A Thesis

ANALYSIS AND MODELING A DISTRIBUTED CO-OPERATIVE MULTI AGENT SYSTEM FOR SCALING-UP BUSINESS INTELLIGENCE

Submitted to

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Rajkot [Gujarat]

For the award of
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Submitted by
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ABSTRACT

Modeling A Distributed Co-Operative Multi Agent System in the area of Business Intelligence is the newer topic. During the work carried out a software Integrated Intelligent Advisory Model (IIAM) has been develop, which is a personal finance portfolio management kind of software to achieve business intelligence in term of maximizing profit and speed-up the finance decisions. The model acts as a true advisor, which suggests how to manage financial assets and liabilities in a best possible way. In our model different types of agents like, Data Retrieving agent, Data filtering agent, Mining agent, and Communication agent works together co-operatively to achieve the goal.

The complete work carried out can be consider as a hybrid models, First is non-deterministic simulation forecasting model, that generate recommendations using business intelligence for three asset categories ULIP, Mutual Funds and Common Stocks, and Second is optimization financial model, where rest of work contributed for accounting and managing details of personal portfolio.

The implementation of IIAM involves the integration of Expert System, Data Mining, financial econometrics and Agent Technology that performs successful predictions and helps to achieve intelligence. Dimensional modeling powered IIAM in a way that information can be organized and enables it to easily formulate. High frequency data may contain additional 'patterns', which are the result of the way that the financial market works; it has given consideration in the IIAM. Expert system uses the backward chaining through rule-based data mining to take decisions from its knowledge base incorporated with feed forward backpropagation neural network. Finally Agent technology can make IIAM self sustainable as data mining agent functions within a data warehouse structure to discover changes in business trends of

potential interest, and other agent keeps data warehouse up to date by retrieving and filtering required data, and communicate the recommendations to intended user group.

By using four Years of data related to BSE-Index, corporate stock prises, mutual fund data and ULIP data, the different model has tested and results are compared with benchmark index.

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At last, I thank the one and all, for the divine blessings.

Satyen Parikh

DECLARATION

I hereby declare that the work presented in the thesis has been developed based on the references as shown in the bibliography. I have quoted several statistics and information directly from various sources, which have been mentioned as footnote reference.

Apart from these, all other information, findings, analysis and interpretations of the data have been of my own and created originally by me.

Moreover, I also declare that for work done in the thesis, either this university or any other university has conferred any degree, diploma or distinction on me, before.

Date:

(Satyen M. Parikh)

CERTIFICATE

I hereby certify that Mr. Satyen M. Parikh has completed his thesis for doctoral research on the topic *"Analysis And Modeling A Distributed Co-Operative Multi Agent System For Scaling-Up Business Intelligence"* under my supervision.

I further certify that work done by him is of his own and original and tends to general advancement of knowledge. For the thesis that he has submitted, he has not been awarded any degree or diploma in any university or other institution according to best of my knowledge.

Place: **(Dr. N. N. Jani)**

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Chapter- I

Introduction to Topic:

Distributed co-operative multi agent-learning model in the area of Business Intelligence helps to achieve business intelligence in term of maximizing profit and speed-up the finance decisions. The model acts as a true advisor, which suggests how to manage financial assets and liabilities in a best possible way. The finance management is basic need of all human being. India is one of the most emerging countries of the world and now people of India is transforming from saver to investors. According to Nasscom[1] in year 2008 exposure to financial services is about 40% highest than any other industry. In past 25 years of business and economics scientific world witnessed the emergence of new computational techniques useful in decision-making.

The finance management is key of financial success, and it makes a vast difference in financial strength in a longer run. One can achieve great financial success by proper planning and managing investment than other even both persons have same income and expenses. Different financial planning makes them different in term of financial strength. The model is targeted to assist finance management. Finance management required for all the people, who wish to do financial growth by their investments and meet liquidity, on requirement. Undoubtedly investment is an attempt to carefully plan evaluate and allocate funds to various investments outlets which offers safety of principle and moderate and continues return over a long period of time. It is having lot of complexity, when we look closely. The need to be well-managed personal finance is required because of several reasons.

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[1] Article "Investors brace for a muted Q4 for IT sector 10 Apr 2008", Source www.etintelligence.com/etig/researchchannels/sectors/itNews

- To make investment return to keep pace with inflation
- To accomplish social liabilities, children education etc
- To maintain standard of living especially in old age
- Return on investment is depends on associated risk.

Most of people are not financial literate to understand the value of financial kind of management or they have not enough time to exercise all possibilities.

