0.44))
+ if (AvgOfcountFact2documentLength<6.88206E-06,1,if (AvgOfcountFact2documentLength>3.65915E-05,0,0.48))
+ if (documentLength2timespent<7538.84,1,if (documentLength2timespent>13056.3,0,0.4))
+ if (documentLength2mouseDistance<2273.78,1,if (documentLength2mouseDistance>5258.09,0,0.5))
+ if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0236,1,0.52))
+ if (nImages2mouseSpeed<9.00015,1,if (nImages2mouseSpeed>45.4493,0,0.5))
+ if (nImages2mouseXFactor<16.2376,1,if (nImages2mouseXFactor>66.246,0,0.3))
+ if (imagesArea2documentLength2mouseYFactorr<122.842,1,if (imagesArea2documentLength2mouseYFactorr>413.432,1,0.4))
+ if (documentLength2scrollYDistance<3576.44,1,if (documentLength2scrollYDistance>7719.66,1,0.423076923))
+ if (nImages2scrollYDistance<5.81499,0,if (nImages2scrollYDistance>53.0018,0,0.576923077))
+ if (imagesArea2documentLength2scrollYDistance<120.239,1,if (imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ if (nTables2documentLength2scrollYDistance<0.000972923,0,if (nTables2documentLength2scrollYDistance>0.00934362,0,0.652173913))
+ if (documentLength2scrollYSpeed<1676.81,0,if (documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ if (nLists2scrollYSpeed<0.215336,1,if (nLists2scrollYSpeed>1.56152,1,0.347826087))
+ if (nObjects2documentLength2scrollYSpeed<0,0,if (nObjects2documentLength2scrollYSpeed>0.00015516,0,0.517241379))) / 17.74633837

Terms	Term name	F-ratio
	nPagesVisited	5.355e+008
	AvgOfmouseDistance	1.272e+009
	AvgOfmouseYFactor	2.774e+010
	AvgOfscrollYDistance	2.133e+004
	AvgOfscrollYSpeed	6.047e+007
	AvgOfcountFact2documentLength	2.366e+009
	documentLength2timespent	5.256e+009
	documentLength2mouseDistance	2.521e+009
	nTables2mouseDistance	1.806e+007
	nImages2mouseSpeed	2.675e+006
	nImages2mouseXFactor	5.985e+007
	imagesArea2documentLength2mouseYFactorr	2.25e+008
	documentLength2scrollYDistance	1.606e+009
	nImages2scrollYDistance	2.517e+007
	imagesArea2documentLength2scrollYDistance	7.654e+009
	nTables2documentLength2scrollYDistance	9.196e+008
	documentLength2scrollYSpeed	3.054e+008
	nLists2scrollYSpeed	2.21e+005
	nObjects2documentLength2scrollYSpeed	4.074e+009

Rule name	PSI2	Dimension of learning style		Sensing/Intuitive	
Std. error	98.27%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOftimespent<192433000,0,if (AvgOftimespent>769424000,0,0.705882353))
+ if (AvgOfmouseDistance<1.44292,0,if (AvgOfmouseDistance>3.08505,0,0.648648649))
+ if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714))
+ if (AvgOfimagesArea2documentLength<48.859,1,if
(AvgOfimagesArea2documentLength>120.33,0,0.5))
+ if (AvgOfcountQuestionMarks2documentLength<0.000143468,1,if
(AvgOfcountQuestionMarks2documentLength>0.000409581,1,0.272727273))
+ if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if
(AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667))
+ if (imagesArea2timespent<165499,0,if (imagesArea2timespent>912391,0,0.631578947))
+ if (nImages2documentLength2mouseDistance<0.00199047,1,if
(nImages2documentLength2mouseDistance>0.00703923,0,0.636363636))
+ if (nObjects2documentLength2mouseDistance<0,0,if
(nObjects2documentLength2mouseDistance>0.000182664,0,0.533333333))
+ if (documentLength2mouseSpeed<3887.07,1,if
(documentLength2mouseSpeed>12489.7,0,0.5))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615))
+ if (imagesArea2mouseXFactor<198913,0,if
(imagesArea2mouseXFactor>746376,1,0.512195122))
+ if (imagesArea2mouseYFactor<324452,0,if
(imagesArea2mouseYFactor>1074420,0,0.631578947))
+ if (nLists2documentLength2mouseYFactor<0.000222495,0,if
(nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286))
+ if (imagesArea2scrollYDistance<122694,1,if
(imagesArea2scrollYDistance>400961,0,0.454545455))
+ if (nLists2documentLength2scrollYDistance<2.87574E-05,1,if
(nLists2documentLength2scrollYDistance>0.000847426,0,0.538461538))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.0531216,0,0.727272727))
+ if (nTables2scrollYPeaks<3.1,0,if (nTables2scrollYPeaks>8.84314,0,0.727272727))
+ if (nLists2scrollYPeaks<0.324324,0,if (nLists2scrollYPeaks>0.729167,0,0.685714286))) /
15.59238087

Terms	Term name	F-ratio
	AvgOftimespent	8.123e+010
	AvgOfmouseDistance	5.555e+009
	AvgOfscrollYSpeed	1.249e+011
	AvgOfimagesArea2documentLength	2.314e+007
	AvgOfcountQuestionMarks2documentLength	9.614e+005
	AvgOfcountQuestion2documentLength	4.434e+010
	imagesArea2timespent	1.248e+011
	nImages2documentLength2mouseDistance	5.448e+008
	nObjects2documentLength2mouseDistance	1.318e+009
	documentLength2mouseSpeed	4.438e+009
	nObjects2mouseSpeed	2.066e+009
	imagesArea2mouseXFactor	5.73e+009
	imagesArea2mouseYFactor	4.12e+010
	nLists2documentLength2mouseYFactor	5.977e+008
	imagesArea2scrollYDistance	8.3e+010
	nLists2documentLength2scrollYDistance	9.31e+009
	nObjects2scrollYSpeed	6.921e+010
	nTables2scrollYPeaks	4.178e+007
	nLists2scrollYPeaks	1.089e+009

Rule name	PVV2	Dimension of learning style		Visual/Verbal	
Std. error	101.23%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.567134,1,0.466666667))
+ if (AvgOfdocumentLength<4817.63,1,if (AvgOfdocumentLength>7970.65,0,0.210526316))
+ if (AvgOfimagesArea<141901,1,if (AvgOfimagesArea>538274,1,0.428571429))
+ if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.142857,1,0.448275862))
+ if (AvgOfimagesArea2documentLength<64.8333,1,if
(AvgOfimagesArea2documentLength>123.973,0,0.375))
+ if (AvgOfcountExclamationMarks2documentLength<0.000167676,1,if
(AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.36))
+ if (AvgOfcountDiagram2documentLength<0.000013739,1,if
(AvgOfcountDiagram2documentLength>3.77287E-05,0,0.3))
+ if (documentLength2timespent<7538.84,1,if
(documentLength2timespent>20416.7,1,0.333333333))
+ if (nImages2mouseDistance<5.01113,1,if
(nImages2mouseDistance>29.3771,1,0.466666667))
+ if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0976,0,0.592592593))
+ if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.025966,1,0.428571429))
+ if (nImages2documentLength2mouseDistance<0.00214675,1,if
(nImages2documentLength2mouseDistance>0.00430382,1,0.304347826))
+ if (documentLength2mouseSpeed<4012.86,1,if
(documentLength2mouseSpeed>11564.1,1,0.407407407))
+ if (imagesArea2documentLength2mouseSpeed<58.2908,1,if
(imagesArea2documentLength2mouseSpeed>110.784,1,0.304347826))
+ if (documentLength2mouseXFactor<6624.63,1,if
(documentLength2mouseXFactor>13100.5,1,0.238095238))
+ if (nImages2documentLength2mouseXFactor<0.00320142,1,if
(nImages2documentLength2mouseXFactor>0.0171758,1,0.428571429))
+ if (imagesArea2documentLength2scrollYDistance<108.712,1,if
(imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826))
+ if (nTables2documentLength2scrollYDistance<0.000972923,0,if
(nTables2documentLength2scrollYDistance>0.00934362,0,0.695652174))
+ if (nObjects2documentLength2scrollYSpeed<0,0,if
(nObjects2documentLength2scrollYSpeed>0.00015516,0,0.516129032))) / 17.8043738

Terms	Term name	F-ratio
	AvgOfmouseYFactor	1.429e+011
	AvgOfdocumentLength	3.075e+010
	AvgOfimagesArea	4.023e+006
	AvgOfnObjects	1.367e+011
	AvgOfimagesArea2documentLength	1.999e+010
	AvgOfcountExclamationMarks2documentLength	7.713e+009
	AvgOfcountDiagram2documentLength	6.463e+010
	documentLength2timespent	2.621e+009
	nImages2mouseDistance	6.04e+009
	nTables2mouseDistance	1.013e+011
	nObjects2mouseDistance	1.671e+009
	nImages2documentLength2mouseDistance	2.838e+008
	documentLength2mouseSpeed	5.812e+007
	imagesArea2documentLength2mouseSpeed	3008
	documentLength2mouseXFactor	6.795e+009
	nImages2documentLength2mouseXFactor	8.137e+008
	imagesArea2documentLength2scrollYDistance	4.735e+010
	nTables2documentLength2scrollYDistance	1.363e+008
	nObjects2documentLength2scrollYSpeed	5.264e+007

Rule name	PSG2	Dimension of learning style		Sequential/Global	
Std. error	127.64%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfcountExclamationMarks2documentLength<0.000115955,0,if (AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.487804878))
+ if (AvgOfcountFact2documentLength<0,0,if (AvgOfcountFact2documentLength>3.89784E-05,1,0.454545455))
+ if (AvgOfcountPrevious2documentLength<1.98992E-06,1,if (AvgOfcountPrevious2documentLength>0.000123235,0,0.480769231))
+ if (imagesArea2timespent<206049,0,if (imagesArea2timespent>840018,0,0.808080808))
+ if (nTables2timespent<7.90323,1,if (nTables2timespent>33.4951,1,0.373134328))
+ if (nObjects2timespent<0,0,if (nObjects2timespent>0.344311,1,0.416666667))
+ if (nTables2mouseDistance<2.22275,1,if (nTables2mouseDistance>16.0976,1,0.416666667))
+ if (nImages2documentLength2mouseDistance<0.00214675,0,if (nImages2documentLength2mouseDistance>0.017863,0,0.571428571))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.320984,1,0.454545455))
+ if (nObjects2documentLength2mouseSpeed<0,0,if (nObjects2documentLength2mouseSpeed>0.000428824,0,0.519480519))
+ if (nObjects2mouseXFactor<0,0,if (nObjects2mouseXFactor>0.479857,1,0.454545455))
+ if (imagesArea2documentLength2mouseXFactor<64.6073,1,if (imagesArea2documentLength2mouseXFactor>183.425,0,0.52238806))
+ if (nObjects2documentLength2mouseXFactor<0,0,if (nObjects2documentLength2mouseXFactor>0.000524074,1,0.416666667))
+ if (documentLength2mouseYFactor<7371.52,0,if (documentLength2mouseYFactor>13620.6,1,0.476190476))
+ if (nTables2documentLength2mouseYFactor<0.00217229,1,if (nTables2documentLength2mouseYFactor>0.0146279,0,0.486111111))
+ if (nLists2scrollYDistance<0.247841,0,if (nLists2scrollYDistance>1.82946,0,0.634920635))
+ if (nLists2documentLength2scrollYDistance<2.87574E-05,0,if (nLists2documentLength2scrollYDistance>0.00170749,0,0.544217687))
+ if (nImages2scrollYSpeed<4.92419,0,if (nImages2scrollYSpeed>18.9242,0,0.571428571))
+ if (nImages2documentLength2scrollYPeaks<0.00204827,0,if (nImages2documentLength2scrollYPeaks>0.0128001,0,0.601503759))) / 16.25106055

Terms	Term name	F-ratio
	AvgOfcountExclamationMarks2documentLength	3.608e+009
	AvgOfcountFact2documentLength	1.363e+010
	AvgOfcountPrevious2documentLength	7.784e+008
	imagesArea2timespent	2.216e+010
	nTables2timespent	819.3
	nObjects2timespent	2.818e+009
	nTables2mouseDistance	9.296e+008
	nImages2documentLength2mouseDistance	5.064e+009
	nObjects2mouseSpeed	2.913e+009
	nObjects2documentLength2mouseSpeed	3.582e+009
	nObjects2mouseXFactor	3.463e+007
	imagesArea2documentLength2mouseXFactor	4.421e+009
	nObjects2documentLength2mouseXFactor	3.557e+009
	documentLength2mouseYFactor	2.419e+010
	nTables2documentLength2mouseYFactor	1.179e+008
	nLists2scrollYDistance	2.16e+010
	nLists2documentLength2scrollYDistance	5.909e+009
	nImages2scrollYSpeed	1.437e+009
	nImages2documentLength2scrollYPeaks	2.784e+005

Rule name	PAR2W	Dimension of learning style		Active/Reflective	
Std. error	114.72%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(5.36E+08* if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ 1.27E+09* if (AvgOfmouseDistance<2.20644,1,if
(AvgOfmouseDistance>3.37677,0,0.277777778))
+ 2.77E+10* if (AvgOfmouseYFactor<0.421104,1,if
(AvgOfmouseYFactor>0.557359,1,0.444444444))
+ 2.13E+04* if (AvgOfscrollYDistance<0.773601,1,if (AvgOfscrollYDistance>3.64042,0,0.5))
+ 6.05E+07* if (AvgOfscrollYSpeed<0.82605,1,if (AvgOfscrollYSpeed>2.83884,0,0.44))
+ 2.37E+09* if (AvgOfcountFact2documentLength<6.88206E-06,1,if
(AvgOfcountFact2documentLength>3.65915E-05,0,0.48))
+ 5.26E+09* if (documentLength2timespent<7538.84,1,if
(documentLength2timespent>13056.3,0,0.4))
+ 2.52E+09* if (documentLength2mouseDistance<2273.78,1,if
(documentLength2mouseDistance>5258.09,0,0.5))
+ 1.81E+07* if (nTables2mouseDistance<2.22275,0,if
(nTables2mouseDistance>16.0236,1,0.52))
+ 2.68E+06* if (nImages2mouseSpeed<9.00015,1,if (nImages2mouseSpeed>45.4493,0,0.5))
+ 5.99E+07* if (nImages2mouseXFactor<16.2376,1,if (nImages2mouseXFactor>66.246,0,0.3))
+ 2.25E+08* if (imagesArea2documentLength2mouseYFactorr<122.842,1,if
(imagesArea2documentLength2mouseYFactorr>413.432,1,0.4))
+ 1.61E+09* if (documentLength2scrollYDistance<3576.44,1,if
(documentLength2scrollYDistance>7719.66,1,0.423076923))
+ 2.52E+07* if (nImages2scrollYDistance<5.81499,0,if
(nImages2scrollYDistance>53.0018,0,0.576923077))
+ 7.65E+09* if (imagesArea2documentLength2scrollYDistance<120.239,1,if
(imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ 9.20E+08* if (nTables2documentLength2scrollYDistance<0.000972923,0,if
(nTables2documentLength2scrollYDistance>0.00934362,0,0.652173913))
+ 3.05E+08* if (documentLength2scrollYSpeed<1676.81,0,if
(documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ 2.21E+05* if (nLists2scrollYSpeed<0.215336,1,if
(nLists2scrollYSpeed>1.56152,1,0.347826087))
+ 4.07E+09* if (nObjects2documentLength2scrollYSpeed<0,0,if
(nObjects2documentLength2scrollYSpeed>0.00015516,0,0.517241379))) / 5.23E+10

Terms	Term name	F-ratio
	nPagesVisited	5.355e+008
	AvgOfmouseDistance	1.272e+009
	AvgOfmouseYFactor	2.774e+010
	AvgOfscrollYDistance	2.133e+004
	AvgOfscrollYSpeed	6.047e+007
	AvgOfcountFact2documentLength	2.366e+009
	documentLength2timespent	5.256e+009
	documentLength2mouseDistance	2.521e+009
	nTables2mouseDistance	1.806e+007
	nImages2mouseSpeed	2.675e+006
	nImages2mouseXFactor	5.985e+007
	imagesArea2documentLength2mouseYFactorr	2.25e+008
	documentLength2scrollYDistance	1.606e+009
	nImages2scrollYDistance	2.517e+007
	imagesArea2documentLength2scrollYDistance	7.654e+009
	nTables2documentLength2scrollYDistance	9.196e+008
	documentLength2scrollYSpeed	3.054e+008
	nLists2scrollYSpeed	2.21e+005
	nObjects2documentLength2scrollYSpeed	4.074e+009

