Knowledge Discovery in Virtual Worlds Usage Data: approaching Web Mining concepts to 3D Virtual Environments

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Abstract

This paper examines the relationships between Web and Virtual Worlds, and how these relationships can be used to approach concepts of knowledge discovery from Web Mining to 3D environments, such as Virtual Worlds. Also it will explain how to track information of usage data for knowledge discovery and what goals can be planned for this process. Every theoretical concept will be shown with examples, including the usage options to collect, data input to the entire process, relevant information extraction from raw data, techniques to discover knowledge and several considerations to decide and represent what knowledge is useful for the user. Based on these concepts a framework is presented in which, by comparison and approach to Web Usage Mining, may be defined an entire process of Knowledge Discovery and Data Analysis.

Keywords: Knowledge Discovery, Data Mining, Usage Data, Virtual Worlds, Web Mining

1. Introduction

Online interactive technologies have the potential to reach a large amount of people, whatever age, social environment, or culture. One of these technologies is Virtual Worlds, or Multiuser Virtual Environments (MUVEs) [1]. In a Virtual World, the user creates a virtual *alter ego* or avatar, representing him in a simulated space. Through avatars, the users can interact with the 3D environment, other users or another kinds of contents [2]. For example, some uses of Virtual Worlds regard to eLearning [3], playing [4], marketing or ecommerce [5], socializing [6], etc.

The Web Mining is a research area that uses data mining techniques to automatically discover and extract information from Web documents and Services [7]. These techniques, or others, could be used to solve the information overload problems of "finding relevant information, creating new knowledge out of the information available on the Web, personalization of information, or learning about consumers or individual users" [8].

Regarding Web Mining, we may find the knowledge discovery and data mining (KDD) field, which draws on findings from statistics, databases and artificial intelligence to construct tools that let the users gain insight from massive data sets [9], also it's defined as "the process of identifying valid, novel, useful, and understandable patterns in data" [10].

A special field of Web Mining is Web Usage Mining, which can be defined as "the application of data mining techniques to discover usage patterns from Web data, in order to understand and better serve the needs of Web-based applications" [11].

Web Usage Mining today is a key area for know everything that goes on within a certain portal or web. This knowledge can be generated to be understood by administrators, managers or designers, or even to be automatically understood by the system.

Through knowledge or nontrivial data found from the application of these techniques can enhance various sections of systems, or optimize resources require users to use. In the same way, the knowledge discovery applied to Virtual Worlds make designers of these (game designers, etc.) can improve, redesign or change in any way the 3D environment according to the characteristics, needs or data extracted from these processes.

This paper will present the result of the binding of these concepts through various sections of content, such as 2) Main similarities between Web and Virtual Worlds, 3) Goals of Knowledge Discovery in Virtual Worlds, 4) Data Inputs, 5) Knowledge extraction and discovery process, 6) What knowledge is useful and what not, 7) One real example of Knowledge Discovery, 8) How can be shown the knowledge, and 9) Concluding Remarks of the paper.

2. Main similarities between Web and 3D Virtual Worlds

This study set out with the aim of provides approaching Web Usage Mining concepts to reach knowledge discovery in Virtual Worlds. For this purpose, it is necessary showing what concepts are similar and what relationships in architecture could be established between web pages or web applications and 3D virtual environments. From these similarities we will purpose many metrics later.

From the observed relationships, we could highlight:

- A web page as a set is composed by several web pages; a virtual environment also is composed by a set of territories, islands and regions. In the same way that web pages, Virtual Worlds have main islands or territories from where users can be redirected to other territories.
- In web pages, data about items, events and users are collected in log files, databases, and other persistent data files. The most of Virtual Worlds and 3D Environments adopt or adapt this kind of data organization to their specifics.
- Such as in web applications, Virtual Worlds also have concepts such as login, logout, login, user profile data, viewers or browser used, etc.
- A web page or web application may depend of a set of servers or only one, in Virtual Worlds occur in the same way, it is possible having a standalone server or a grid of servers, this is based on the workload they will support.
- Starting from the idea that we can resemble a virtual island with a web page, we could pro-

pose metrics like entries or visits to the territory, and outputs to other regions (inbound and outbound traffic). That is, we analyze the traffic generated within the application, the inbound traffic, the outbound one, the calls to third-party resources, etc.