The core technical part of model is based on Business Intelligence for financial modeling. Which provides the capability to model to act as an expert finance advisor. Latest presentation techniques like dashboard help actors to monitor key performance indicators. Data warehouse techniques like Dimensional modeling empowered model to organize huge amount of financial data in a best way, Agent technology helps to distribute the lot of work among agents, and make system self motivated. In our model different types of agents like Mining agent, Data Retrieving agent, Data filtering agent, Communication agent works together co-operatively to achieve the goal. Mining agent functions within a data warehouse structure to discover changes in business trends of potential interest, and other agent keeps data warehouse up to date by retrieving and filtering required data, and another agent communicate the alerts and required information to intended user group hence scaling up business intelligence one step ahead. The complete model is having number of sub models delegated to one core finance activity.

The main objectives to build intelligent financial models based for some of the investment vehicle and that models must

- Helps to manage portfolio for customized requirement.
- Helps to predict future cash flow and helps to make provision for future requirements.

- It helps in risk management and protects the actors from huge financial loss.
- Support to get better ROI by suggesting investment in risk segments, It helps to continuous monitoring and assists to firm effective timely decisions,
- As per recommendations performance of equity stocks and derived products should beat the benchmarks indicators.
- It should provide the help in what-if analysis for different scenarios.

In the following section of the chapter we will discuss about the emergence of Business intelligence and it's scope.

1.1 Emergence of Business Intelligence:

Artificial Intelligence (AI) is considered most important developments of past century. After emergence of modern computer during the 1940s and 1950s, the most commercial development of AI began from 1977, when Edward Feigenbaum[2] emphasized the fact that the real power of an expert system comes from knowledge it possesses rather than the particular inference scheme and other formalism it employs (International Joint Conference on AI-1977). Now people realize the power of AI, and much of the work done in AI at that time called knowledge-based system. In many applications knowledge-based systems equal or exceed human abilities, and become an important part of most business operations and activities. This growth will remain continue with the development of computer systems as well as corporate world. The victim is development of e-commerce and e-business. We can see wining enterprises like Amazon are realizing that e-business is much more than a simple

[2] Edward A. Feigenbaum "The art of artificial intelligence: I. Themes and case studies of knowledge engineering" Stanford University, USA Technical Report: CS-TR-77-621, 1977

buy/sell transaction and they opted right e-strategies are the key to successfully increasingly competitiveness in the marketplaces by find the way to attract the customers and to offer better services than other competitors. This strategy is emergence the word Business Intelligence (BI). Business Intelligence uses the software intelligence for business applications in the right direction. Software intelligence achieved by using intelligent technologies (like Data mining, Agent Technology etc.) Processing power, and connectivity available to interact with environment. The acceleration in development of e-commerce application will create opportunities for business intelligence in future.

Definition of Business Intelligence: *Business intelligence (BI) is a broad category of applications and technologies for gathering, storing, analysing, and providing access to data to help enterprise users make better business decisions. BI applications include the activities of decision support systems, query and reporting, online analytical processing (OLAP), statistical analysis, forecasting, and data mining." (WHATIS.COM[3], 2001)*

1.2 Architecture of Business Intelligence Applications:

Business Intelligence applications are based on Business Intelligence Models. These models are created by number of business intelligence software modules; these software modules incorporated the BI strategies in order to develop intelligence. Business Intelligence applications utilized this knowledge or information properly in the right direction so organization enhances the profitability. Like the knowledge of customers' behavior will help to improve customer relationships and make business strategies.