Rule name	PSI2W	Dimension of learning style			Sensing/Intuitive
Std. error	107.81%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(8.123e+010* if (AvgOftimespent<192433000,0,if (AvgOftimespent>769424000,0,0.705882353))
+ 5.555e+009* if (AvgOfmouseDistance<1.44292,0,if (AvgOfmouseDistance>3.08505,0,0.648648649))
+ 1.249e+011* if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714))
+ 2.314e+007* if (AvgOfimagesArea2documentLength<48.859,1,if (AvgOfimagesArea2documentLength>120.33,0,0.5))
+ 9.614e+005* if (AvgOfcountQuestionMarks2documentLength<0.000143468,1,if (AvgOfcountQuestionMarks2documentLength>0.000409581,1,0.272727273))
+ 4.434e+010* if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if (AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667))
+ 1.248e+011* if (imagesArea2timespent<165499,0,if (imagesArea2timespent>912391,0,0.631578947))
+ 5.448e+008* if (nImages2documentLength2mouseDistance<0.00199047,1,if (nImages2documentLength2mouseDistance>0.00703923,0,0.636363636))
+ 1.318e+009* if (nObjects2documentLength2mouseDistance<0,0,if (nObjects2documentLength2mouseDistance>0.000182664,0,0.533333333))
+ 4.438e+009* if (documentLength2mouseSpeed<3887.07,1,if (documentLength2mouseSpeed>12489.7,0,0.5))
+ 2.066e+009* if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615))
+ 5.73e+009* if (imagesArea2mouseXFactor<198913,0,if (imagesArea2mouseXFactor>746376,1,0.512195122))
+ 4.12e+010* if (imagesArea2mouseYFactor<324452,0,if (imagesArea2mouseYFactor>1074420,0,0.631578947))
+ 5.977e+008* if (nLists2documentLength2mouseYFactor<0.000222495,0,if (nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286))
+ 8.3e+010* if (imagesArea2scrollYDistance<122694,1,if (imagesArea2scrollYDistance>400961,0,0.454545455))
+ 9.31e+009* if (nLists2documentLength2scrollYDistance<2.87574E-05,1,if (nLists2documentLength2scrollYDistance>0.000847426,0,0.538461538))
+ 6.921e+010* if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.0531216,0,0.727272727))
+ 4.178e+007* if (nTables2scrollYPeaks<3.1,0,if (nTables2scrollYPeaks>8.84314,0,0.727272727))
+ 1.089e+009* if (nLists2scrollYPeaks<0.324324,0,if (nLists2scrollYPeaks>0.729167,0,0.685714286))) / 4.92E+11

Terms	Term name	F-ratio
	AvgOftimespent	8.123e+010
	AvgOfmouseDistance	5.555e+009
	AvgOfscrollYSpeed	1.249e+011
	AvgOfimagesArea2documentLength	2.314e+007
	AvgOfcountQuestionMarks2documentLength	9.614e+005
	AvgOfcountQuestion2documentLength	4.434e+010
	imagesArea2timespent	1.248e+011
	nImages2documentLength2mouseDistance	5.448e+008
	nObjects2documentLength2mouseDistance	1.318e+009
	documentLength2mouseSpeed	4.438e+009
	nObjects2mouseSpeed	2.066e+009
	imagesArea2mouseXFactor	5.73e+009
	imagesArea2mouseYFactor	4.12e+010
	nLists2documentLength2mouseYFactor	5.977e+008
	imagesArea2scrollYDistance	8.3e+010
	nLists2documentLength2scrollYDistance	9.31e+009
	nObjects2scrollYSpeed	6.921e+010
	nTables2scrollYPeaks	4.178e+007
	nLists2scrollYPeaks	1.089e+009

Rule name	PVV2W	Dimension of learning style		Visual/Verbal	
Std. error	106.76%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(1.43E+11* if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.567134,1,0.466666667))
+ 3.08E+10* if (AvgOfdocumentLength<4817.63,1,if (AvgOfdocumentLength>7970.65,0,0.210526316))
+ 4.02E+06* if (AvgOfimagesArea<141901,1,if (AvgOfimagesArea>538274,1,0.428571429))
+ 1.37E+11* if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.142857,1,0.448275862))
+ 2.00E+10* if (AvgOfimagesArea2documentLength<64.8333,1,if (AvgOfimagesArea2documentLength>123.973,0,0.375))
+ 7.71E+09* if (AvgOfcountExclamationMarks2documentLength<0.000167676,1,if (AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.36))
+ 6.46E+10* if (AvgOfcountDiagram2documentLength<0.000013739,1,if (AvgOfcountDiagram2documentLength>3.77287E-05,0,0.3))
+ 2.62E+09* if (documentLength2timespent<7538.84,1,if (documentLength2timespent>20416.7,1,0.333333333))
+ 6.04E+09* if (nImages2mouseDistance<5.01113,1,if (nImages2mouseDistance>29.3771,1,0.466666667))
+ 1.01E+11* if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0976,0,0.592592593))
+ 1.67E+09* if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.025966,1,0.428571429))
+ 2.84E+08* if (nImages2documentLength2mouseDistance<0.00214675,1,if (nImages2documentLength2mouseDistance>0.00430382,1,0.304347826))
+ 5.81E+07* if (documentLength2mouseSpeed<4012.86,1,if (documentLength2mouseSpeed>11564.1,1,0.407407407))
+ 3.01E+03* if (imagesArea2documentLength2mouseSpeed<58.2908,1,if (imagesArea2documentLength2mouseSpeed>110.784,1,0.304347826))
+ 6.80E+09* if (documentLength2mouseXFactor<6624.63,1,if (documentLength2mouseXFactor>13100.5,1,0.238095238))
+ 8.14E+08* if (nImages2documentLength2mouseXFactor<0.00320142,1,if (nImages2documentLength2mouseXFactor>0.0171758,1,0.428571429))
+ 4.74E+10* if (imagesArea2documentLength2scrollYDistance<108.712,1,if (imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826))
+ 1.36E+08* if (nTables2documentLength2scrollYDistance<0.000972923,0,if (nTables2documentLength2scrollYDistance>0.00934362,0,0.695652174))
+ 5.26E+07* if (nObjects2documentLength2scrollYSpeed<0,0,if (nObjects2documentLength2scrollYSpeed>0.00015516,0,0.516129032))) / 5.28E+11

Terms	Term name	F-ratio
	AvgOfmouseYFactor	1.429e+011
	AvgOfdocumentLength	3.075e+010
	AvgOfimagesArea	4.023e+006
	AvgOfnObjects	1.367e+011
	AvgOfimagesArea2documentLength	1.999e+010
	AvgOfcountExclamationMarks2documentLength	7.713e+009
	AvgOfcountDiagram2documentLength	6.463e+010
	documentLength2timespent	2.621e+009
	nImages2mouseDistance	6.04e+009
	nTables2mouseDistance	1.013e+011
	nObjects2mouseDistance	1.671e+009
	nImages2documentLength2mouseDistance	2.838e+008
	documentLength2mouseSpeed	5.812e+007
	imagesArea2documentLength2mouseSpeed	3008
	documentLength2mouseXFactor	6.795e+009
	nImages2documentLength2mouseXFactor	8.137e+008
	imagesArea2documentLength2scrollYDistance	4.735e+010
	nTables2documentLength2scrollYDistance	1.363e+008
	nObjects2documentLength2scrollYSpeed	5.264e+007

Rule name	PSG2W	Dimension of learning style		Sequential/Global	
Std. error	158.50%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(3.61E+09* if (AvgOfcountExclamationMarks2documentLength<0.000115955,0,if (AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.487804878))
+ 1.36E+10* if (AvgOfcountFact2documentLength<0,0,if (AvgOfcountFact2documentLength>3.89784E-05,1,0.454545455))
+ 7.78E+08* if (AvgOfcountPrevious2documentLength<1.98992E-06,1,if (AvgOfcountPrevious2documentLength>0.000123235,0,0.480769231))
+ 2.22E+10* if (imagesArea2timespent<206049,0,if (imagesArea2timespent>840018,0,0.808080808))
+ 8.19E+02* if (nTables2timespent<7.90323,1,if (nTables2timespent>33.4951,1,0.373134328))
+ 2.82E+09* if (nObjects2timespent<0,0,if (nObjects2timespent>0.344311,1,0.416666667))
+ 9.30E+08* if (nTables2mouseDistance<2.22275,1,if (nTables2mouseDistance>16.0976,1,0.416666667))
+ 5.06E+09* if (nImages2documentLength2mouseDistance<0.00214675,0,if (nImages2documentLength2mouseDistance>0.017863,0,0.571428571))
+ 2.91E+09* if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.320984,1,0.454545455))
+ 3.58E+09* if (nObjects2documentLength2mouseSpeed<0,0,if (nObjects2documentLength2mouseSpeed>0.000428824,0,0.519480519))
+ 3.46E+07* if (nObjects2mouseXFactor<0,0,if (nObjects2mouseXFactor>0.479857,1,0.454545455))
+ 4.42E+09* if (imagesArea2documentLength2mouseXFactor<64.6073,1,if (imagesArea2documentLength2mouseXFactor>183.425,0,0.52238806))
+ 3.56E+09* if (nObjects2documentLength2mouseXFactor<0,0,if (nObjects2documentLength2mouseXFactor>0.000524074,1,0.416666667))
+ 2.42E+10* if (documentLength2mouseYFactor<7371.52,0,if (documentLength2mouseYFactor>13620.6,1,0.476190476))
+ 1.18E+08* if (nTables2documentLength2mouseYFactor<0.00217229,1,if (nTables2documentLength2mouseYFactor>0.0146279,0,0.486111111))
+ 2.16E+10* if (nLists2scrollYDistance<0.247841,0,if (nLists2scrollYDistance>1.82946,0,0.634920635))
+ 5.91E+09* if (nLists2documentLength2scrollYDistance<2.87574E-05,0,if (nLists2documentLength2scrollYDistance>0.00170749,0,0.544217687))
+ 1.44E+09* if (nImages2scrollYSpeed<4.92419,0,if (nImages2scrollYSpeed>18.9242,0,0.571428571))
+ 2.78E+05* if (nImages2documentLength2scrollYPeaks<0.00204827,0,if (nImages2documentLength2scrollYPeaks>0.0128001,0,0.601503759))) / 9.74E+10

Terms	Term name	F-ratio
	AvgOfcountExclamationMarks2documentLength	3.608e+009
	AvgOfcountFact2documentLength	1.363e+010
	AvgOfcountPrevious2documentLength	7.784e+008
	imagesArea2timespent	2.216e+010
	nTables2timespent	819.3
	nObjects2timespent	2.818e+009
	nTables2mouseDistance	9.296e+008
	nImages2documentLength2mouseDistance	5.064e+009
	nObjects2mouseSpeed	2.913e+009
	nObjects2documentLength2mouseSpeed	3.582e+009
	nObjects2mouseXFactor	3.463e+007
	imagesArea2documentLength2mouseXFactor	4.421e+009
	nObjects2documentLength2mouseXFactor	3.557e+009
	documentLength2mouseYFactor	2.419e+010
	nTables2documentLength2mouseYFactor	1.179e+008
	nLists2scrollYDistance	2.16e+010
	nLists2documentLength2scrollYDistance	5.909e+009
	nImages2scrollYSpeed	1.437e+009
	nImages2documentLength2scrollYPeaks	2.784e+005

Rule name	PAR2B	Dimension of learning style		Active/Reflective	
Std. error	N/A	Class. Prob.	90%	Class. Eff.	71.43%

Rule Expression

((if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ if (AvgOfmouseDistance<2.20644,1,if (AvgOfmouseDistance>3.37677,0,0.277777778))
+ if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.557359,1,0.444444444))
+ if (AvgOfscrollYDistance<0.773601,1,if (AvgOfscrollYDistance>3.64042,0,0.5))
+ if (AvgOfscrollYSpeed<0.82605,1,if (AvgOfscrollYSpeed>2.83884,0,0.44))
+ if (AvgOfcountFact2documentLength<6.88206E-06,1,if (AvgOfcountFact2documentLength>3.65915E-05,0,0.48))
+ if (documentLength2timespent<7538.84,1,if (documentLength2timespent>13056.3,0,0.4))
+ if (documentLength2mouseDistance<2273.78,1,if (documentLength2mouseDistance>5258.09,0,0.5))
+ if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0236,1,0.52))
+ if (nImages2mouseSpeed<9.00015,1,if (nImages2mouseSpeed>45.4493,0,0.5))
+ if (nImages2mouseXFactor<16.2376,1,if (nImages2mouseXFactor>66.246,0,0.3))
+ if (imagesArea2documentLength2mouseYFactorr<122.842,1,if (imagesArea2documentLength2mouseYFactorr>413.432,1,0.4))
+ if (documentLength2scrollYDistance<3576.44,1,if (documentLength2scrollYDistance>7719.66,1,0.423076923))
+ if (nImages2scrollYDistance<5.81499,0,if (nImages2scrollYDistance>53.0018,0,0.576923077))
+ if (imagesArea2documentLength2scrollYDistance<120.239,1,if (imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ if (nTables2documentLength2scrollYDistance<0.000972923,0,if (nTables2documentLength2scrollYDistance>0.00934362,0,0.652173913))
+ if (documentLength2scrollYSpeed<1676.81,0,if (documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ if (nLists2scrollYSpeed<0.215336,1,if (nLists2scrollYSpeed>1.56152,1,0.347826087))
+ if (nObjects2documentLength2scrollYSpeed<0,0,if (nObjects2documentLength2scrollYSpeed>0.00015516,0,0.517241379))) / 17.74633837) >=0.5

Terms	Term name	F-ratio
	nPagesVisited	5.355e+008
	AvgOfmouseDistance	1.272e+009
	AvgOfmouseYFactor	2.774e+010
	AvgOfscrollYDistance	2.133e+004
	AvgOfscrollYSpeed	6.047e+007
	AvgOfcountFact2documentLength	2.366e+009
	documentLength2timespent	5.256e+009
	documentLength2mouseDistance	2.521e+009
	nTables2mouseDistance	1.806e+007
	nImages2mouseSpeed	2.675e+006
	nImages2mouseXFactor	5.985e+007
	imagesArea2documentLength2mouseYFactorr	2.25e+008
	documentLength2scrollYDistance	1.606e+009
	nImages2scrollYDistance	2.517e+007
	imagesArea2documentLength2scrollYDistance	7.654e+009
	nTables2documentLength2scrollYDistance	9.196e+008
	documentLength2scrollYSpeed	3.054e+008
	nLists2scrollYSpeed	2.21e+005
	nObjects2documentLength2scrollYSpeed	4.074e+009

Rule name	PSI2	Dimension of learning style		Sensing/Intuitive	
Std. error	N/A	Class. Prob.	55%	Class. Eff.	-28.57%

Rule Expression

((if (AvgOftimespent<192433000,0,if (AvgOftimespent>769424000,0,0.705882353))
+ if (AvgOfmouseDistance<1.44292,0,if (AvgOfmouseDistance>3.08505,0,0.648648649))
+ if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714))
+ if (AvgOfimagesArea2documentLength<48.859,1,if (AvgOfimagesArea2documentLength>120.33,0,0.5))
+ if (AvgOfcountQuestionMarks2documentLength<0.000143468,1,if (AvgOfcountQuestionMarks2documentLength>0.000409581,1,0.272727273))
+ if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if (AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667))
+ if (imagesArea2timespent<165499,0,if (imagesArea2timespent>912391,0,0.631578947))
+ if (nImages2documentLength2mouseDistance<0.00199047,1,if (nImages2documentLength2mouseDistance>0.00703923,0,0.636363636))
+ if (nObjects2documentLength2mouseDistance<0,0,if (nObjects2documentLength2mouseDistance>0.000182664,0,0.533333333))
+ if (documentLength2mouseSpeed<3887.07,1,if (documentLength2mouseSpeed>12489.7,0,0.5))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615))
+ if (imagesArea2mouseXFactor<198913,0,if (imagesArea2mouseXFactor>746376,1,0.512195122))
+ if (imagesArea2mouseYFactor<324452,0,if (imagesArea2mouseYFactor>1074420,0,0.631578947))
+ if (nLists2documentLength2mouseYFactor<0.000222495,0,if (nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286))
+ if (imagesArea2scrollYDistance<122694,1,if (imagesArea2scrollYDistance>400961,0,0.454545455))
+ if (nLists2documentLength2scrollYDistance<2.87574E-05,1,if (nLists2documentLength2scrollYDistance>0.000847426,0,0.538461538))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.0531216,0,0.727272727))
+ if (nTables2scrollYPeaks<3.1,0,if (nTables2scrollYPeaks>8.84314,0,0.727272727))
+ if (nLists2scrollYPeaks<0.324324,0,if (nLists2scrollYPeaks>0.729167,0,0.685714286))) / 15.59238087) >=0.5

Terms	Term name	F-ratio
	AvgOftimespent	8.123e+010
	AvgOfmouseDistance	5.555e+009
	AvgOfscrollYSpeed	1.249e+011
	AvgOfimagesArea2documentLength	2.314e+007
	AvgOfcountQuestionMarks2documentLength	9.614e+005
	AvgOfcountQuestion2documentLength	4.434e+010
	imagesArea2timespent	1.248e+011
	nImages2documentLength2mouseDistance	5.448e+008
	nObjects2documentLength2mouseDistance	1.318e+009
	documentLength2mouseSpeed	4.438e+009
	nObjects2mouseSpeed	2.066e+009
	imagesArea2mouseXFactor	5.73e+009
	imagesArea2mouseYFactor	4.12e+010
	nLists2documentLength2mouseYFactor	5.977e+008
	imagesArea2scrollYDistance	8.3e+010
	nLists2documentLength2scrollYDistance	9.31e+009
	nObjects2scrollYSpeed	6.921e+010
	nTables2scrollYPeaks	4.178e+007
	nLists2scrollYPeaks	1.089e+009

Rule name	PVV2	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	85%	Class. Eff.	40%