- The content and functionality, that provide a default virtual environment, can be extended by new tools, as well as web applications. Then, data assessment and information generating methods are needed.

3. Goals of Knowledge Discovery in Virtual Worlds

Before to the start any action regarding treatment of data and knowledge discovery in a Virtual World platform, it is essential to know or specify what kind of knowledge is going to be obtained, which metrics about system use must be analyzed and which not, so we should plan in detail the methods and techniques to be applied in this regard.

In the case of usage analysis and knowledge discovery in Virtual Worlds, such as in Web Usage Mining, the goals will have to be aimed to the use of the system, among which we can define three main branches to analyze:

- *Understanding the global use of the platform.* In this section will have to fit all metrics about user connection time, connection schedules, inputs / outputs of the territories, flows of movement within the Virtual World, traces of user profiles, etc.
- *Analysis of interaction between the user and the virtual environment*. This case deals with the acquisition of knowledge about how the user relates to the environment, objects used, patterns of use of objects, etc.
- *Usability analysis*. Regarding the above analysis area (analysis of user interaction with the virtual environment) knowledge about errors, failures and misuse 3D environment gathered. With this knowledge, it is possible to find patterns or sequences about unexpected, confusing or misleading uses.

In each of these analysis areas, or other that may arise, can be defined various objectives, among which include the followings:

- Knowledge of time patterns of users: what time usually the users login, logout, or make any usage event in the system.
- Knowledge of patterns of dates in which users uses virtual environments: what moments or days of the year are using the users the system.
- Average usage per user: average time spent in Virtual World.
- Average usage time and total of each particular user.
- Determining user groups or profiles based on their similarities: analyzing the characteristics of each user, grouping them by likenesses.
- Patterns of exploration of the virtual environment: measurements of how users move around the Virtual World, trying to establish the reasons of new movements, and why the users search certain territories, etc.
- Movement flows for users between territories, for instance, analyzing movement flows comparing with time and characteristics of users.
- Degree of inputs/outputs of the virtual lands: examine entry and

exit rates of regions and find reasons why they occur (may reach examine whether an island has a lot or lack of interest, etc.).
- Degree of use of virtual objects in enclosed spaces (territory, building, etc.). Both to determine which are most commonly used as the least.
- Patterns of use of relevant objects in the Virtual World: inspect order in the usage of 3D objects or items.
- Errors in the use of virtual objects: analyze errors and why they have occurred.
- Teleport failures patterns (failures pattern in teleportation by users between regions or islands).
- Any other discoverable error: internal server errors, failures in use of third party resources, etc.

4. Data Inputs

Web Usage Mining is based on three phases: *preprocessing*, *pattern discovery* and *pattern analysis* (Fig. 1). Prior to the development of these three phases, it is needed the creation of dataset that includes every information will be required to data mining tasks. To reach this dataset setup, many sources should be consulted in order to recollect data, for instance, servers, proxy servers, databases, or any other persistent data container.

It is necessary to note that this dataset grows with the usage of the users, which means that it is always changing and it is necessary that the technology associated with the collection and compaction in a single set should be prepared for this and the techniques of data mining and knowledge discovery can be automated.

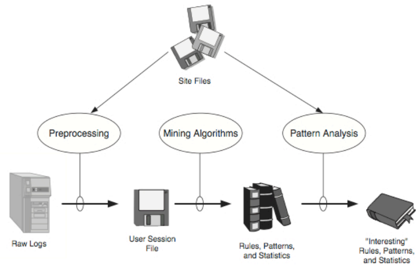

Fig. 1: Usage Mining Process [16].

As we mentioned in the introduction, there are several 3D and Virtual Worlds. In the case of this article will discuss the virtual environment called OpenSimulator (OpenSim) [12], due to its open source nature and the possibilities it offers in terms of information extraction. Regarding this matter, the managers and administrators of the platform have multiple resources offered by the system in terms of data collection by all users.