[3] http://whatis.techtarget.com/definitionsAlpha

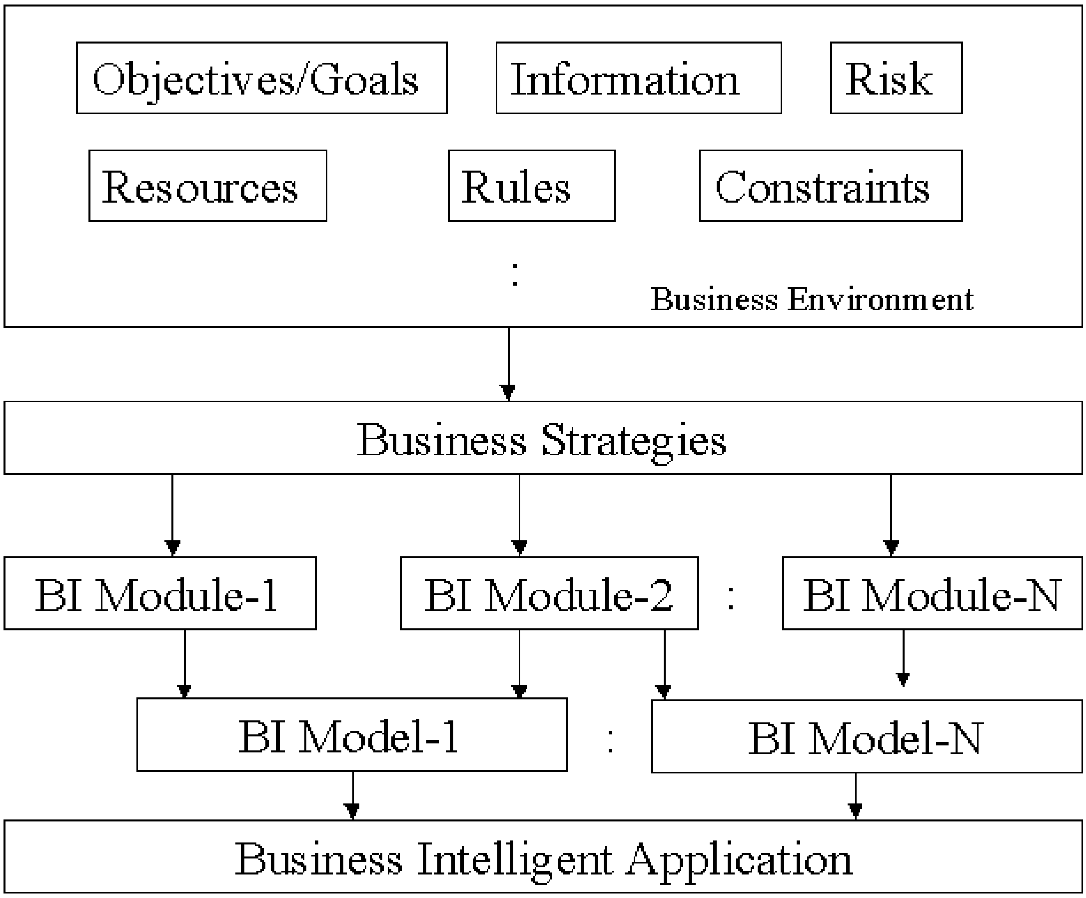

Figure: 1.1Business Intelligence Application Architecture

So we can say Business Intelligence (BI) is a terminology representing a collection of processes, tools and technologies helpful in achieving more profit by considerably improving the productivity, sales and service of an enterprise. With the help of BI methods, the corporate data can be organized, analyzed in a better way and then converted into a useful knowledge of information needed to initiate a profitable business action. Business intelligence in financial system the model helps to removing uncertainties, calculating and managing risks and optimizes the returns on investment.

The first step to achieve it is risk perception.

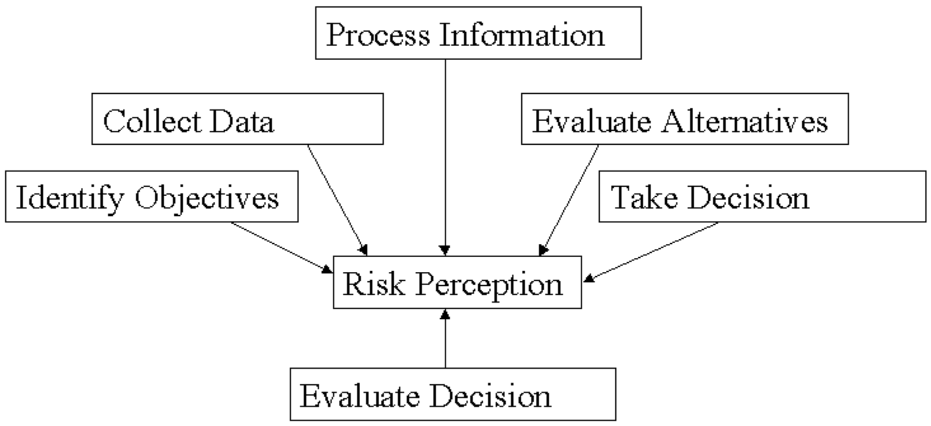

Figure 1.2: Risk Perception

Risk Perception is a process that helps to understand impact of risk on the business, The process of risk resolution involve analysis of the factors, like information about process, Data Collection, priority in different business objectives, risk alternative analysis.

If require then risk perception is followed by the process of risk resolution.