Rule Expression

((if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.567134,1,0.466666667))
+ if (AvgOfdocumentLength<4817.63,1,if (AvgOfdocumentLength>7970.65,0,0.210526316))
+ if (AvgOfimagesArea<141901,1,if (AvgOfimagesArea>538274,1,0.428571429))
+ if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.142857,1,0.448275862))
+ if (AvgOfimagesArea2documentLength<64.8333,1,if (AvgOfimagesArea2documentLength>123.973,0,0.375))
+ if (AvgOfcountExclamationMarks2documentLength<0.000167676,1,if (AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.36))
+ if (AvgOfcountDiagram2documentLength<0.000013739,1,if (AvgOfcountDiagram2documentLength>3.77287E-05,0,0.3))
+ if (documentLength2timespent<7538.84,1,if (documentLength2timespent>20416.7,1,0.333333333))
+ if (nImages2mouseDistance<5.01113,1,if (nImages2mouseDistance>29.3771,1,0.466666667))
+ if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0976,0,0.592592593))
+ if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.025966,1,0.428571429))
+ if (nImages2documentLength2mouseDistance<0.00214675,1,if (nImages2documentLength2mouseDistance>0.00430382,1,0.304347826))
+ if (documentLength2mouseSpeed<4012.86,1,if (documentLength2mouseSpeed>11564.1,1,0.407407407))
+ if (imagesArea2documentLength2mouseSpeed<58.2908,1,if (imagesArea2documentLength2mouseSpeed>110.784,1,0.304347826))
+ if (documentLength2mouseXFactor<6624.63,1,if (documentLength2mouseXFactor>13100.5,1,0.238095238))
+ if (nImages2documentLength2mouseXFactor<0.00320142,1,if (nImages2documentLength2mouseXFactor>0.0171758,1,0.428571429))
+ if (imagesArea2documentLength2scrollYDistance<108.712,1,if (imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826))
+ if (nTables2documentLength2scrollYDistance<0.000972923,0,if (nTables2documentLength2scrollYDistance>0.00934362,0,0.695652174))
+ if (nObjects2documentLength2scrollYSpeed<0,0,if (nObjects2documentLength2scrollYSpeed>0.00015516,0,0.516129032))) / 17.8043738) >=0.5

Terms	Term name	F-ratio
	AvgOfmouseYFactor	1.429e+011
	AvgOfdocumentLength	3.075e+010
	AvgOfimagesArea	4.023e+006
	AvgOfnObjects	1.367e+011
	AvgOfimagesArea2documentLength	1.999e+010
	AvgOfcountExclamationMarks2documentLength	7.713e+009
	AvgOfcountDiagram2documentLength	6.463e+010
	documentLength2timespent	2.621e+009
	nImages2mouseDistance	6.04e+009
	nTables2mouseDistance	1.013e+011
	nObjects2mouseDistance	1.671e+009
	nImages2documentLength2mouseDistance	2.838e+008
	documentLength2mouseSpeed	5.812e+007
	imagesArea2documentLength2mouseSpeed	3008
	documentLength2mouseXFactor	6.795e+009
	nImages2documentLength2mouseXFactor	8.137e+008
	imagesArea2documentLength2scrollYDistance	4.735e+010
	nTables2documentLength2scrollYDistance	1.363e+008
	nObjects2documentLength2scrollYSpeed	5.264e+007

Rule name	PSG2	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	50%	Class. Eff.	-11.11%

Rule Expression

((if (AvgOfcountExclamationMarks2documentLength<0.000115955,0,if (AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.487804878))
+ if (AvgOfcountFact2documentLength<0,0,if (AvgOfcountFact2documentLength>3.89784E-05,1,0.454545455))
+ if (AvgOfcountPrevious2documentLength<1.98992E-06,1,if (AvgOfcountPrevious2documentLength>0.000123235,0,0.480769231))
+ if (imagesArea2timespent<206049,0,if (imagesArea2timespent>840018,0,0.808080808))
+ if (nTables2timespent<7.90323,1,if (nTables2timespent>33.4951,1,0.373134328))
+ if (nObjects2timespent<0,0,if (nObjects2timespent>0.344311,1,0.416666667))
+ if (nTables2mouseDistance<2.22275,1,if (nTables2mouseDistance>16.0976,1,0.416666667))
+ if (nImages2documentLength2mouseDistance<0.00214675,0,if (nImages2documentLength2mouseDistance>0.017863,0,0.571428571))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.320984,1,0.454545455))
+ if (nObjects2documentLength2mouseSpeed<0,0,if (nObjects2documentLength2mouseSpeed>0.000428824,0,0.519480519))
+ if (nObjects2mouseXFactor<0,0,if (nObjects2mouseXFactor>0.479857,1,0.454545455))
+ if (imagesArea2documentLength2mouseXFactor<64.6073,1,if (imagesArea2documentLength2mouseXFactor>183.425,0,0.52238806))
+ if (nObjects2documentLength2mouseXFactor<0,0,if (nObjects2documentLength2mouseXFactor>0.000524074,1,0.416666667))
+ if (documentLength2mouseYFactor<7371.52,0,if (documentLength2mouseYFactor>13620.6,1,0.476190476))
+ if (nTables2documentLength2mouseYFactor<0.00217229,1,if (nTables2documentLength2mouseYFactor>0.0146279,0,0.486111111))
+ if (nLists2scrollYDistance<0.247841,0,if (nLists2scrollYDistance>1.82946,0,0.634920635))
+ if (nLists2documentLength2scrollYDistance<2.87574E-05,0,if (nLists2documentLength2scrollYDistance>0.00170749,0,0.544217687))
+ if (nImages2scrollYSpeed<4.92419,0,if (nImages2scrollYSpeed>18.9242,0,0.571428571))
+ if (nImages2documentLength2scrollYPeaks<0.00204827,0,if (nImages2documentLength2scrollYPeaks>0.0128001,0,0.601503759))) / 16.25106055) >=0.5

Terms	Term name	F-ratio
	AvgOfcountExclamationMarks2documentLength	3.608e+009
	AvgOfcountFact2documentLength	1.363e+010
	AvgOfcountPrevious2documentLength	7.784e+008
	imagesArea2timespent	2.216e+010
	nTables2timespent	819.3
	nObjects2timespent	2.818e+009
	nTables2mouseDistance	9.296e+008
	nImages2documentLength2mouseDistance	5.064e+009
	nObjects2mouseSpeed	2.913e+009
	nObjects2documentLength2mouseSpeed	3.582e+009
	nObjects2mouseXFactor	3.463e+007
	imagesArea2documentLength2mouseXFactor	4.421e+009
	nObjects2documentLength2mouseXFactor	3.557e+009
	documentLength2mouseYFactor	2.419e+010
	nTables2documentLength2mouseYFactor	1.179e+008
	nLists2scrollYDistance	2.16e+010
	nLists2documentLength2scrollYDistance	5.909e+009
	nImages2scrollYSpeed	1.437e+009
	nImages2documentLength2scrollYPeaks	2.784e+005

Rule name	PAR2W	Dimension of learning style		Active/Reflective	
Std. error	N/A	Class. Prob.	80%	Class. Eff.	42.86%

Rule Expression

((5.36E+08* if (nPagesVisited<20,1,if (nPagesVisited>58,1,0.4))
+ 1.27E+09* if (AvgOfmouseDistance<2.20644,1,if (AvgOfmouseDistance>3.37677,0,0.277777778))
+ 2.77E+10* if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.557359,1,0.444444444))
+ 2.13E+04* if (AvgOfscrollYDistance<0.773601,1,if (AvgOfscrollYDistance>3.64042,0,0.5))
+ 6.05E+07* if (AvgOfscrollYSpeed<0.82605,1,if (AvgOfscrollYSpeed>2.83884,0,0.44))
+ 2.37E+09* if (AvgOfcountFact2documentLength<6.88206E-06,1,if (AvgOfcountFact2documentLength>3.65915E-05,0,0.48))
+ 5.26E+09* if (documentLength2timespent<7538.84,1,if (documentLength2timespent>13056.3,0,0.4))
+ 2.52E+09* if (documentLength2mouseDistance<2273.78,1,if (documentLength2mouseDistance>5258.09,0,0.5))
+ 1.81E+07* if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0236,1,0.52))
+ 2.68E+06* if (nImages2mouseSpeed<9.00015,1,if (nImages2mouseSpeed>45.4493,0,0.5))
+ 5.99E+07* if (nImages2mouseXFactor<16.2376,1,if (nImages2mouseXFactor>66.246,0,0.3))
+ 2.25E+08* if (imagesArea2documentLength2mouseYFactorr<122.842,1,if (imagesArea2documentLength2mouseYFactorr>413.432,1,0.4))
+ 1.61E+09* if (documentLength2scrollYDistance<3576.44,1,if (documentLength2scrollYDistance>7719.66,1,0.423076923))
+ 2.52E+07* if (nImages2scrollYDistance<5.81499,0,if (nImages2scrollYDistance>53.0018,0,0.576923077))
+ 7.65E+09* if (imagesArea2documentLength2scrollYDistance<120.239,1,if (imagesArea2documentLength2scrollYDistance>208.006,0,0.333333333))
+ 9.20E+08* if (nTables2documentLength2scrollYDistance<0.000972923,0,if (nTables2documentLength2scrollYDistance>0.00934362,0,0.652173913))
+ 3.05E+08* if (documentLength2scrollYSpeed<1676.81,0,if (documentLength2scrollYSpeed>7446.08,1,0.538461538))
+ 2.21E+05* if (nLists2scrollYSpeed<0.215336,1,if (nLists2scrollYSpeed>1.56152,1,0.347826087))
+ 4.07E+09* if (nObjects2documentLength2scrollYSpeed<0,0,if (nObjects2documentLength2scrollYSpeed>0.00015516,0,0.517241379))) / 5.23E+10) >=0.5

Terms	Term name	F-ratio
	nPagesVisited	5.355e+008
	AvgOfmouseDistance	1.272e+009
	AvgOfmouseYFactor	2.774e+010
	AvgOfscrollYDistance	2.133e+004
	AvgOfscrollYSpeed	6.047e+007
	AvgOfcountFact2documentLength	2.366e+009
	documentLength2timespent	5.256e+009
	documentLength2mouseDistance	2.521e+009
	nTables2mouseDistance	1.806e+007
	nImages2mouseSpeed	2.675e+006
	nImages2mouseXFactor	5.985e+007
	imagesArea2documentLength2mouseYFactorr	2.25e+008
	documentLength2scrollYDistance	1.606e+009
	nImages2scrollYDistance	2.517e+007
	imagesArea2documentLength2scrollYDistance	7.654e+009
	nTables2documentLength2scrollYDistance	9.196e+008
	documentLength2scrollYSpeed	3.054e+008
	nLists2scrollYSpeed	2.21e+005
	nObjects2documentLength2scrollYSpeed	4.074e+009

Rule name	PSI2W	Dimension of learning style		Sensing/Intuitive	
Std. error	N/A	Class. Prob.	60%	Class. Eff.	-14.29%

Rule Expression

((8.123e+010* if (AvgOftimespent<192433000,0,if (AvgOftimespent>769424000,0,0.705882353))
+ 5.555e+009* if (AvgOfmouseDistance<1.44292,0,if (AvgOfmouseDistance>3.08505,0,0.648648649))
+ 1.249e+011* if (AvgOfscrollYSpeed<1.12213,0,if (AvgOfscrollYSpeed>1.84219,1,0.714285714))
+ 2.314e+007* if (AvgOfimagesArea2documentLength<48.859,1,if (AvgOfimagesArea2documentLength>120.33,0,0.5))
+ 9.614e+005* if (AvgOfcountQuestionMarks2documentLength<0.000143468,1,if (AvgOfcountQuestionMarks2documentLength>0.000409581,1,0.272727273))
+ 4.434e+010* if (AvgOfcountQuestion2documentLength<3.33349E-06,1,if (AvgOfcountQuestion2documentLength>0.000141004,0,0.416666667))
+ 1.248e+011* if (imagesArea2timespent<165499,0,if (imagesArea2timespent>912391,0,0.631578947))
+ 5.448e+008* if (nImages2documentLength2mouseDistance<0.00199047,1,if (nImages2documentLength2mouseDistance>0.00703923,0,0.636363636))
+ 1.318e+009* if (nObjects2documentLength2mouseDistance<0,0,if (nObjects2documentLength2mouseDistance>0.000182664,0,0.533333333))
+ 4.438e+009* if (documentLength2mouseSpeed<3887.07,1,if (documentLength2mouseSpeed>12489.7,0,0.5))
+ 2.066e+009* if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.136668,0,0.615384615))
+ 5.73e+009* if (imagesArea2mouseXFactor<198913,0,if (imagesArea2mouseXFactor>746376,1,0.512195122))
+ 4.12e+010* if (imagesArea2mouseYFactor<324452,0,if (imagesArea2mouseYFactor>1074420,0,0.631578947))
+ 5.977e+008* if (nLists2documentLength2mouseYFactor<0.000222495,0,if (nLists2documentLength2mouseYFactor>0.00215396,0,0.685714286))
+ 8.3e+010* if (imagesArea2scrollYDistance<122694,1,if (imagesArea2scrollYDistance>400961,0,0.454545455))
+ 9.31e+009* if (nLists2documentLength2scrollYDistance<2.87574E-05,1,if (nLists2documentLength2scrollYDistance>0.000847426,0,0.538461538))
+ 6.921e+010* if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.0531216,0,0.727272727))
+ 4.178e+007* if (nTables2scrollYPeaks<3.1,0,if (nTables2scrollYPeaks>8.84314,0,0.727272727))
+ 1.089e+009* if (nLists2scrollYPeaks<0.324324,0,if (nLists2scrollYPeaks>0.729167,0,0.685714286))) / 4.92E+11) >= 0.5

Terms	Term name	F-ratio
	AvgOftimespent	8.123e+010
	AvgOfmouseDistance	5.555e+009
	AvgOfscrollYSpeed	1.249e+011
	AvgOfimagesArea2documentLength	2.314e+007
	AvgOfcountQuestionMarks2documentLength	9.614e+005
	AvgOfcountQuestion2documentLength	4.434e+010
	imagesArea2timespent	1.248e+011
	nImages2documentLength2mouseDistance	5.448e+008
	nObjects2documentLength2mouseDistance	1.318e+009
	documentLength2mouseSpeed	4.438e+009
	nObjects2mouseSpeed	2.066e+009
	imagesArea2mouseXFactor	5.73e+009
	imagesArea2mouseYFactor	4.12e+010
	nLists2documentLength2mouseYFactor	5.977e+008
	imagesArea2scrollYDistance	8.3e+010
	nLists2documentLength2scrollYDistance	9.31e+009
	nObjects2scrollYSpeed	6.921e+010
	nTables2scrollYPeaks	4.178e+007
	nLists2scrollYPeaks	1.089e+009

Rule name	PVV2W	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	80%	Class. Eff.	20%

Rule Expression

((1.43E+11* if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.567134,1,0.466666667))
+ 3.08E+10* if (AvgOfdocumentLength<4817.63,1,if (AvgOfdocumentLength>7970.65,0,0.210526316))
+ 4.02E+06* if (AvgOfimagesArea<141901,1,if (AvgOfimagesArea>538274,1,0.428571429))
+ 1.37E+11* if (AvgOfnObjects<0,0,if (AvgOfnObjects>0.142857,1,0.448275862))
+ 2.00E+10* if (AvgOfimagesArea2documentLength<64.8333,1,if (AvgOfimagesArea2documentLength>123.973,0,0.375))
+ 7.71E+09* if (AvgOfcountExclamationMarks2documentLength<0.000167676,1,if (AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.36))
+ 6.46E+10* if (AvgOfcountDiagram2documentLength<0.000013739,1,if (AvgOfcountDiagram2documentLength>3.77287E-05,0,0.3))
+ 2.62E+09* if (documentLength2timespent<7538.84,1,if (documentLength2timespent>20416.7,1,0.333333333))
+ 6.04E+09* if (nImages2mouseDistance<5.01113,1,if (nImages2mouseDistance>29.3771,1,0.466666667))
+ 1.01E+11* if (nTables2mouseDistance<2.22275,0,if (nTables2mouseDistance>16.0976,0,0.592592593))
+ 1.67E+09* if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>0.025966,1,0.428571429))
+ 2.84E+08* if (nImages2documentLength2mouseDistance<0.00214675,1,if (nImages2documentLength2mouseDistance>0.00430382,1,0.304347826))
+ 5.81E+07* if (documentLength2mouseSpeed<4012.86,1,if (documentLength2mouseSpeed>11564.1,1,0.407407407))
+ 3.01E+03* if (imagesArea2documentLength2mouseSpeed<58.2908,1,if (imagesArea2documentLength2mouseSpeed>110.784,1,0.304347826))
+ 6.80E+09* if (documentLength2mouseXFactor<6624.63,1,if (documentLength2mouseXFactor>13100.5,1,0.238095238))
+ 8.14E+08* if (nImages2documentLength2mouseXFactor<0.00320142,1,if (nImages2documentLength2mouseXFactor>0.0171758,1,0.428571429))
+ 4.74E+10* if (imagesArea2documentLength2scrollYDistance<108.712,1,if (imagesArea2documentLength2scrollYDistance>285.822,1,0.304347826))
+ 1.36E+08* if (nTables2documentLength2scrollYDistance<0.000972923,0,if (nTables2documentLength2scrollYDistance>0.00934362,0,0.695652174))
+ 5.26E+07* if (nObjects2documentLength2scrollYSpeed<0,0,if (nObjects2documentLength2scrollYSpeed>0.00015516,0,0.516129032))) / 5.28E+11) >=0.5