As it is shown in Fig. 2, the different data sources that can be consulted for knowledge discovery, we may highlight the following ones:

- *OpenSim log files:* They store all the information about the internal use of the Virtual World, including logins, logout, teleports, external API calls, etc. For grid-type servers, we will have two files: OpenSim.log and Robust.log [13].
- *Databases*: They collect all the information related to Virtual World users, objects and territories, such as ID, group membership, features, objects and clothing textures, positions within the 3D environment, etc.
- *Data sent through Virtual World 3D objects and collected by servers*: Inside the 3D environment can be programmed data flows with extra

information about events Virtual World from 3D objects to web servers. Records are kept in log files to allow desired queries by developers or managers of 3D environment.

- *Web server log files*: Virtual Worlds can extend its functionality via plugins [14], which can operate through web servers [15]. In these log files of server programs are charged use data from the plugins that might be interesting in collecting data for the knowledge discovery process.

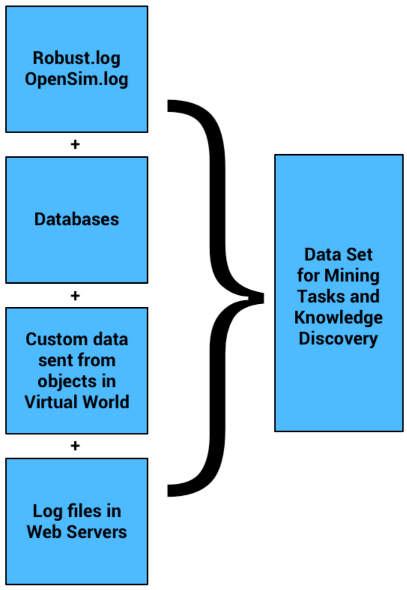

Fig. 2: Information sources for Knowledge Discovery.

5. Knowledge extraction and discovery process

Web Usage Mining techniques have been used for a long time to discover frequent item-sets, association rules, clusters of similar contents and users, sequential patterns, and perform path analysis.

As discussed above, the data used for analysis will be organized into a dataset. Within this dataset, we would highlight different broad types of data available such as:

- *Content*: Real data from the system, i.e., all the contents from the Virtual World.
- *Structure:* These are data that describe the organization of content, including how data are represented in 3D environment (arrangement of virtual objects, islands, etc.).
- *Usage:* The data that describe patterns of usage, such as IP addresses, references, viewers, date and time of accesses.
- *Administrative*: Information that cannot be automatically obtained from log files, including user registration data, object IDs,, textures, etc.

About these data types, it is possible to abstract different kinds of analysis, such as:

- *Stay in territory:* Collecting information about visits to the territories, it is possible to detect movement patterns or information about users' stays in virtual lands. This abstracted type of analysis allows to reach targets of analysis such as "Patterns of exploration of the virtual environment" or "Movement flows for users between territories" for instance.
- *Region types:* Regions, islands or territories can be classified into different types depending on the activities, contents or events taking place there. This classification in territories can help to create profiles or clusters of users.
- *Click-stream*: A click-stream is the sequence of accessed

resources, or interaction sequences with 3D environment performed by a user during usage of Virtual World. This would help to reach analysis targets like "Patterns of use of relevant objects in the Virtual World", "Knowledge of patterns of dates in which users use virtual environments", etc.

- *Transactions*: A user transaction can be understood as "unit of meaningful interaction between the user and server" [16]. This provides information about server resources usage and workload in it, so administrators can use for manage the servers and backend system structure.

There are several possible techniques and algorithms for application to data analysis, so it is important to plan which will apply depending on the objectives. Some of the goals that have been raised do not require large engineering processes, methods or data processing complex, however, it does pose some other challenges for the processing to be done to extract knowledge from them.

For example, for the target called "Average usage time and total of each particular user", simply calculate the duration of each session connection by a selected user and make the average the total. Other goals, such as "Degree of use of virtual objects in enclosed spaces", also include simple treatments, will require only the calculation of clicks segmenting the data obtained by the object ID. However, many the other goals that have been proposed pose greater challenges than calculating a mean or count numbers of clicks. In these goals intended to go further, it is necessary to apply any of the aforementioned techniques of data mining or knowledge discovery.