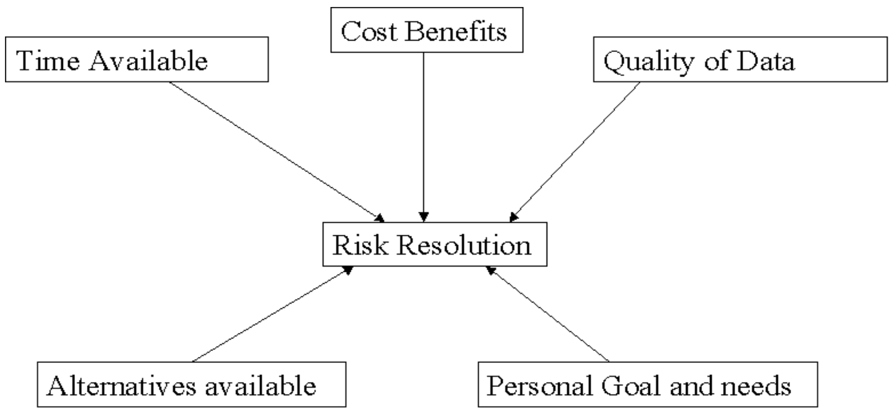

Figure 1.3: Risk Resolution

Once risk is taken care, the process of decision-making suitable for business growth takes place.

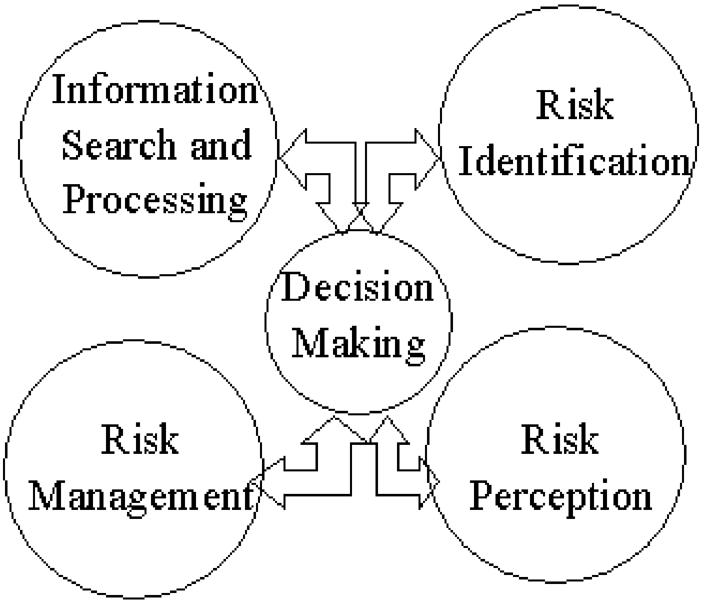

Figure 1.4: Decision Making

Once everything is done more properly in a way an organization want them to be, then the benefit that comes out of it is priceless.

In other words, Business Intelligence can be a weapon that allows a company to identify threats and opportunities, to establish defensive strategies, and to conquer market shares.

Thus its about turning a raw, collected data into an intelligent information by analyzing and re-arranging the data according to the relationships between the data items by knowing what data to collect and manage and in what context.

1.3 Technologies used in Business Intelligence:

As Business Intelligence demands the supporting technologies must possesses the knowledge required for decision support system, online analytical processing and forecasting.

The following AI methods used in Business Intelligence:

- Expert System
- Artificial Neural Network (ANN)
- Evolutionary Algorithm (EA)

- Hybrid Systems, (the AI methods that are used to complement, or in combination with these); Fuzzy Logic and Data Mining.

Conceptually all methods are developed in AI are based on learning model, which learns the knowledge from environment and uses it for future prediction requirements. As Business Intelligence demands the knowledge required for decision support system, online analytical processing and forecasting.