Terms	Term name	F-ratio
	AvgOfmouseYFactor	1.429e+011
	AvgOfdocumentLength	3.075e+010
	AvgOfimagesArea	4.023e+006
	AvgOfnObjects	1.367e+011
	AvgOfimagesArea2documentLength	1.999e+010
	AvgOfcountExclamationMarks2documentLength	7.713e+009
	AvgOfcountDiagram2documentLength	6.463e+010
	documentLength2timespent	2.621e+009
	nImages2mouseDistance	6.04e+009
	nTables2mouseDistance	1.013e+011
	nObjects2mouseDistance	1.671e+009
	nImages2documentLength2mouseDistance	2.838e+008
	documentLength2mouseSpeed	5.812e+007
	imagesArea2documentLength2mouseSpeed	3008
	documentLength2mouseXFactor	6.795e+009
	nImages2documentLength2mouseXFactor	8.137e+008
	imagesArea2documentLength2scrollYDistance	4.735e+010
	nTables2documentLength2scrollYDistance	1.363e+008
	nObjects2documentLength2scrollYSpeed	5.264e+007

Rule name	PSG2W	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	60%	Class. Eff.	11%

Rule Expression

((3.61E+09* if (AvgOfcountExclamationMarks2documentLength<0.000115955,0,if
(AvgOfcountExclamationMarks2documentLength>0.000579503,1,0.487804878))
+ 1.36E+10* if (AvgOfcountFact2documentLength<0,0,if
(AvgOfcountFact2documentLength>3.89784E-05,1,0.454545455))
+ 7.78E+08* if (AvgOfcountPrevious2documentLength<1.98992E-06,1,if
(AvgOfcountPrevious2documentLength>0.000123235,0,0.480769231))
+ 2.22E+10* if (imagesArea2timespent<206049,0,if
(imagesArea2timespent>840018,0,0.808080808))
+ 8.19E+02* if (nTables2timespent<7.90323,1,if (nTables2timespent>33.4951,1,0.373134328))
+ 2.82E+09* if (nObjects2timespent<0,0,if (nObjects2timespent>0.344311,1,0.416666667))
+ 9.30E+08* if (nTables2mouseDistance<2.22275,1,if
(nTables2mouseDistance>16.0976,1,0.416666667))
+ 5.06E+09* if (nImages2documentLength2mouseDistance<0.00214675,0,if
(nImages2documentLength2mouseDistance>0.017863,0,0.571428571))
+ 2.91E+09* if (nObjects2mouseSpeed<0,0,if
(nObjects2mouseSpeed>0.320984,1,0.454545455))
+ 3.58E+09* if (nObjects2documentLength2mouseSpeed<0,0,if
(nObjects2documentLength2mouseSpeed>0.000428824,0,0.519480519))
+ 3.46E+07* if (nObjects2mouseXFactor<0,0,if
(nObjects2mouseXFactor>0.479857,1,0.454545455))
+ 4.42E+09* if (imagesArea2documentLength2mouseXFactor<64.6073,1,if
(imagesArea2documentLength2mouseXFactor>183.425,0,0.52238806))
+ 3.56E+09* if (nObjects2documentLength2mouseXFactor<0,0,if
(nObjects2documentLength2mouseXFactor>0.000524074,1,0.416666667))
+ 2.42E+10* if (documentLength2mouseYFactor<7371.52,0,if
(documentLength2mouseYFactor>13620.6,1,0.476190476))
+ 1.18E+08* if (nTables2documentLength2mouseYFactor<0.00217229,1,if
(nTables2documentLength2mouseYFactor>0.0146279,0,0.486111111))
+ 2.16E+10* if (nLists2scrollYDistance<0.247841,0,if
(nLists2scrollYDistance>1.82946,0,0.634920635))
+ 5.91E+09* if (nLists2documentLength2scrollYDistance<2.87574E-05,0,if
(nLists2documentLength2scrollYDistance>0.00170749,0,0.544217687))
+ 1.44E+09* if (nImages2scrollYSpeed<4.92419,0,if
(nImages2scrollYSpeed>18.9242,0,0.571428571))
+ 2.78E+05* if (nImages2documentLength2scrollYPeaks<0.00204827,0,if
(nImages2documentLength2scrollYPeaks>0.0128001,0,0.601503759))) / 9.74E+10) >=0.5

Terms	Term name	F-ratio
	AvgOfcountExclamationMarks2documentLength	3.608e+009
	AvgOfcountFact2documentLength	1.363e+010
	AvgOfcountPrevious2documentLength	7.784e+008
	imagesArea2timespent	2.216e+010
	nTables2timespent	819.3
	nObjects2timespent	2.818e+009
	nTables2mouseDistance	9.296e+008
	nImages2documentLength2mouseDistance	5.064e+009
	nObjects2mouseSpeed	2.913e+009
	nObjects2documentLength2mouseSpeed	3.582e+009
	nObjects2mouseXFactor	3.463e+007
	imagesArea2documentLength2mouseXFactor	4.421e+009
	nObjects2documentLength2mouseXFactor	3.557e+009
	documentLength2mouseYFactor	2.419e+010
	nTables2documentLength2mouseYFactor	1.179e+008
	nLists2scrollYDistance	2.16e+010
	nLists2documentLength2scrollYDistance	5.909e+009
	nImages2scrollYSpeed	1.437e+009
	nImages2documentLength2scrollYPeaks	2.784e+005

Rule name	AR10	Dimension of learning style	Active/Reflective
Output	Boolean: TRUE if Active, FALSE if Reflective		
Rule Expression	0.6021 < (+1.35827 -0.270108*AvgOfscrollYSpeed +1627.55*AvgOfcountQuestion2documentLength -4332.00*AvgOfcountDiagram2documentLength +0.00324498*nImages2mouseDistance +577.339*nObjects2documentLength2mouseDistance -0.00448830*nImages2mouseSpeed -0.750130*nObjects2mouseSpeed -9.78564e-005*documentLength2scrollYDistance +0.0157272*nImages2scrollYDistance +0.201881*nLists2scrollYDistance -81.3427*nLists2documentLength2scrollYDistance -4.86654e-005*documentLength2scrollYSpeed -1516.07*nObjects2documentLength2scrollYSpeed +9.00459e-007*imagesArea2scrollYPeaks)		
Terms	**Term name**		**F-Ratio**
	AvgOfscrollYSpeed		28.12
	AvgOfcountQuestion2documentLength		2.554
	AvgOfcountDiagram2documentLength		3.861
	nImages2mouseDistance		5.511
	nObjects2documentLength2mouseDistance		3.437
	nImages2mouseSpeed		15.51
	nObjects2mouseSpeed		10.24
	documentLength2scrollYDistance		11.64
	nImages2scrollYDistance		13.16
	nLists2scrollYDistance		11.3
	nLists2documentLength2scrollYDistance		2.89
	documentLength2scrollYSpeed		4.501
	nObjects2documentLength2scrollYSpeed		10.32
	imagesArea2scrollYPeaks		2.274
Classification probability	96.2%	**Standard deviation**	0.264
Classification efficiency	88.2%	**Standard error**	0.5601
P-value	1.88E-11	**R-squared**	0.6863
Significance Index	0.3522		

Rule name	SI8	Dimension of learning style	Sensing / Intuitive
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.3883 < (-0.0144897*nPagesVisited -3.06674e-010*AvgOftimespent +1.53826*AvgOfmouseXFactor +2335.12*AvgOfcountQuestion2documentLength -1.36563*nImages2documentLength2mouseSpeed)		
Terms	**Term name**		**F-Ratio**
	nPagesVisited		9.875
	AvgOftimespent		3.489
	AvgOfmouseXFactor		23.9
	AvgOfcountQuestion2documentLength		3.015
	nImages2documentLength2mouseSpeed		2.576
Classification probability	73.6%	**Standard deviation**	0.4409
Classification efficiency	43.2%	**Standard error**	0.8737
P-value	0.3641	**R-squared**	0.2367
Significance Index	-1.109		

Rule name	**VV8**	**Dimension of learning style**	Visual / Verbal
Output	Boolean: TRUE if Visual, FALSE if Verbal		
Rule Expression	0.4556 < (+0.868763*AvgOfrelativeTimeSpent +1.30920*AvgOfmouseXFactor -1.09027e-006*AvgOfimagesArea - 0.000450230*AvgOfimagesArea2documentLength - 133.380*AvgOfnImages2documentLength - 1092.49*AvgOfcountQuestionMarks2documentLength - 591.091*AvgOfcountExclamationMarks2documentLength +0.00832754*nTables2timespent +0.916607*nObjects2mouseDistance +62.6350*nLists2documentLength2mouseDistance +57.3676*nImages2documentLength2mouseYFactor - 0.000187652*documentLength2scrollYDistance +5.78193e-007*imagesArea2scrollYDistance +0.0432383*nTables2scrollYDistance +0.0991761*nLists2scrollYDistance - 58.5561*nTables2documentLength2scrollYDistance)		

Terms	**Term name**	**F-Ratio**
	AvgOfrelativeTimeSpent	11.89
	AvgOfmouseXFactor	8.857
	AvgOfimagesArea	5.272
	AvgOfimagesArea2documentLength	11.22
	AvgOfnImages2documentLength	9.739
	AvgOfcountQuestionMarks2documentLength	14.23
	AvgOfcountExclamationMarks2documentLength	16.47
	nTables2timespent	5.634
	nObjects2mouseDistance	5.974
	nLists2documentLength2mouseDistance	10.89
	nImages2documentLength2mouseYFactor	13.85
	documentLength2scrollYDistance	38.84
	imagesArea2scrollYDistance	4.796
	nTables2scrollYDistance	15.57
	nLists2scrollYDistance	11.03
	nTables2documentLength2scrollYDistance	25.17

Classification probability	98.1%	**Standard deviation**	0.2179
Classification efficiency	91.7%	**Standard error**	0.5156
P-value	1.84E-09	**R-squared**	0.7341
Significance Index	0.1123		

Rule name	SG6	Dimension of learning style	Sequential / Global
Output	Boolean: TRUE if Sensing, FALSE if Intuitive		
Rule Expression	0.5164 < (-1.83885 +3.14020*AvgOfmouseXFactor - 0.123543*AvgOfscrollYPeaks +1726.81*AvgOfcountQuestionMarks2documentLength - 1407.39*AvgOfcountExample2documentLength - 10475.9*AvgOfcountFact2documentLength +2813.63*AvgOfcountPrevious2documentLength +13.3349*nImages2documentLength2mouseDistance - 0.00280923*nImages2mouseSpeed +0.0218050*nTables2mouseXFactor - 0.00510718*nImages2mouseYFactor - 64.9688*nTables2documentLength2mouseYFactor +8.99326e-007*imagesArea2scrollYDistance -0.0125460*nImages2scrollYDistance +1.09164*nObjects2scrollYDistance +0.467885*nLists2scrollYSpeed - 15.0311*nImages2documentLength2scrollYSpeed - 0.000663883*imagesArea2documentLength2scrollYPeaks)		
Terms	**Term name**		**F-Ratio**
	AvgOfmouseXFactor		11.27
	AvgOfscrollYPeaks		3.438
	AvgOfcountQuestionMarks2documentLength		23.06
	AvgOfcountExample2documentLength		3.68
	AvgOfcountFact2documentLength		7.06
	AvgOfcountPrevious2documentLength		19.02
	nImages2documentLength2mouseDistance		10.23
	nImages2mouseSpeed		3.35
	nTables2mouseXFactor		2.607
	nImages2mouseYFactor		2.227
	nTables2documentLength2mouseYFactor		14.46
	imagesArea2scrollYDistance		6.595
	nImages2scrollYDistance		4.056
	nObjects2scrollYDistance		11.38
	nLists2scrollYSpeed		30.61
	nImages2documentLength2scrollYSpeed		2.09
	imagesArea2documentLength2scrollYPeaks		2.103
Classification probability	94.3%	**Standard deviation**	0.2721
Classification efficiency	87.5%	**Standard error**	0.5415
P-value	8.90E-13	**R-squared**	0.7068
Significance Index	1.003		

Rule name	PAR3	Dimension of learning style		Active/Reflective	
Std. error	146.40%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (nPagesVisited<11,0,if (nPagesVisited>59,1,0.495495495))
+ if (AvgOfrelativeTimeSpent<1,0,if (AvgOfrelativeTimeSpent>1.30445,0,0.502215657))
+ if (AvgOfmouseDistance<1.2195,0,if (AvgOfmouseDistance>3.55497,0,0.52991453))
+ if (AvgOfmouseYFactor<0.395771,1,if (AvgOfmouseYFactor>0.601982,0,0.494752624))
+ if (AvgOfnImages<4.34211,0,if (AvgOfnImages>27.6222,0,0.518292683))
+ if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,1,if (AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.47267356))
+ if (AvgOfcountQuestion2documentLength<0,0,if (AvgOfcountQuestion2documentLength>7.46276E-05,1,0.43956044))
+ if (AvgOfcountDiagram2documentLength<0,0,if (AvgOfcountDiagram2documentLength>4.96904E-05,0,0.516986706))
+ if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>0.000381947,0,0.494905386))
+ if (scrollYPeaks2timespent<1.46333,1,if (scrollYPeaks2timespent>8.19887,0,0.502283105))
+ if (documentLength2timespent<3673.47,0,if (documentLength2timespent>15185.2,0,0.536912752))
+ if (nImages2mouseSpeed<8.86512,1,if (nImages2mouseSpeed>45.4493,0,0.494417863))
+ if (imagesArea2mouseYFactor<334070,1,if (imagesArea2mouseYFactor>1155270,0,0.462519936))
+ if (nImages2scrollYDistance<3.53808,1,if (nImages2scrollYDistance>53.0018,0,0.47976012))
+ if (nTables2scrollYDistance<1.74299,0,if (nTables2scrollYDistance>24.018,0,0.396039604))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.346337,0,0.365630713))
+ if (imagesArea2scrollYPeaks<86000.1,1,if (imagesArea2scrollYPeaks>433558,0,0.328820116)))/12.8609

Terms	Term name	F-ratio
	nPagesVisited	8.874
	AvgOfrelativeTimeSpent	26.53
	AvgOfmouseDistance	5.109
	AvgOfmouseYFactor	38.95
	AvgOfnImages	8.789
	AvgOfcountQuestionMarks2documentLength	5.656
	AvgOfcountQuestion2documentLength	14.85
	AvgOfcountDiagram2documentLength	20.91
	AvgOfcountPrevious2documentLength	3.508
	scrollYPeaks2timespent	4.805
	documentLength2timespent	15.76
	nImages2mouseSpeed	16.26
	imagesArea2mouseYFactor	36.85
	nImages2scrollYDistance	12.1
	nTables2scrollYDistance	3.16
	nObjects2scrollYSpeed	5.866
	imagesArea2scrollYPeaks	2.432

Rule name	PSI3	Dimension of learning style		Sensing/Intuitive	
Std. error	132.11%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfmouseXFactor<0.551396,0,if (AvgOfmouseXFactor>0.760082,0,0.564308682))
+ if (AvgOfnObjects2documentLength<0,0,if (AvgOfnObjects2documentLength>0.000434228,1,0.49661181))
+ if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>0.000390108,0,0.522749274))
+ if (imagesArea2timespent<165499,0,if (imagesArea2timespent>2215140,0,0.581270183))
+ if (nLists2mouseDistance<0.0119441,0,if (nLists2mouseDistance>22.0296,1,0.522243714))
+ if (nLists2documentLength2mouseSpeed<9.17595E-07,0,if (nLists2documentLength2mouseSpeed>0.00193473,0,0.536246276))
+ if (imagesArea2documentLength2mouseYFactorr<67.8955,1,if (imagesArea2documentLength2mouseYFactorr>1655.96,1,0.49661181))
+ if (nObjects2documentLength2mouseYFactor<0,0,if (nObjects2documentLength2mouseYFactor>0.00106483,1,0.49661181))
+ if (documentLength2scrollYDistance<1563.53,1,if (documentLength2scrollYDistance>8584.47,0,0.496424923))
+ if (imagesArea2scrollYDistance<78707.4,0,if (imagesArea2scrollYDistance>763653,0,0.522749274))
+ if (imagesArea2scrollYSpeed<45135.9,1,if (imagesArea2scrollYSpeed>620971,1,0.483101392))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.346337,1,0.49661181)))/ 9.72732369

Terms	Term name	F-ratio
	AvgOfmouseXFactor	3.886
	AvgOfnObjects2documentLength	3.169
	AvgOfcountPrevious2documentLength	9.724
	imagesArea2timespent	8.842
	nLists2mouseDistance	19.17
	nLists2documentLength2mouseSpeed	10.12
	imagesArea2documentLength2mouseYFactorr	3.354
	nObjects2documentLength2mouseYFactor	3.805
	documentLength2scrollYDistance	45.37
	imagesArea2scrollYDistance	14.83
	imagesArea2scrollYSpeed	2.099
	nObjects2scrollYSpeed	5.466