In the analysis target "Patterns of exploration of the virtual environment", for instance, is proposed the Association Rules technique, as discussed in [17], the application domains of Association Rules range from decision support to diagnosis and prediction of events or behaviors that are represented by a group of study data because [18]. By applying these techniques of Association Rules, the system can get predictions, with varying success rate and confidence, about the destiny of a user's movement between territories as their place of origin, globally or specializing the result only for that user. It is important to bear in mind that in Usage Mining, as with many data mining domains, thresholds for values such as support and confidence are often used to limit the number of discovered rules to a manageable number. However, high thresholds rarely discover any knowledge that was not previously known and low thresholds usually results in an unmanageable number of rules [16]. In other cases, such as, for example, the discovering of error patterns, as the goal of analysis "Teleport failures patterns", may be needed other algorithms, such as the classification ones. In this case, rather than trying to find failure rules, it may be tried to find a more complete operating pattern that helps to completely reproduce the behavior of certain failures. As expressed in [19], the decision trees (a classification specific algorithm) can be applied to any classification context. The most relevant aspect regarding the decision trees is that are presented with a number of relevant cases in the classification task and implement them through a decision tree top-down (from the root to the leaves), guided by the frequency of occurrence of the relevant information. This kind of classification techniques, and possibly others (other trees for example), could be taken as valid in another goals, for instance in

"Patterns of use of relevant objects in the Virtual World", which could be assessed in the same way with the decisions or choosing paths that the user select to reach a final result.
Finally, the targets related to user groups or features, such as "Determining user groups or profiles based on their similarities" or similar, it is possible to use other typical data mining technique: clustering. The clustering applied to user groups can help to build an approximation of different sets and models that correspond to the patterns of behavior for different kind of users [20]. Making clustering of users in communities with similar performance characteristics is the first step in establishing profiles and types of users, since they can be obtained through the common characteristics of these clusters. Through the creation of communities, groups or clusters of users, as discussed previously, it is possible having better sensitive information about users, which can help make decisions about the use, design and usability of the virtual environment, for example [21].

6. One real example of Knowledge Discovery

This section presents an example of Knowledge Discovery application with real data. These data were recolected from a Virtual World belonging to the University of Salamanca, the project USALSIM [22].
In this Virtual World, based on OpenSim framework, data records have been collected from movements (teleports) of users between different regions or islands of the virtual environment, that could be related with the analysis kind of *Stay in territory* (movement patterns or information about users' stays in virtual lands).

As mentioned previously in this paper, it is essential first to discern which data sources provided by the Virtual World can provide the information that will be used to extract Knowledge. In case of teleports or movements between regions, this information is allocated in log file of OpenSim (*OpenSim.log*). The relevant data in this case are those related to the start and end of the movement, as well as the user who performs it, and the region from which parts and which is taken as the target.
These data were organized according the *arff* files format [23], to later be imported and processed by Data Mining Software, Weka [24].
It is appropriate at this moment, before advancing in the explanation on the application of algorithms, remember what the goals to be achieved by the application of Data Mining algorithms:

- *Find patterns in users teleports:* Applying Data Mining algorithms to know the behavior of a user on the movement in virtual space. For example, being able to meet through the application of these algorithms, the probability that a user makes a teleport to a specific region, knowing in that region is at a given time that user.
- *Find patterns teleports between regions:* Knowing what patterns of movement are between the differents islands or regions. Through this objective is possible to know the teleports distribution function of each island, or which is the probability that any user in a particular island moves to another well known.

In order to find these user behavior patterns in the movements within the virtual space, is proposed to use of Association Rules algorithms, which seek to establish relationships between individual data or groups of data, discovering patterns hidden in plain sight in the data [25]. The particular algorithm is proposed to apply to the data and to discover the rules of behavior is known as *Predictive Apriori*, which provides as a result a set of rules that relate different data and gives them a probability of occurrence.

To apply this proposed algorithm in the Weka software is necessary to access the Associate tab, select the algorithm to implement the data on origin and destination regions and, where appropriate, the user performing the movement. Depending on the confidence, probability values are desired minimum, etc.. is necessary to configure the Predictive Apriori algorithm in the example have assumed those proposed by default in the software.

The rules resulting from the application of the algorithm (Fig. 3), will be of the type:

$$(\text{User}), \text{originRegion} \rightarrow \text{destinationRegion}, \text{probability}$$

Fig. 3: View the results of the *Predictive Apriori* algorithm application in Weka software.

The rules obtained through this, or any similar algorithm, must be tested and validated to provide truly understand whether knowledge about the problem in question, as discussed in the next section.

7. What knowledge is useful and what not?

Not all rules, clusters, or decision trees obtained through the proposed analysis techniques are interesting [2] or any other user who reviews the knowledge extracted ("Is this knowledge, and is it useful?"). Many of the results may seem obvious, trivial, or so strange that add nothing to the problem domain treated. Once obtained the results of data mining techniques or knowledge discovery, is essential to have some means to help us separate the valid and useful knowledge which is not.

There are various metrics or features that can help discern the actual relevance of knowledge extracted, for instance, a common theme among the various criteria for interestingness is the concept of novelty or unexpectedness of a rule (in case of Association Rules). Results that were previously known by the data analyst are not considered interesting [16]. As mentioned, in the process of validation of knowledge discovered, it is important to have data analysts and domain experts [26] who through observation of results and previous knowledge about the problem context can give feedback to improve systems and knowledge discovery process.

The data analyst and domain expert do not need to be the same person. Depending on the problem and the specific case, we need a more technical feedback (with a data analyst) or feedback on the appropriateness of the results concerning the context of the problem domain (the problem domain expert).

8. How can be shown the knowledge?

Upon completion of the Knowledge Discovery phase, it is necessary that the end user interested in that information may have proper access to it [27]. We must find the taxonomies and visualization types suitable to the type of knowledge generated, is not same clustering users, that association rules, for example.

Furthermore, we must bear in mind the end user, so that there should be a user-centered design [28]. For example, in advanced information visualization tools you need to understand various aspects of the user who performes the analysis [29]:

- Researchers or data analysts rarely start with clearly set of defined tasks, i.e., part of their work is discovering what questions to ask.
- Researchers must learn to reformulate their data analysis strategies to accommodate new tools.
- Exploratory data analysis may take place over days or weeks.

In light of these and other considerations, it is necessary to follow a good design process [30] to create visual information tools and provide them an appropriate set of features and capabilities for all potential users would be useful. Also, the visualization tools that are created must be able to deal with large amount of data, virtual worlds can continuously generate data based on users who are using the system. Even should cope with real-time analysis of the data as generated.

Moreover, in addition to following a process of designing and creating appropriate data visualization, it is necessary evaluating an information visualization or knowledge discovery tool to help identify usability problems and validate an innovative design idea [29]. The significance of empirical evaluations of these systems as well as specific features of visualization must be known, understood and well applied to create and improve the visual tools [31][32].

9. Concluding Remarks

The data analysis and knowledge discovery applied to data generated by the use by users of virtual worlds and 3D platform, provides the opportunity to meet a number of hidden data on these platforms in a way that would not be possible without these techniques or procedures. This knowledge can be used by managers, developers, designers and other staff related to these systems for interpretation and decision-making from it.

In any case, to be able to get this knowledge, it is necessary, as stated above, following a specific process to ensure the viability of the result. You cannot just mix data and apply an algorithm on them. To be able to get adequate knowledge, valid and useful, it must go beyond, and adequately preparing the raw data, processing it, applying appropriate techniques, showing the results, and validating them as far as possible, what the extracted knowledge is valid and useful for its use by the human analyst.

Thus, there should be such a widespread usage analysis, well known and proven, such as the web usage mining. Through that framework of procedures, techniques and processes can be proposed, as intended in this paper, a framework with similar characteristics applied in the case of 3D virtual environments, thus inheriting the advantages of and providing clear guidance for realizing the process.

As additional and future research on this exposed framework, we could propose different Knowledge Discovery algorithms with real application examples, and a set of visual tools that comprised both the validation of knowledge as the display of results would help in decisions about these Virtual Worlds.

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