Rule name	PVV3	Dimension of learning style		Visual/Verbal	
Std. error	161.93%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfmouseDistance<1.07872,1 ,if (AvgOfmouseDistance>4.59619,1,0.481012658))
+ if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.609726,0,0.493506494))
+ if (AvgOfimagesArea2documentLength<34.6354,0,if (AvgOfimagesArea2documentLength>416.843,0,0.552808989))
+ if (AvgOfcountDiagram2documentLength<0,0,if (AvgOfcountDiagram2documentLength>8.61535E-05,1,0.4875))
+ if (nLists2documentLength2timespent<0,0,if (nLists2documentLength2timespent>0.000836962,1,0.438356164)))/ 4.552809

Terms	Term name	F-ratio
	AvgOfmouseDistance	2.447
	AvgOfmouseYFactor	4.892
	AvgOfimagesArea2documentLength	3.035
	AvgOfcountDiagram2documentLength	3.09
	nLists2documentLength2timespent	3.106

Rule name	PSG3	Dimension of learning style		Sequential/Global	
Std. error	118.79%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfscrollYSpeed<0.284125,1,if (AvgOfscrollYSpeed>3.4356,0,0.5))
+ if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+ if (AvgOfimagesAverageArea<14564.4,0,if
(AvgOfimagesAverageArea>62373,1,0.459549625))
+ if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if
(AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+ if (AvgOfcountExclamationMarks2documentLength<2.99909E-06,0,if
(AvgOfcountExclamationMarks2documentLength>0.00201898,1,0.487022901))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if
(AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+ if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.545454545))
+ if (nTables2timespent<3.77056,1,if (nTables2timespent>68.3291,1,0.454545455))
+ if (nImages2mouseDistance<3.24716,1,if
(nImages2mouseDistance>105.389,1,0.466666667))
+ if (nTables2documentLength2mouseSpeed<0.000797437,1,if
(nTables2documentLength2mouseSpeed>0.0271064,0,0.5))
+ if (documentLength2mouseXFactor<4095.19,1,if
(documentLength2mouseXFactor>20803.9,1,0.454545455))
+ if (imagesArea2scrollYDistance<97335,1,if
(imagesArea2scrollYDistance>763653,0,0.477272727))
+ if (nLists2documentLength2scrollYSpeed<0,0,if
(nLists2documentLength2scrollYSpeed>0.000772062,1,0.47826087)))/ 12.067194

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	20.98
	AvgOfscrollYPeaks	19.7
	AvgOfimagesAverageArea	32.86
	AvgOfcountQuestionMarks2documentLength	22.32
	AvgOfcountExclamationMarks2documentLength	5.798
	AvgOfcountExample2documentLength	7.071
	AvgOfcountDiagram2documentLength	5.019
	nTables2timespent	5.582
	nImages2mouseDistance	4.845
	nTables2documentLength2mouseSpeed	14.07
	documentLength2mouseXFactor	3.514
	imagesArea2scrollYDistance	13.09
	nLists2documentLength2scrollYSpeed	9.596

Rule name	PAR3W	Dimension of learning style		Active/Reflective	
Std. error	145.21%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(8.87E+00* if (nPagesVisited<11,0,if (nPagesVisited>59,1,0.495495495))
+2.65E+01* if (AvgOfrelativeTimeSpent<1,0,if
(AvgOfrelativeTimeSpent>1.30445,0,0.502215657))
+5.11E+00* if (AvgOfmouseDistance<1.2195,0,if
(AvgOfmouseDistance>3.55497,0,0.52991453))
+3.90E+01* if (AvgOfmouseYFactor<0.395771,1,if
(AvgOfmouseYFactor>0.601982,0,0.494752624))
+8.79E+00* if (AvgOfnImages<4.34211,0,if (AvgOfnImages>27.6222,0,0.518292683))
+5.66E+00* if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,1,if
(AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.47267356))
+1.49E+01* if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>7.46276E-05,1,0.43956044))
+2.09E+01* if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.516986706))
+3.51E+00* if (AvgOfcountPrevious2documentLength<0,0,if
(AvgOfcountPrevious2documentLength>0.000381947,0,0.494905386))
+4.81E+00* if (scrollYPeaks2timespent<1.46333,1,if
(scrollYPeaks2timespent>8.19887,0,0.502283105))
+1.58E+01* if (documentLength2timespent<3673.47,0,if
(documentLength2timespent>15185.2,0,0.536912752))
+1.63E+01* if (nImages2mouseSpeed<8.86512,1,if
(nImages2mouseSpeed>45.4493,0,0.494417863))
+3.69E+01* if (imagesArea2mouseYFactor<334070,1,if
(imagesArea2mouseYFactor>1155270,0,0.462519936))
+1.21E+01* if (nImages2scrollYDistance<3.53808,1,if
(nImages2scrollYDistance>53.0018,0,0.47976012))
+3.16E+00* if (nTables2scrollYDistance<1.74299,0,if
(nTables2scrollYDistance>24.018,0,0.396039604))
+5.87E+00* if (nObjects2scrollYSpeed<0,0,if
(nObjects2scrollYSpeed>0.346337,0,0.365630713))
+2.43E+00* if (imagesArea2scrollYPeaks<86000.1,1,if
(imagesArea2scrollYPeaks>433558,0,0.328820116)))/ 185.7677

Terms	Term name	F-ratio
	nPagesVisited	8.874
	AvgOfrelativeTimeSpent	26.53
	AvgOfmouseDistance	5.109
	AvgOfmouseYFactor	38.95
	AvgOfnImages	8.789
	AvgOfcountQuestionMarks2documentLength	5.656
	AvgOfcountQuestion2documentLength	14.85
	AvgOfcountDiagram2documentLength	20.91
	AvgOfcountPrevious2documentLength	3.508
	scrollYPeaks2timespent	4.805
	documentLength2timespent	15.76
	nImages2mouseSpeed	16.26
	imagesArea2mouseYFactor	36.85
	nImages2scrollYDistance	12.1
	nTables2scrollYDistance	3.16
	nObjects2scrollYSpeed	5.866
	imagesArea2scrollYPeaks	2.432

Rule name	PSI3W	**Dimension of learning style**		Sensing/Intuitive	
Std. error	132.18%	**Class. Prob.**	N/A	**Class. Eff.**	N/A

Rule Expression

(3.89E+00* if (AvgOfmouseXFactor<0.551396,0,if
(AvgOfmouseXFactor>0.760082,0,0.564308682))
+3.17E+00* if (AvgOfnObjects2documentLength<0,0,if
(AvgOfnObjects2documentLength>0.000434228,1,0.49661181))
+9.72E+00* if (AvgOfcountPrevious2documentLength<0,0,if
(AvgOfcountPrevious2documentLength>0.000390108,0,0.522749274))
+8.84E+00* if (imagesArea2timespent<165499,0,if
(imagesArea2timespent>2215140,0,0.581270183))
+1.92E+01* if (nLists2mouseDistance<0.0119441,0,if
(nLists2mouseDistance>22.0296,1,0.522243714))
+1.01E+01* if (nLists2documentLength2mouseSpeed<9.17595E-07,0,if
(nLists2documentLength2mouseSpeed>0.00193473,0,0.536246276))
+3.35E+00* if (imagesArea2documentLength2mouseYFactorr<67.8955,1,if
(imagesArea2documentLength2mouseYFactorr>1655.96,1,0.49661181))
+3.81E+00* if (nObjects2documentLength2mouseYFactor<0,0,if
(nObjects2documentLength2mouseYFactor>0.00106483,1,0.49661181))
+4.54E+01* if (documentLength2scrollYDistance<1563.53,1,if
(documentLength2scrollYDistance>8584.47,0,0.496424923))
+1.48E+01* if (imagesArea2scrollYDistance<78707.4,0,if
(imagesArea2scrollYDistance>763653,0,0.522749274))
+2.10E+00* if (imagesArea2scrollYSpeed<45135.9,1,if
(imagesArea2scrollYSpeed>620971,1,0.483101392))
+5.47E+00* if (nObjects2scrollYSpeed<0,0,if
(nObjects2scrollYSpeed>0.346337,1,0.49661181)))/ 1.08E+02

Terms	**Term name**	**F-ratio**
	AvgOfmouseXFactor	3.886
	AvgOfnObjects2documentLength	3.169
	AvgOfcountPrevious2documentLength	9.724
	imagesArea2timespent	8.842
	nLists2mouseDistance	19.17
	nLists2documentLength2mouseSpeed	10.12
	imagesArea2documentLength2mouseYFactorr	3.354
	nObjects2documentLength2mouseYFactor	3.805
	documentLength2scrollYDistance	45.37
	imagesArea2scrollYDistance	14.83
	imagesArea2scrollYSpeed	2.099
	nObjects2scrollYSpeed	5.466

Rule name	PVV3W	Dimension of learning style		Visual/Verbal	
Std. error	160.54%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(2.45E+00* if (AvgOfmouseDistance<1.07872,1,if (AvgOfmouseDistance>4.59619,1,0.481012658)) +4.89E+00* if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.609726,0,0.493506494)) +3.04E+00* if (AvgOfimagesArea2documentLength<34.6354,0,if (AvgOfimagesArea2documentLength>416.843,0,0.552808989)) +3.09E+00* if (AvgOfcountDiagram2documentLength<0,0,if (AvgOfcountDiagram2documentLength>8.61535E-05,1,0.4875)) +3.11E+00* if (nLists2documentLength2timespent<0,0,if (nLists2documentLength2timespent>0.000836962,1,0.438356164)))/ 1.52E+01

Terms	Term name	F-ratio
	AvgOfmouseDistance	2.447
	AvgOfmouseYFactor	4.892
	AvgOfimagesArea2documentLength	3.035
	AvgOfcountDiagram2documentLength	3.09
	nLists2documentLength2timespent	3.106

Rule name	PSG3W	Dimension of learning style		Sequential/Global	
Std. error	119.78%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(2.10E+01* if (AvgOfscrollYSpeed<0.284125,1,if (AvgOfscrollYSpeed>3.4356,0,0.5))
+1.97E+01* if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+3.29E+01* if (AvgOfimagesAverageArea<14564.4,0,if (AvgOfimagesAverageArea>62373,1,0.459549625))
+2.23E+01* if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if (AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+5.80E+00* if (AvgOfcountExclamationMarks2documentLength<2.99909E-06,0,if (AvgOfcountExclamationMarks2documentLength>0.00201898,1,0.487022901))
+7.07E+00* if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+5.02E+00* if (AvgOfcountDiagram2documentLength<0,0,if (AvgOfcountDiagram2documentLength>4.96904E-05,0,0.545454545))
+5.58E+00* if (nTables2timespent<3.77056,1,if (nTables2timespent>68.3291,1,0.454545455))
+4.85E+00* if (nImages2mouseDistance<3.24716,1,if (nImages2mouseDistance>105.389,1,0.466666667))
+1.41E+01* if (nTables2documentLength2mouseSpeed<0.000797437,1,if (nTables2documentLength2mouseSpeed>0.0271064,0,0.5))
+3.51E+00* if (documentLength2mouseXFactor<4095.19,1,if (documentLength2mouseXFactor>20803.9,1,0.454545455))
+1.31E+01* if (imagesArea2scrollYDistance<97335,1,if (imagesArea2scrollYDistance>763653,0,0.477272727))
+9.60E+00* if (nLists2documentLength2scrollYSpeed<0,0,if (nLists2documentLength2scrollYSpeed>0.000772062,1,0.47826087)))/ 1.53E+02

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	20.98
	AvgOfscrollYPeaks	19.7
	AvgOfimagesAverageArea	32.86
	AvgOfcountQuestionMarks2documentLength	22.32
	AvgOfcountExclamationMarks2documentLength	5.798
	AvgOfcountExample2documentLength	7.071
	AvgOfcountDiagram2documentLength	5.019
	nTables2timespent	5.582
	nImages2mouseDistance	4.845
	nTables2documentLength2mouseSpeed	14.07
	documentLength2mouseXFactor	3.514
	imagesArea2scrollYDistance	13.09
	nLists2documentLength2scrollYSpeed	9.596

Rule name	PAR3B	Dimension of learning style		Active/Reflective	
Std. error	N/A	Class. Prob.	67%	Class. Eff.	0%

Rule Expression

((if (nPagesVisited<11,0,if (nPagesVisited>59,1,0.495495495))
+ if (AvgOfrelativeTimeSpent<1,0,if (AvgOfrelativeTimeSpent>1.30445,0,0.502215657))
+ if (AvgOfmouseDistance<1.2195,0,if (AvgOfmouseDistance>3.55497,0,0.52991453))
+ if (AvgOfmouseYFactor<0.395771,1,if (AvgOfmouseYFactor>0.601982,0,0.494752624))
+ if (AvgOfnImages<4.34211,0,if (AvgOfnImages>27.6222,0,0.518292683))
+ if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,1,if (AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.47267356))
+ if (AvgOfcountQuestion2documentLength<0,0,if (AvgOfcountQuestion2documentLength>7.46276E-05,1,0.43956044))
+ if (AvgOfcountDiagram2documentLength<0,0,if (AvgOfcountDiagram2documentLength>4.96904E-05,0,0.516986706))
+ if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>0.000381947,0,0.494905386))
+ if (scrollYPeaks2timespent<1.46333,1,if (scrollYPeaks2timespent>8.19887,0,0.502283105))
+ if (documentLength2timespent<3673.47,0,if (documentLength2timespent>15185.2,0,0.536912752))
+ if (nImages2mouseSpeed<8.86512,1,if (nImages2mouseSpeed>45.4493,0,0.494417863))
+ if (imagesArea2mouseYFactor<334070,1,if (imagesArea2mouseYFactor>1155270,0,0.462519936))
+ if (nImages2scrollYDistance<3.53808,1,if (nImages2scrollYDistance>53.0018,0,0.47976012))
+ if (nTables2scrollYDistance<1.74299,0,if (nTables2scrollYDistance>24.018,0,0.396039604))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.346337,0,0.365630713))
+ if (imagesArea2scrollYPeaks<86000.1,1,if (imagesArea2scrollYPeaks>433558,0,0.328820116)))/12.8609) >= 0.5

Terms	Term name	F-ratio
	nPagesVisited	8.874
	AvgOfrelativeTimeSpent	26.53
	AvgOfmouseDistance	5.109
	AvgOfmouseYFactor	38.95
	AvgOfnImages	8.789
	AvgOfcountQuestionMarks2documentLength	5.656
	AvgOfcountQuestion2documentLength	14.85
	AvgOfcountDiagram2documentLength	20.91
	AvgOfcountPrevious2documentLength	3.508
	scrollYPeaks2timespent	4.805
	documentLength2timespent	15.76
	nImages2mouseSpeed	16.26
	imagesArea2mouseYFactor	36.85
	nImages2scrollYDistance	12.1
	nTables2scrollYDistance	3.16
	nObjects2scrollYSpeed	5.866
	imagesArea2scrollYPeaks	2.432

Rule name	PSI3B	Dimension of learning style		Sensing/Intuitive	
Std. error	N/A	Class. Prob.	54.72%	Class. Eff.	7.69%

Rule Expression

((if (AvgOfmouseXFactor<0.551396,0,if (AvgOfmouseXFactor>0.760082,0,0.564308682))
+ if (AvgOfnObjects2documentLength<0,0,if
(AvgOfnObjects2documentLength>0.000434228,1,0.49661181))
+ if (AvgOfcountPrevious2documentLength<0,0,if
(AvgOfcountPrevious2documentLength>0.000390108,0,0.522749274))
+ if (imagesArea2timespent<165499,0,if (imagesArea2timespent>2215140,0,0.581270183))
+ if (nLists2mouseDistance<0.0119441,0,if (nLists2mouseDistance>22.0296,1,0.522243714))
+ if (nLists2documentLength2mouseSpeed<9.17595E-07,0,if
(nLists2documentLength2mouseSpeed>0.00193473,0,0.536246276))
+ if (imagesArea2documentLength2mouseYFactorr<67.8955,1,if
(imagesArea2documentLength2mouseYFactorr>1655.96,1,0.49661181))
+ if (nObjects2documentLength2mouseYFactor<0,0,if
(nObjects2documentLength2mouseYFactor>0.00106483,1,0.49661181))
+ if (documentLength2scrollYDistance<1563.53,1,if
(documentLength2scrollYDistance>8584.47,0,0.496424923))
+ if (imagesArea2scrollYDistance<78707.4,0,if
(imagesArea2scrollYDistance>763653,0,0.522749274))
+ if (imagesArea2scrollYSpeed<45135.9,1,if
(imagesArea2scrollYSpeed>620971,1,0.483101392))
+ if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.346337,1,0.49661181)))/
9.72732369) >= 0.5

Terms	Term name	F-ratio
	AvgOfmouseXFactor	3.886
	AvgOfnObjects2documentLength	3.169
	AvgOfcountPrevious2documentLength	9.724
	imagesArea2timespent	8.842
	nLists2mouseDistance	19.17
	nLists2documentLength2mouseSpeed	10.12
	imagesArea2documentLength2mouseYFactorr	3.354
	nObjects2documentLength2mouseYFactor	3.805
	documentLength2scrollYDistance	45.37
	imagesArea2scrollYDistance	14.83
	imagesArea2scrollYSpeed	2.099
	nObjects2scrollYSpeed	5.466

Rule name	PVV3B	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	79.25%	Class. Eff.	8.33%

Rule Expression

((if (AvgOfmouseDistance<1.07872,1,if (AvgOfmouseDistance>4.59619,1,0.481012658))
+ if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.609726,0,0.493506494))
+ if (AvgOfimagesArea2documentLength<34.6354,0,if
(AvgOfimagesArea2documentLength>416.843,0,0.552808989))
+ if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>8.61535E-05,1,0.4875))
+ if (nLists2documentLength2timespent<0,0,if
(nLists2documentLength2timespent>0.000836962,1,0.438356164)))/ 4.552809) >= 0.5

Terms	Term name	F-ratio
	AvgOfmouseDistance	2.447
	AvgOfmouseYFactor	4.892
	AvgOfimagesArea2documentLength	3.035
	AvgOfcountDiagram2documentLength	3.09
	nLists2documentLength2timespent	3.106

Rule name	PSG3B	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	54.72%	Class. Eff.	0%

Rule Expression

((if (AvgOfscrollYSpeed<0.284125,1,if (AvgOfscrollYSpeed>3.4356,0,0.5))
+ if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+ if (AvgOfimagesAverageArea<14564.4,0,if
(AvgOfimagesAverageArea>62373,1,0.459549625))
+ if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if
(AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+ if (AvgOfcountExclamationMarks2documentLength<2.99909E-06,0,if
(AvgOfcountExclamationMarks2documentLength>0.00201898,1,0.487022901))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if
(AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+ if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.545454545))
+ if (nTables2timespent<3.77056,1,if (nTables2timespent>68.3291,1,0.454545455))
+ if (nImages2mouseDistance<3.24716,1,if
(nImages2mouseDistance>105.389,1,0.466666667))
+ if (nTables2documentLength2mouseSpeed<0.000797437,1,if
(nTables2documentLength2mouseSpeed>0.0271064,0,0.5))
+ if (documentLength2mouseXFactor<4095.19,1,if
(documentLength2mouseXFactor>20803.9,1,0.454545455))
+ if (imagesArea2scrollYDistance<97335,1,if
(imagesArea2scrollYDistance>763653,0,0.477272727))
+ if (nLists2documentLength2scrollYSpeed<0,0,if
(nLists2documentLength2scrollYSpeed>0.000772062,1,0.47826087)))/ 12.067194) >= 0.5

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	20.98
	AvgOfscrollYPeaks	19.7
	AvgOfimagesAverageArea	32.86
	AvgOfcountQuestionMarks2documentLength	22.32
	AvgOfcountExclamationMarks2documentLength	5.798
	AvgOfcountExample2documentLength	7.071
	AvgOfcountDiagram2documentLength	5.019
	nTables2timespent	5.582
	nImages2mouseDistance	4.845
	nTables2documentLength2mouseSpeed	14.07
	documentLength2mouseXFactor	3.514
	imagesArea2scrollYDistance	13.09
	nLists2documentLength2scrollYSpeed	9.596

Rule name	PAR3WB	Dimension of learning style		Active/Reflective	
Std. error	N/A	Class. Prob.	71.70%	Class. Eff.	11.76%

Rule Expression

((8.87E+00* if (nPagesVisited<11,0,if (nPagesVisited>59,1,0.495495495))
+2.65E+01* if (AvgOfrelativeTimeSpent<1,0,if
(AvgOfrelativeTimeSpent>1.30445,0,0.502215657))
+5.11E+00* if (AvgOfmouseDistance<1.2195,0,if
(AvgOfmouseDistance>3.55497,0,0.52991453))
+3.90E+01* if (AvgOfmouseYFactor<0.395771,1,if
(AvgOfmouseYFactor>0.601982,0,0.494752624))
+8.79E+00* if (AvgOfnImages<4.34211,0,if (AvgOfnImages>27.6222,0,0.518292683))
+5.66E+00* if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,1,if
(AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.47267356))
+1.49E+01* if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>7.46276E-05,1,0.43956044))
+2.09E+01* if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.516986706))
+3.51E+00* if (AvgOfcountPrevious2documentLength<0,0,if
(AvgOfcountPrevious2documentLength>0.000381947,0,0.494905386))
+4.81E+00* if (scrollYPeaks2timespent<1.46333,1,if
(scrollYPeaks2timespent>8.19887,0,0.502283105))
+1.58E+01* if (documentLength2timespent<3673.47,0,if
(documentLength2timespent>15185.2,0,0.536912752))
+1.63E+01* if (nImages2mouseSpeed<8.86512,1,if
(nImages2mouseSpeed>45.4493,0,0.494417863))
+3.69E+01* if (imagesArea2mouseYFactor<334070,1,if
(imagesArea2mouseYFactor>1155270,0,0.462519936))
+1.21E+01* if (nImages2scrollYDistance<3.53808,1,if
(nImages2scrollYDistance>53.0018,0,0.47976012))
+3.16E+00* if (nTables2scrollYDistance<1.74299,0,if
(nTables2scrollYDistance>24.018,0,0.396039604))
+5.87E+00* if (nObjects2scrollYSpeed<0,0,if
(nObjects2scrollYSpeed>0.346337,0,0.365630713))
+2.43E+00* if (imagesArea2scrollYPeaks<86000.1,1,if
(imagesArea2scrollYPeaks>433558,0,0.328820116)))/ 185.7677) >= 0.5

Terms	Term name	F-ratio
	nPagesVisited	8.874
	AvgOfrelativeTimeSpent	26.53
	AvgOfmouseDistance	5.109
	AvgOfmouseYFactor	38.95
	AvgOfnImages	8.789
	AvgOfcountQuestionMarks2documentLength	5.656
	AvgOfcountQuestion2documentLength	14.85
	AvgOfcountDiagram2documentLength	20.91
	AvgOfcountPrevious2documentLength	3.508
	scrollYPeaks2timespent	4.805
	documentLength2timespent	15.76
	nImages2mouseSpeed	16.26
	imagesArea2mouseYFactor	36.85
	nImages2scrollYDistance	12.1
	nTables2scrollYDistance	3.16
	nObjects2scrollYSpeed	5.866
	imagesArea2scrollYPeaks	2.432

Rule name	PSI3WB	Dimension of learning style		Sensing/Intuitive	
Std. error	N/A	Class. Prob.	60.38%	Class. Eff.	19.23%

Rule Expression

((3.89E+00* if (AvgOfmouseXFactor<0.551396,0,if (AvgOfmouseXFactor>0.760082,0,0.564308682))
+3.17E+00* if (AvgOfnObjects2documentLength<0,0,if (AvgOfnObjects2documentLength>0.000434228,1,0.49661181))
+9.72E+00* if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>0.000390108,0,0.522749274))
+8.84E+00* if (imagesArea2timespent<165499,0,if (imagesArea2timespent>2215140,0,0.581270183))
+1.92E+01* if (nLists2mouseDistance<0.0119441,0,if (nLists2mouseDistance>22.0296,1,0.522243714))
+1.01E+01* if (nLists2documentLength2mouseSpeed<9.17595E-07,0,if (nLists2documentLength2mouseSpeed>0.00193473,0,0.536246276))
+3.35E+00* if (imagesArea2documentLength2mouseYFactorr<67.8955,1,if (imagesArea2documentLength2mouseYFactorr>1655.96,1,0.49661181))
+3.81E+00* if (nObjects2documentLength2mouseYFactor<0,0,if (nObjects2documentLength2mouseYFactor>0.00106483,1,0.49661181))
+4.54E+01* if (documentLength2scrollYDistance<1563.53,1,if (documentLength2scrollYDistance>8584.47,0,0.496424923))
+1.48E+01* if (imagesArea2scrollYDistance<78707.4,0,if (imagesArea2scrollYDistance>763653,0,0.522749274))
+2.10E+00* if (imagesArea2scrollYSpeed<45135.9,1,if (imagesArea2scrollYSpeed>620971,1,0.483101392))
+5.47E+00* if (nObjects2scrollYSpeed<0,0,if (nObjects2scrollYSpeed>0.346337,1,0.49661181)))/ 1.08E+02) >= 0.5

Terms	Term name	F-ratio
	AvgOfmouseXFactor	3.886
	AvgOfnObjects2documentLength	3.169
	AvgOfcountPrevious2documentLength	9.724
	imagesArea2timespent	8.842
	nLists2mouseDistance	19.17
	nLists2documentLength2mouseSpeed	10.12
	imagesArea2documentLength2mouseYFactorr	3.354
	nObjects2documentLength2mouseYFactor	3.805
	documentLength2scrollYDistance	45.37
	imagesArea2scrollYDistance	14.83
	imagesArea2scrollYSpeed	2.099
	nObjects2scrollYSpeed	5.466

Rule name	PVV3WB	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	67.92%	Class. Eff.	-41.67%

Rule Expression

((2.45E+00* if (AvgOfmouseDistance<1.07872,1,if (AvgOfmouseDistance>4.59619,1,0.481012658))
+4.89E+00* if (AvgOfmouseYFactor<0.421104,1,if (AvgOfmouseYFactor>0.609726,0,0.493506494))
+3.04E+00* if (AvgOfimagesArea2documentLength<34.6354,0,if (AvgOfimagesArea2documentLength>416.843,0,0.552808989))
+3.09E+00* if (AvgOfcountDiagram2documentLength<0,0,if (AvgOfcountDiagram2documentLength>8.61535E-05,1,0.4875))
+3.11E+00* if (nLists2documentLength2timespent<0,0,if (nLists2documentLength2timespent>0.000836962,1,0.438356164)))/ 1.52E+01) >= 0.5

Terms	Term name	F-ratio
	AvgOfmouseDistance	2.447
	AvgOfmouseYFactor	4.892
	AvgOfimagesArea2documentLength	3.035
	AvgOfcountDiagram2documentLength	3.09
	nLists2documentLength2timespent	3.106

Rule name	PSG3WB	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	50.94%	Class. Eff.	-8.33%

Rule Expression

((2.10E+01* if (AvgOfscrollYSpeed<0.284125,1,if (AvgOfscrollYSpeed>3.4356,0,0.5))
+1.97E+01* if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+3.29E+01* if (AvgOfimagesAverageArea<14564.4,0,if
(AvgOfimagesAverageArea>62373,1,0.459549625))
+2.23E+01* if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if
(AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+5.80E+00* if (AvgOfcountExclamationMarks2documentLength<2.99909E-06,0,if
(AvgOfcountExclamationMarks2documentLength>0.00201898,1,0.487022901))
+7.07E+00* if (AvgOfcountExample2documentLength<4.09929E-05,1,if
(AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+5.02E+00* if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.545454545))
+5.58E+00* if (nTables2timespent<3.77056,1,if (nTables2timespent>68.3291,1,0.454545455))
+4.85E+00* if (nImages2mouseDistance<3.24716,1,if
(nImages2mouseDistance>105.389,1,0.466666667))
+1.41E+01* if (nTables2documentLength2mouseSpeed<0.000797437,1,if
(nTables2documentLength2mouseSpeed>0.0271064,0,0.5))
+3.51E+00* if (documentLength2mouseXFactor<4095.19,1,if
(documentLength2mouseXFactor>20803.9,1,0.454545455))
+1.31E+01* if (imagesArea2scrollYDistance<97335,1,if
(imagesArea2scrollYDistance>763653,0,0.477272727))
+9.60E+00* if (nLists2documentLength2scrollYSpeed<0,0,if
(nLists2documentLength2scrollYSpeed>0.000772062,1,0.47826087)))/ 1.53E+02) >= 0.5

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	20.98
	AvgOfscrollYPeaks	19.7
	AvgOfimagesAverageArea	32.86
	AvgOfcountQuestionMarks2documentLength	22.32
	AvgOfcountExclamationMarks2documentLength	5.798
	AvgOfcountExample2documentLength	7.071
	AvgOfcountDiagram2documentLength	5.019
	nTables2timespent	5.582
	nImages2mouseDistance	4.845
	nTables2documentLength2mouseSpeed	14.07
	documentLength2mouseXFactor	3.514
	imagesArea2scrollYDistance	13.09
	nLists2documentLength2scrollYSpeed	9.596

Rule name	PAR4	Dimension of learning style		Active/Reflective	
Std. error	139.11%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfscrollYSpeed<0.326657,1,if (AvgOfscrollYSpeed>3.4356,0,0.485294118))
+ if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>7.46276E-05,1,0.4375))
+ if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.514705882))
+ if (nImages2mouseDistance<3.49928,0,if
(nImages2mouseDistance>90.8479,0,0.516071429))
+ if (nObjects2documentLength2mouseDistance<0,0,if
(nObjects2documentLength2mouseDistance>0.000190849,1,0.492957746))
+ if (nImages2mouseSpeed<8.86512,1,if (nImages2mouseSpeed>45.4493,0,0.492063492))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.607407,0,0.514285714))
+ if (documentLength2scrollYDistance<1375.72,1,if
(documentLength2scrollYDistance>8258.06,0,0.485294118))
+ if (nImages2scrollYDistance<3.53808,1,if (nImages2scrollYDistance>53.0018,0,0.47761194))
+ if (nLists2scrollYDistance<0.00239089,0,if (nLists2scrollYDistance>5.31651,0,0.510164569))
+ if (nLists2documentLength2scrollYDistance<1.34244E-07,0,if
(nLists2documentLength2scrollYDistance>0.0084252,1,0.493908154))
+ if (documentLength2scrollYSpeed<1114.44,0,if
(documentLength2scrollYSpeed>7790.63,0,0.509840675))
+ if (nObjects2documentLength2scrollYSpeed<0,0,if
(nObjects2documentLength2scrollYSpeed>0.00015516,0,0.507042254))
+ if (imagesArea2scrollYPeaks<86000.1,1,if
(imagesArea2scrollYPeaks>433558,0,0.47761194))) / 11.07211052

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	28.12
	AvgOfcountQuestion2documentLength	2.554
	AvgOfcountDiagram2documentLength	3.861
	nImages2mouseDistance	5.511
	nObjects2documentLength2mouseDistance	3.437
	nImages2mouseSpeed	15.51
	nObjects2mouseSpeed	10.24
	documentLength2scrollYDistance	11.64
	nImages2scrollYDistance	13.16
	nLists2scrollYDistance	11.3
	nLists2documentLength2scrollYDistance	2.89
	documentLength2scrollYSpeed	4.501
	nObjects2documentLength2scrollYSpeed	10.32
	imagesArea2scrollYPeaks	2.274

Rule name	PSI4	Dimension of learning style		Sensing/Intuitive	
Std. error	169.3%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (nPagesVisited<16,1,if (nPagesVisited>59,0,0.477272727))
+ if (AvgOftimespent<137223000,0,if (AvgOftimespent>1090920000,0,0.566037736))
+ if (AvgOfmouseXFactor<0.551396,0,if (AvgOfmouseXFactor>0.760082,0,0.583153348))
+ if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>0.000179325,1,0.509433962))
+ if (nImages2documentLength2mouseSpeed<0.00211388,0,if
(nImages2documentLength2mouseSpeed>0.0267422,0,0.550458716))) / 3.6996498

Terms	Term name	F-ratio
	nPagesVisited	9.875
	AvgOftimespent	3.489
	AvgOfmouseXFactor	23.9
	AvgOfcountQuestion2documentLength	3.015
	nImages2documentLength2mouseSpeed	2.576

Rule name	PVV4	Dimension of learning style		Visual/Verbal	
Std. error	156.9%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(if (AvgOfrelativeTimeSpent<1,0,if (AvgOfrelativeTimeSpent>1.2704,1,0.453333333))
+ if (AvgOfmouseXFactor<0.551396,1,if (AvgOfmouseXFactor>0.787437,0,0.493670886))
+ if (AvgOfimagesArea<141811,1,if (AvgOfimagesArea>538274,1,0.445945946))
+ if (AvgOfimagesArea2documentLength<34.6354,0,if
(AvgOfimagesArea2documentLength>416.843,0,0.552808989))
+ if (AvgOfnImages2documentLength<0.00192356,1,if
(AvgOfnImages2documentLength>0.0128108,1,0.430555556))
+ if (AvgOfcountQuestionMarks2documentLength<0.000138728,1,if
(AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.438356164))
+ if (AvgOfcountExclamationMarks2documentLength<0.000107926,1,if
(AvgOfcountExclamationMarks2documentLength>0.00285521,0,0.452054795))
+ if (nTables2timespent<3.77056,1,if (nTables2timespent>52.3422,1,0.460526316))
+ if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>1.15701,0,0.50617284))
+ if (nLists2documentLength2mouseDistance<0,0,if
(nLists2documentLength2mouseDistance>0.00159198,1,0.4875))
+ if (nImages2documentLength2mouseYFactor<0.00393818,1,if
(nImages2documentLength2mouseYFactor>0.0340762,1,0.445945946))
+ if (documentLength2scrollYDistance<1375.72,1,if
(documentLength2scrollYDistance>8584.47,1,0.481012658))
+ if (imagesArea2scrollYDistance<86345.7,1,if
(imagesArea2scrollYDistance>763653,1,0.481012658))
+ if (nTables2scrollYDistance<1.24013,0,if (nTables2scrollYDistance>22.6149,1,0.509249184))
+ if (nLists2scrollYDistance<0,0,if (nLists2scrollYDistance>2.00649,1,0.474358974))
+ if (nTables2documentLength2scrollYDistance<0.000315945,1,if
(nTables2documentLength2scrollYDistance>0.0157391,0,0.5))) / 15.05898

Terms	Term name	F-ratio
	AvgOfrelativeTimeSpent	11.89
	AvgOfmouseXFactor	8.857
	AvgOfimagesArea	5.272
	AvgOfimagesArea2documentLength	11.22
	AvgOfnImages2documentLength	9.739
	AvgOfcountQuestionMarks2documentLength	14.23
	AvgOfcountExclamationMarks2documentLength	16.47
	nTables2timespent	5.634
	nObjects2mouseDistance	5.974
	nLists2documentLength2mouseDistance	10.89
	nImages2documentLength2mouseYFactor	13.85
	documentLength2scrollYDistance	38.84
	imagesArea2scrollYDistance	4.796
	nTables2scrollYDistance	15.57
	nLists2scrollYDistance	11.03
	nTables2documentLength2scrollYDistance	25.17

Rule name	**PSG4**	**Dimension of learning style**		Sequential/Global	
Std. error	114.8%	**Class. Prob.**	N/A	**Class. Eff.**	N/A

Rule Expression

(if (AvgOfmouseXFactor<0.427223,1,if (AvgOfmouseXFactor>0.787437,1,0.47826087))
+ if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+ if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if
(AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if
(AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+ if (AvgOfcountFact2documentLength<0,0,if
(AvgOfcountFact2documentLength>0.000051277,1,0.489361702))
+ if (AvgOfcountPrevious2documentLength<0,0,if
(AvgOfcountPrevious2documentLength>0.000381947,1,0.466666667))
+ if (nImages2documentLength2mouseDistance<0.00127034,1,if
(nImages2documentLength2mouseDistance>0.0643883,0,0.5))
+ if (nImages2mouseSpeed<7.42169,1,if (nImages2mouseSpeed>221.068,1,0.47826087))
+ if (nTables2mouseXFactor<3.6856,1,if (nTables2mouseXFactor>26.7674,0,0.488888889))
+ if (nImages2mouseYFactor<13.5242,1,if (nImages2mouseYFactor>78.5638,0,0.465116279))
+ if (nTables2documentLength2mouseYFactor<0.0016584,0,if
(nTables2documentLength2mouseYFactor>0.0171737,0,0.519790889))
+ if (imagesArea2scrollYDistance<97335,1,if
(imagesArea2scrollYDistance>763653,0,0.477272727))
+ if (nImages2scrollYDistance<3.91531,1,if (nImages2scrollYDistance>65.34,0,0.465116279))
+ if (nObjects2scrollYDistance<0,0,if (nObjects2scrollYDistance>1.22134,0,0.510638298))
+ if (nLists2scrollYSpeed<0,0,if (nLists2scrollYSpeed>1.56152,1,0.454545455))
+ if (nImages2documentLength2scrollYSpeed<0.000623057,1,if
(nImages2documentLength2scrollYSpeed>0.0109988,0,0.511627907))
+ if (imagesArea2documentLength2scrollYPeaks<27.5811,1,if
(imagesArea2documentLength2scrollYPeaks>416.843,0,0.5)))/15.552168

Terms	**Term name**	**F-ratio**
	AvgOfmouseXFactor	11.27
	AvgOfscrollYPeaks	3.438
	AvgOfcountQuestionMarks2documentLength	23.06
	AvgOfcountExample2documentLength	3.68
	AvgOfcountFact2documentLength	7.06
	AvgOfcountPrevious2documentLength	19.02
	nImages2documentLength2mouseDistance	10.23
	nImages2mouseSpeed	3.35
	nTables2mouseXFactor	2.607
	nImages2mouseYFactor	2.227
	nTables2documentLength2mouseYFactor	14.46
	imagesArea2scrollYDistance	6.595
	nImages2scrollYDistance	4.056
	nObjects2scrollYDistance	11.38
	nLists2scrollYSpeed	30.61
	nImages2documentLength2scrollYSpeed	2.09
	imagesArea2documentLength2scrollYPeaks	2.103

Rule name	PAR4W	Dimension of learning style		Active/Reflective	
Std. error	135.62%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(2.81E+01* if (AvgOfscrollYSpeed<0.326657,1,if (AvgOfscrollYSpeed>3.4356,0,0.487444609)) +
2.55E+00* if (AvgOfcountQuestion2documentLength<0,0,if (AvgOfcountQuestion2documentLength>7.46276E-05,1,0.43956044)) +
3.86E+00* if (AvgOfcountDiagram2documentLength<0,0,if (AvgOfcountDiagram2documentLength>4.96904E-05,0,0.516986706)) +
5.51E+00* if (nImages2mouseDistance<3.49928,0,if (nImages2mouseDistance>90.8479,0,0.518292683)) +
3.44E+00* if (nObjects2documentLength2mouseDistance<0,0,if (nObjects2documentLength2mouseDistance>0.000190849,1,0.495049505)) +
1.55E+01* if (nImages2mouseSpeed<8.86512,1,if (nImages2mouseSpeed>45.4493,0,0.494417863)) +
1.02E+01* if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.607407,0,0.516499283)) +
1.16E+01* if (documentLength2scrollYDistance<1375.72,1,if (documentLength2scrollYDistance>8258.06,0,0.487444609)) +
1.32E+01* if (nImages2scrollYDistance<3.53808,1,if (nImages2scrollYDistance>53.0018,0,0.47976012)) +
1.13E+01* if (nLists2scrollYDistance<0.00239089,0,if (nLists2scrollYDistance>5.31651,0,0.512396694)) +
2.89E+00* if (nLists2documentLength2scrollYDistance<1.34244E-07,0,if (nLists2documentLength2scrollYDistance>0.0084252,1,0.496)) +
4.50E+00* if (documentLength2scrollYSpeed<1114.44,0,if (documentLength2scrollYSpeed>7790.63,0,0.512)) +
1.03E+01* if (nObjects2documentLength2scrollYSpeed<0,0,if (nObjects2documentLength2scrollYSpeed>0.00015516,0,0.509193777)) +
2.27E+00* if (imagesArea2scrollYPeaks<86000.1,1,if (imagesArea2scrollYPeaks>433558,0,0.47976012)))/ 1.03E+02

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	28.12
	AvgOfcountQuestion2documentLength	2.554
	AvgOfcountDiagram2documentLength	3.861
	nImages2mouseDistance	5.511
	nObjects2documentLength2mouseDistance	3.437
	nImages2mouseSpeed	15.51
	nObjects2mouseSpeed	10.24
	documentLength2scrollYDistance	11.64
	nImages2scrollYDistance	13.16
	nLists2scrollYDistance	11.3
	nLists2documentLength2scrollYDistance	2.89
	documentLength2scrollYSpeed	4.501
	nObjects2documentLength2scrollYSpeed	10.32
	imagesArea2scrollYPeaks	2.274

Rule name	PSI4W	Dimension of learning style		Sensing/Intuitive	
Std. error	195.6%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(9.88E+00* if (nPagesVisited<16,1,if (nPagesVisited>59,0,0.477272727))
+ 3.49E+00* if (AvgOftimespent<137223000,0,if
(AvgOftimespent>1090920000,0,0.566037736))
+ 2.39E+01* if (AvgOfmouseXFactor<0.551396,0,if
(AvgOfmouseXFactor>0.760082,0,0.583153348))
+ 3.02E+00* if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>0.000179325,1,0.509433962))
+ 2.58E+00* if (nImages2documentLength2mouseSpeed<0.00211388,0,if
(nImages2documentLength2mouseSpeed>0.0267422,0,0.550458716))) / 3.02E+01

Terms	Term name	F-ratio
	nPagesVisited	9.875
	AvgOftimespent	3.489
	AvgOfmouseXFactor	23.9
	AvgOfcountQuestion2documentLength	3.015
	nImages2documentLength2mouseSpeed	2.576

Rule name	PVV4W	Dimension of learning style		Visual/Verbal	
Std. error	152.8%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(1.19E+01* if (AvgOfrelativeTimeSpent<1,0,if (AvgOfrelativeTimeSpent>1.2704,1,0.453333333))
+ 8.86E+00* if (AvgOfmouseXFactor<0.551396,1,if (AvgOfmouseXFactor>0.787437,0,0.493670886))
+ 5.27E+00* if (AvgOfimagesArea<141811,1,if (AvgOfimagesArea>538274,1,0.445945946))
+ 1.12E+01* if (AvgOfimagesArea2documentLength<34.6354,0,if (AvgOfimagesArea2documentLength>416.843,0,0.552808989))
+ 9.74E+00* if (AvgOfnImages2documentLength<0.00192356,1,if (AvgOfnImages2documentLength>0.0128108,1,0.430555556))
+ 1.42E+01* if (AvgOfcountQuestionMarks2documentLength<0.000138728,1,if (AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.438356164))
+ 1.65E+01* if (AvgOfcountExclamationMarks2documentLength<0.000107926,1,if (AvgOfcountExclamationMarks2documentLength>0.00285521,0,0.452054795))
+ 5.63E+00* if (nTables2timespent<3.77056,1,if (nTables2timespent>52.3422,1,0.460526316))
+ 5.97E+00* if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>1.15701,0,0.50617284))
+ 1.09E+01* if (nLists2documentLength2mouseDistance<0,0,if (nLists2documentLength2mouseDistance>0.00159198,1,0.4875))
+ 1.39E+01* if (nImages2documentLength2mouseYFactor<0.00393818,1,if (nImages2documentLength2mouseYFactor>0.0340762,1,0.445945946))
+ 3.88E+01* if (documentLength2scrollYDistance<1375.72,1,if (documentLength2scrollYDistance>8584.47,1,0.481012658))
+ 4.80E+00* if (imagesArea2scrollYDistance<86345.7,1,if (imagesArea2scrollYDistance>763653,1,0.481012658))
+ 1.56E+01* if (nTables2scrollYDistance<1.24013,0,if (nTables2scrollYDistance>22.6149,1,0.509249184))
+ 1.10E+01* if (nLists2scrollYDistance<0,0,if (nLists2scrollYDistance>2.00649,1,0.474358974))
+ 2.52E+01* if (nTables2documentLength2scrollYDistance<0.000315945,1,if (nTables2documentLength2scrollYDistance>0.0157391,0,0.5)))/ 2.01E+02

Terms	Term name	F-ratio
	AvgOfrelativeTimeSpent	11.89
	AvgOfmouseXFactor	8.857
	AvgOfimagesArea	5.272
	AvgOfimagesArea2documentLength	11.22
	AvgOfnImages2documentLength	9.739
	AvgOfcountQuestionMarks2documentLength	14.23
	AvgOfcountExclamationMarks2documentLength	16.47
	nTables2timespent	5.634
	nObjects2mouseDistance	5.974
	nLists2documentLength2mouseDistance	10.89
	nImages2documentLength2mouseYFactor	13.85
	documentLength2scrollYDistance	38.84
	imagesArea2scrollYDistance	4.796
	nTables2scrollYDistance	15.57
	nLists2scrollYDistance	11.03
	nTables2documentLength2scrollYDistance	25.17

Rule name	PSG4W	Dimension of learning style		Sequential/Global	
Std. error	114.3%	Class. Prob.	N/A	Class. Eff.	N/A

Rule Expression

(1.13E+01* if (AvgOfmouseXFactor<0.427223,1,if (AvgOfmouseXFactor>0.787437,1,0.47826087))
+ 3.44E+00* if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+ 2.31E+01* if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if (AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+ 3.68E+00* if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+ 7.06E+00* if (AvgOfcountFact2documentLength<0,0,if (AvgOfcountFact2documentLength>0.000051277,1,0.489361702))
+ 1.90E+01* if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>0.000381947,1,0.466666667))
+ 1.02E+01* if (nImages2documentLength2mouseDistance<0.00127034,1,if (nImages2documentLength2mouseDistance>0.0643883,0,0.5))
+ 3.35E+00* if (nImages2mouseSpeed<7.42169,1,if (nImages2mouseSpeed>221.068,1,0.47826087))
+ 2.61E+00* if (nTables2mouseXFactor<3.6856,1,if (nTables2mouseXFactor>26.7674,0,0.488888889))
+ 2.23E+00* if (nImages2mouseYFactor<13.5242,1,if (nImages2mouseYFactor>78.5638,0,0.465116279))
+ 1.45E+01* if (nTables2documentLength2mouseYFactor<0.0016584,0,if (nTables2documentLength2mouseYFactor>0.0171737,0,0.519790889))
+ 6.60E+00* if (imagesArea2scrollYDistance<97335,1,if (imagesArea2scrollYDistance>763653,0,0.477272727))
+ 4.06E+00* if (nImages2scrollYDistance<3.91531,1,if (nImages2scrollYDistance>65.34,0,0.465116279))
+ 1.14E+01* if (nObjects2scrollYDistance<0,0,if (nObjects2scrollYDistance>1.22134,0,0.510638298))
+ 3.06E+01* if (nLists2scrollYSpeed<0,0,if (nLists2scrollYSpeed>1.56152,1,0.454545455))
+ 2.09E+00* if (nImages2documentLength2scrollYSpeed<0.000623057,1,if (nImages2documentLength2scrollYSpeed>0.0109988,0,0.511627907))
+ 2.10E+00* if (imagesArea2documentLength2scrollYPeaks<27.5811,1,if (imagesArea2documentLength2scrollYPeaks>416.843,0,0.5)))/1.43E+02

Terms	Term name	F-ratio
	AvgOfmouseXFactor	11.27
	AvgOfscrollYPeaks	3.438
	AvgOfcountQuestionMarks2documentLength	23.06
	AvgOfcountExample2documentLength	3.68
	AvgOfcountFact2documentLength	7.06
	AvgOfcountPrevious2documentLength	19.02
	nImages2documentLength2mouseDistance	10.23
	nImages2mouseSpeed	3.35
	nTables2mouseXFactor	2.607
	nImages2mouseYFactor	2.227
	nTables2documentLength2mouseYFactor	14.46
	imagesArea2scrollYDistance	6.595
	nImages2scrollYDistance	4.056
	nObjects2scrollYDistance	11.38
	nLists2scrollYSpeed	30.61
	nImages2documentLength2scrollYSpeed	2.09
	imagesArea2documentLength2scrollYPeaks	2.103

Rule name	PAR4B	Dimension of learning style		Active/Reflective	
Std. error	N/A	Class. Prob.	67%	Class. Eff.	0%

Rule Expression

((if (AvgOfscrollYSpeed<0.326657,1,if (AvgOfscrollYSpeed>3.4356,0,0.485294118))
+ if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>7.46276E-05,1,0.4375))
+ if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.514705882))
+ if (nImages2mouseDistance<3.49928,0,if
(nImages2mouseDistance>90.8479,0,0.516071429))
+ if (nObjects2documentLength2mouseDistance<0,0,if
(nObjects2documentLength2mouseDistance>0.000190849,1,0.492957746))
+ if (nImages2mouseSpeed<8.86512,1,if (nImages2mouseSpeed>45.4493,0,0.492063492))
+ if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.607407,0,0.514285714))
+ if (documentLength2scrollYDistance<1375.72,1,if
(documentLength2scrollYDistance>8258.06,0,0.485294118))
+ if (nImages2scrollYDistance<3.53808,1,if (nImages2scrollYDistance>53.0018,0,0.47761194))
+ if (nLists2scrollYDistance<0.00239089,0,if (nLists2scrollYDistance>5.31651,0,0.510164569))
+ if (nLists2documentLength2scrollYDistance<1.34244E-07,0,if
(nLists2documentLength2scrollYDistance>0.0084252,1,0.493908154))
+ if (documentLength2scrollYSpeed<1114.44,0,if
(documentLength2scrollYSpeed>7790.63,0,0.509840675))
+ if (nObjects2documentLength2scrollYSpeed<0,0,if
(nObjects2documentLength2scrollYSpeed>0.00015516,0,0.507042254))
+ if (imagesArea2scrollYPeaks<86000.1,1,if
(imagesArea2scrollYPeaks>433558,0,0.47761194))) / 11.07211052)>=0.5

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	28.12
	AvgOfcountQuestion2documentLength	2.554
	AvgOfcountDiagram2documentLength	3.861
	nImages2mouseDistance	5.511
	nObjects2documentLength2mouseDistance	3.437
	nImages2mouseSpeed	15.51
	nObjects2mouseSpeed	10.24
	documentLength2scrollYDistance	11.64
	nImages2scrollYDistance	13.16
	nLists2scrollYDistance	11.3
	nLists2documentLength2scrollYDistance	2.89
	documentLength2scrollYSpeed	4.501
	nObjects2documentLength2scrollYSpeed	10.32
	imagesArea2scrollYPeaks	2.274

Rule name	PSI4B	Dimension of learning style		Sensing/Intuitive	
Std. error	N/A	Class. Prob.	54.72%	Class. Eff.	7.69%

Rule Expression

((if (nPagesVisited<16,1,if (nPagesVisited>59,0,0.477272727))
+ if (AvgOftimespent<137223000,0,if (AvgOftimespent>1090920000,0,0.566037736))
+ if (AvgOfmouseXFactor<0.551396,0,if (AvgOfmouseXFactor>0.760082,0,0.583153348))
+ if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>0.000179325,1,0.509433962))
+ if (nImages2documentLength2mouseSpeed<0.00211388,0,if
(nImages2documentLength2mouseSpeed>0.0267422,0,0.550458716))) / 3.6996498)>=0.5

Terms	Term name	F-ratio
	nPagesVisited	9.875
	AvgOftimespent	3.489
	AvgOfmouseXFactor	23.9
	AvgOfcountQuestion2documentLength	3.015
	nImages2documentLength2mouseSpeed	2.576

Rule name	PVV4B	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	79.25%	Class. Eff.	8.33%

Rule Expression

((if (AvgOfrelativeTimeSpent<1,0,if (AvgOfrelativeTimeSpent>1.2704,1,0.453333333))
+ if (AvgOfmouseXFactor<0.551396,1,if (AvgOfmouseXFactor>0.787437,0,0.493670886))
+ if (AvgOfimagesArea<141811,1,if (AvgOfimagesArea>538274,1,0.445945946))
+ if (AvgOfimagesArea2documentLength<34.6354,0,if
(AvgOfimagesArea2documentLength>416.843,0,0.552808989))
+ if (AvgOfnImages2documentLength<0.00192356,1,if
(AvgOfnImages2documentLength>0.0128108,1,0.430555556))
+ if (AvgOfcountQuestionMarks2documentLength<0.000138728,1,if
(AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.438356164))
+ if (AvgOfcountExclamationMarks2documentLength<0.000107926,1,if
(AvgOfcountExclamationMarks2documentLength>0.00285521,0,0.452054795))
+ if (nTables2timespent<3.77056,1,if (nTables2timespent>52.3422,1,0.460526316))
+ if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>1.15701,0,0.50617284))
+ if (nLists2documentLength2mouseDistance<0,0,if
(nLists2documentLength2mouseDistance>0.00159198,1,0.4875))
+ if (nImages2documentLength2mouseYFactor<0.00393818,1,if
(nImages2documentLength2mouseYFactor>0.0340762,1,0.445945946))
+ if (documentLength2scrollYDistance<1375.72,1,if
(documentLength2scrollYDistance>8584.47,1,0.481012658))
+ if (imagesArea2scrollYDistance<86345.7,1,if
(imagesArea2scrollYDistance>763653,1,0.481012658))
+ if (nTables2scrollYDistance<1.24013,0,if (nTables2scrollYDistance>22.6149,1,0.509249184))
+ if (nLists2scrollYDistance<0,0,if (nLists2scrollYDistance>2.00649,1,0.474358974))
+ if (nTables2documentLength2scrollYDistance<0.000315945,1,if
(nTables2documentLength2scrollYDistance>0.0157391,0,0.5))) / 15.05898)>=0.5

Terms	Term name	F-ratio
	AvgOfrelativeTimeSpent	11.89
	AvgOfmouseXFactor	8.857
	AvgOfimagesArea	5.272
	AvgOfimagesArea2documentLength	11.22
	AvgOfnImages2documentLength	9.739
	AvgOfcountQuestionMarks2documentLength	14.23
	AvgOfcountExclamationMarks2documentLength	16.47
	nTables2timespent	5.634
	nObjects2mouseDistance	5.974
	nLists2documentLength2mouseDistance	10.89
	nImages2documentLength2mouseYFactor	13.85
	documentLength2scrollYDistance	38.84
	imagesArea2scrollYDistance	4.796
	nTables2scrollYDistance	15.57
	nLists2scrollYDistance	11.03
	nTables2documentLength2scrollYDistance	25.17

Rule name	PSG4B	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	54.72%	Class. Eff.	0%

Rule Expression

((if (AvgOfmouseXFactor<0.427223,1,if (AvgOfmouseXFactor>0.787437,1,0.47826087))
+ if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+ if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if (AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+ if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+ if (AvgOfcountFact2documentLength<0,0,if (AvgOfcountFact2documentLength>0.000051277,1,0.489361702))
+ if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>0.000381947,1,0.466666667))
+ if (nImages2documentLength2mouseDistance<0.00127034,1,if (nImages2documentLength2mouseDistance>0.0643883,0,0.5))
+ if (nImages2mouseSpeed<7.42169,1,if (nImages2mouseSpeed>221.068,1,0.47826087))
+ if (nTables2mouseXFactor<3.6856,1,if (nTables2mouseXFactor>26.7674,0,0.488888889))
+ if (nImages2mouseYFactor<13.5242,1,if (nImages2mouseYFactor>78.5638,0,0.465116279))
+ if (nTables2documentLength2mouseYFactor<0.0016584,0,if (nTables2documentLength2mouseYFactor>0.0171737,0,0.519790889))
+ if (imagesArea2scrollYDistance<97335,1,if (imagesArea2scrollYDistance>763653,0,0.477272727))
+ if (nImages2scrollYDistance<3.91531,1,if (nImages2scrollYDistance>65.34,0,0.465116279))
+ if (nObjects2scrollYDistance<0,0,if (nObjects2scrollYDistance>1.22134,0,0.510638298))
+ if (nLists2scrollYSpeed<0,0,if (nLists2scrollYSpeed>1.56152,1,0.454545455))
+ if (nImages2documentLength2scrollYSpeed<0.000623057,1,if (nImages2documentLength2scrollYSpeed>0.0109988,0,0.511627907))
+ if (imagesArea2documentLength2scrollYPeaks<27.5811,1,if (imagesArea2documentLength2scrollYPeaks>416.843,0,0.5)))/15.552168)>=0.5

Terms	Term name	F-ratio
	AvgOfmouseXFactor	11.27
	AvgOfscrollYPeaks	3.438
	AvgOfcountQuestionMarks2documentLength	23.06
	AvgOfcountExample2documentLength	3.68
	AvgOfcountFact2documentLength	7.06
	AvgOfcountPrevious2documentLength	19.02
	nImages2documentLength2mouseDistance	10.23
	nImages2mouseSpeed	3.35
	nTables2mouseXFactor	2.607
	nImages2mouseYFactor	2.227
	nTables2documentLength2mouseYFactor	14.46
	imagesArea2scrollYDistance	6.595
	nImages2scrollYDistance	4.056
	nObjects2scrollYDistance	11.38
	nLists2scrollYSpeed	30.61
	nImages2documentLength2scrollYSpeed	2.09
	imagesArea2documentLength2scrollYPeaks	2.103

Rule name	PAR4WB	Dimension of learning style		Active/Reflective	
Std. error	N/A	Class. Prob.	71.70%	Class. Eff.	11.76%

Rule Expression

((2.81E+01* if (AvgOfscrollYSpeed<0.326657,1,if (AvgOfscrollYSpeed>3.4356,0,0.487444609))
+
2.55E+00* if (AvgOfcountQuestion2documentLength<0,0,if
(AvgOfcountQuestion2documentLength>7.46276E-05,1,0.43956044)) +
3.86E+00* if (AvgOfcountDiagram2documentLength<0,0,if
(AvgOfcountDiagram2documentLength>4.96904E-05,0,0.516986706)) +
5.51E+00* if (nImages2mouseDistance<3.49928,0,if
(nImages2mouseDistance>90.8479,0,0.518292683)) +
3.44E+00* if (nObjects2documentLength2mouseDistance<0,0,if
(nObjects2documentLength2mouseDistance>0.000190849,1,0.495049505)) +
1.55E+01* if (nImages2mouseSpeed<8.86512,1,if
(nImages2mouseSpeed>45.4493,0,0.494417863)) +
1.02E+01* if (nObjects2mouseSpeed<0,0,if (nObjects2mouseSpeed>0.607407,0,0.516499283))
+
1.16E+01* if (documentLength2scrollYDistance<1375.72,1,if
(documentLength2scrollYDistance>8258.06,0,0.487444609)) +
1.32E+01* if (nImages2scrollYDistance<3.53808,1,if
(nImages2scrollYDistance>53.0018,0,0.47976012)) +
1.13E+01* if (nLists2scrollYDistance<0.00239089,0,if
(nLists2scrollYDistance>5.31651,0,0.512396694)) +
2.89E+00* if (nLists2documentLength2scrollYDistance<1.34244E-07,0,if
(nLists2documentLength2scrollYDistance>0.0084252,1,0.496)) +
4.50E+00* if (documentLength2scrollYSpeed<1114.44,0,if
(documentLength2scrollYSpeed>7790.63,0,0.512)) +
1.03E+01* if (nObjects2documentLength2scrollYSpeed<0,0,if
(nObjects2documentLength2scrollYSpeed>0.00015516,0,0.509193777)) +
2.27E+00* if (imagesArea2scrollYPeaks<86000.1,1,if
(imagesArea2scrollYPeaks>433558,0,0.47976012)))/ 1.03E+02)>=0.5

Terms	Term name	F-ratio
	AvgOfscrollYSpeed	28.12
	AvgOfcountQuestion2documentLength	2.554
	AvgOfcountDiagram2documentLength	3.861
	nImages2mouseDistance	5.511
	nObjects2documentLength2mouseDistance	3.437
	nImages2mouseSpeed	15.51
	nObjects2mouseSpeed	10.24
	documentLength2scrollYDistance	11.64
	nImages2scrollYDistance	13.16
	nLists2scrollYDistance	11.3
	nLists2documentLength2scrollYDistance	2.89
	documentLength2scrollYSpeed	4.501
	nObjects2documentLength2scrollYSpeed	10.32
	imagesArea2scrollYPeaks	2.274

Rule name	PSI4WB	Dimension of learning style		Sensing/Intuitive	
Std. error	N/A	Class. Prob.	60.38%	Class. Eff.	19.23%

Rule Expression

((9.88E+00* if (nPagesVisited<16,1,if (nPagesVisited>59,0,0.477272727))
+ 3.49E+00* if (AvgOftimespent<137223000,0,if (AvgOftimespent>1090920000,0,0.566037736))
+ 2.39E+01* if (AvgOfmouseXFactor<0.551396,0,if (AvgOfmouseXFactor>0.760082,0,0.583153348))
+ 3.02E+00* if (AvgOfcountQuestion2documentLength<0,0,if (AvgOfcountQuestion2documentLength>0.000179325,1,0.509433962))
+ 2.58E+00* if (nImages2documentLength2mouseSpeed<0.00211388,0,if (nImages2documentLength2mouseSpeed>0.0267422,0,0.550458716))) / 3.02E+01)>=0.5

Terms	Term name	F-ratio
	nPagesVisited	9.875
	AvgOftimespent	3.489
	AvgOfmouseXFactor	23.9
	AvgOfcountQuestion2documentLength	3.015
	nImages2documentLength2mouseSpeed	2.576

Rule name	PVV4WB	Dimension of learning style		Visual/Verbal	
Std. error	N/A	Class. Prob.	67.92%	Class. Eff.	-41.67%

Rule Expression

((1.19E+01* if (AvgOfrelativeTimeSpent<1,0,if (AvgOfrelativeTimeSpent>1.2704,1,0.453333333))
+ 8.86E+00* if (AvgOfmouseXFactor<0.551396,1,if (AvgOfmouseXFactor>0.787437,0,0.493670886))
+ 5.27E+00* if (AvgOfimagesArea<141811,1,if (AvgOfimagesArea>538274,1,0.445945946))
+ 1.12E+01* if (AvgOfimagesArea2documentLength<34.6354,0,if (AvgOfimagesArea2documentLength>416.843,0,0.552808989))
+ 9.74E+00* if (AvgOfnImages2documentLength<0.00192356,1,if (AvgOfnImages2documentLength>0.0128108,1,0.430555556))
+ 1.42E+01* if (AvgOfcountQuestionMarks2documentLength<0.000138728,1,if (AvgOfcountQuestionMarks2documentLength>0.000588168,1,0.438356164))
+ 1.65E+01* if (AvgOfcountExclamationMarks2documentLength<0.000107926,1,if (AvgOfcountExclamationMarks2documentLength>0.00285521,0,0.452054795))
+ 5.63E+00* if (nTables2timespent<3.77056,1,if (nTables2timespent>52.3422,1,0.460526316))
+ 5.97E+00* if (nObjects2mouseDistance<0,0,if (nObjects2mouseDistance>1.15701,0,0.50617284))
+ 1.09E+01* if (nLists2documentLength2mouseDistance<0,0,if (nLists2documentLength2mouseDistance>0.00159198,1,0.4875))
+ 1.39E+01* if (nImages2documentLength2mouseYFactor<0.00393818,1,if (nImages2documentLength2mouseYFactor>0.0340762,1,0.445945946))
+ 3.88E+01* if (documentLength2scrollYDistance<1375.72,1,if (documentLength2scrollYDistance>8584.47,1,0.481012658))
+ 4.80E+00* if (imagesArea2scrollYDistance<86345.7,1,if (imagesArea2scrollYDistance>763653,1,0.481012658))
+ 1.56E+01* if (nTables2scrollYDistance<1.24013,0,if (nTables2scrollYDistance>22.6149,1,0.509249184))
+ 1.10E+01* if (nLists2scrollYDistance<0,0,if (nLists2scrollYDistance>2.00649,1,0.474358974))
+ 2.52E+01* if (nTables2documentLength2scrollYDistance<0.000315945,1,if (nTables2documentLength2scrollYDistance>0.0157391,0,0.5)))/ 2.01E+02)>=0.5

Terms	Term name	F-ratio
	AvgOfrelativeTimeSpent	11.89
	AvgOfmouseXFactor	8.857
	AvgOfimagesArea	5.272
	AvgOfimagesArea2documentLength	11.22
	AvgOfnImages2documentLength	9.739
	AvgOfcountQuestionMarks2documentLength	14.23
	AvgOfcountExclamationMarks2documentLength	16.47
	nTables2timespent	5.634
	nObjects2mouseDistance	5.974
	nLists2documentLength2mouseDistance	10.89
	nImages2documentLength2mouseYFactor	13.85
	documentLength2scrollYDistance	38.84
	imagesArea2scrollYDistance	4.796
	nTables2scrollYDistance	15.57
	nLists2scrollYDistance	11.03
	nTables2documentLength2scrollYDistance	25.17

Rule name	PSG4WB	Dimension of learning style		Sequential/Global	
Std. error	N/A	Class. Prob.	50.94%	Class. Eff.	-8.33%

Rule Expression

((1.13E+01* if (AvgOfmouseXFactor<0.427223,1,if (AvgOfmouseXFactor>0.787437,1,0.47826087))
+ 3.44E+00* if (AvgOfscrollYPeaks<1,0,if (AvgOfscrollYPeaks>3.5,0,0.52173913))
+ 2.31E+01* if (AvgOfcountQuestionMarks2documentLength<6.29328E-05,0,if (AvgOfcountQuestionMarks2documentLength>0.000668668,1,0.487022901))
+ 3.68E+00* if (AvgOfcountExample2documentLength<4.09929E-05,1,if (AvgOfcountExample2documentLength>0.000484727,1,0.466666667))
+ 7.06E+00* if (AvgOfcountFact2documentLength<0,0,if (AvgOfcountFact2documentLength>0.000051277,1,0.489361702))
+ 1.90E+01* if (AvgOfcountPrevious2documentLength<0,0,if (AvgOfcountPrevious2documentLength>0.000381947,1,0.466666667))
+ 1.02E+01* if (nImages2documentLength2mouseDistance<0.00127034,1,if (nImages2documentLength2mouseDistance>0.0643883,0,0.5))
+ 3.35E+00* if (nImages2mouseSpeed<7.42169,1,if (nImages2mouseSpeed>221.068,1,0.47826087))
+ 2.61E+00* if (nTables2mouseXFactor<3.6856,1,if (nTables2mouseXFactor>26.7674,0,0.488888889))
+ 2.23E+00* if (nImages2mouseYFactor<13.5242,1,if (nImages2mouseYFactor>78.5638,0,0.465116279))
+ 1.45E+01* if (nTables2documentLength2mouseYFactor<0.0016584,0,if (nTables2documentLength2mouseYFactor>0.0171737,0,0.519790889))
+ 6.60E+00* if (imagesArea2scrollYDistance<97335,1,if (imagesArea2scrollYDistance>763653,0,0.477272727))
+ 4.06E+00* if (nImages2scrollYDistance<3.91531,1,if (nImages2scrollYDistance>65.34,0,0.465116279))
+ 1.14E+01* if (nObjects2scrollYDistance<0,0,if (nObjects2scrollYDistance>1.22134,0,0.510638298))
+ 3.06E+01* if (nLists2scrollYSpeed<0,0,if (nLists2scrollYSpeed>1.56152,1,0.454545455))
+ 2.09E+00* if (nImages2documentLength2scrollYSpeed<0.000623057,1,if (nImages2documentLength2scrollYSpeed>0.0109988,0,0.511627907))
+ 2.10E+00* if (imagesArea2documentLength2scrollYPeaks<27.5811,1,if (imagesArea2documentLength2scrollYPeaks>416.843,0,0.5)))/1.43E+02)>=0.5

Terms	Term name	F-ratio
	AvgOfmouseXFactor	11.27
	AvgOfscrollYPeaks	3.438
	AvgOfcountQuestionMarks2documentLength	23.06
	AvgOfcountExample2documentLength	3.68
	AvgOfcountFact2documentLength	7.06
	AvgOfcountPrevious2documentLength	19.02
	nImages2documentLength2mouseDistance	10.23
	nImages2mouseSpeed	3.35
	nTables2mouseXFactor	2.607
	nImages2mouseYFactor	2.227
	nTables2documentLength2mouseYFactor	14.46
	imagesArea2scrollYDistance	6.595
	nImages2scrollYDistance	4.056
	nObjects2scrollYDistance	11.38
	nLists2scrollYSpeed	30.61
	nImages2documentLength2scrollYSpeed	2.09
	imagesArea2documentLength2scrollYPeaks	2.103