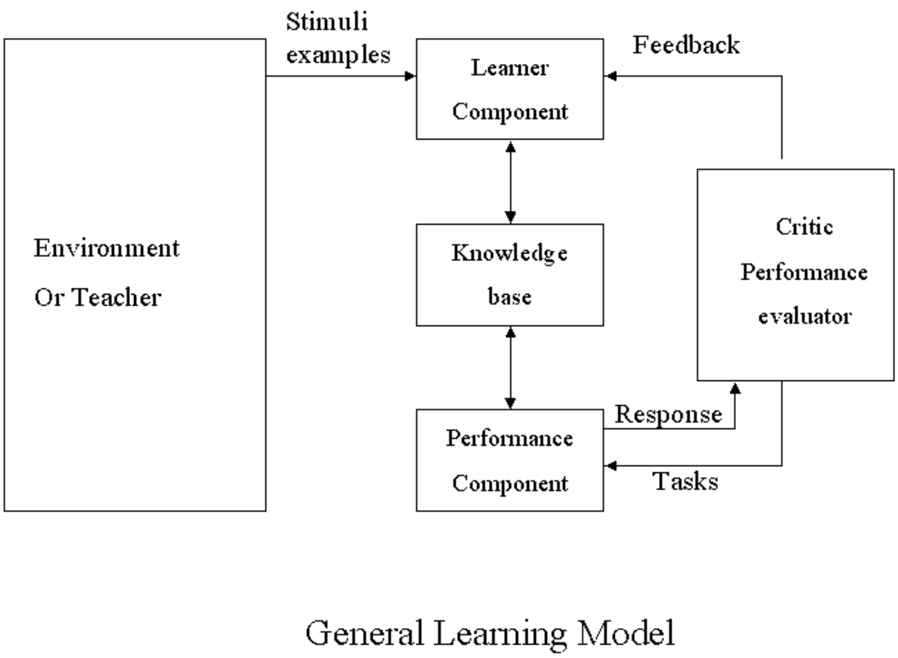

Figure: 1.5 General Learning Model

The following table shows the milestones achieved in learning methods.

Table: 1 Milestone in Learning Methods

Sr.	**Learning Method**	**Proposed By**
1	Mechanical learning	McCullloch-pits 1943
2	Reinforcement learning	Hebb's 1949
3	Perception learning	Minsky and Papert 1969
4	Back propagation learning	Rumelhart 1986
5	Competitive learning	Kohonen 1984, Hecht-Nielsen 1987

1.3.1 Expert System: McCarthy (2000)[4] at Stanford University defines Expert Systems as:

A "knowledge engineer" interviews experts in a certain domain and tries to embody their knowledge in a computer program for carrying out some task."

He explains that during the "knowledge acquisition" it will not only be the "knowledge" of experts that will be cloned and built into these systems, but also their intuition and the way that they reason, so that the best options can be selected under any given set of circumstances.

The expert system's knowledge is obtained from expert sources and coded in form suitable for the system to use in its inference or reasoning process.

The Expert System is an AI application that makes decisions based on knowledge and inference (the ability to react on the knowledge), as defined by experts in a certain domain and to solve problems in that domain.

1.3.2 Artificial Neural Network: Artificial Neural Network normally refers to software-based solution to build artificial intelligent system. Aleksander and Morton (1990)[5], in their book "An Introduction to Neural Computing," define Neural Computing as:

"Neural computing is the study of networks of adaptable nodes which, through a process of learning from task examples, store experimental knowledge and make it available for use." (ALEKSANDER, MORTON, 1990)

[4] http://www-formal.stanford.edu/jmc/whatisai

[5] Igor Aleksander and Helen Morton, "An Introduction to Neural Computing", Van Nostrand Reinhold Co. New York, NY, USA 1990.

Neural Network learns by supervised, unsupervised learning process or reinforcement learning process.

Artificial Neural Network can do forecasting, which is essential to business. Jiang[6] (2001) explain, in the article "Marketing category forecasting…" in the journal "Decision Sciences", that the advantages of They have several advantages over conventional statistical models: they handle noisy data better, do not have to fulfill any statistical assumptions, artificial neural networks generally better at handling large amounts of data with many variables, and the ability to handle non-linearity, which are common in business. Artificial Neural Networks pattern recognition capability makes it useful to forecast time series in business. A Neural Network can easily recognize patterns that have too many variables for humans to see.

1.3.3 Evolutionary Algorithms: "An algorithm that maintains a population of structures (usually randomly generated initially) that evolves according to rules of selection, recombination, mutation and survival referred to as genetic operators. A shared "environment" determines the fitness or performance of each individual in the population. It also tells us that the fittest individuals are more likely to be selected for reproduction (retention or duplication), while recombination and mutation modify those individuals, yielding potentially superior ones." (Howe[7], 1993).

There are currently four main paradigms in (EA) research:

Genetic Algorithm (GA):

"Genetic algorithms are inspired by Darwin's theory about evolution. Solution to a problem solved by genetic algorithms is evolved.

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[6] Jiang, Zhong, Maosen, "Marketing category forecasting: An alternative of BVAR--artificial neural networks", Decision Sciences, October 1, 2000

Algorithm is started with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions are selected to form new solutions (offspring) are selected according to their fitness - the more suitable they are the more chances they have to reproduce. This is repeated until some condition (for example number of populations or improvement of the best solution) is satisfied." (Obitko[8])

Genetic Programming: Genetic programming (GP) is a programming technique that extends the Genetic Algorithm to the domain of whole computer programs. In GP, populations of programs are genetically bred to solve problems.

Evolutionary Programming & Evolution Strategy:

Evolution programming uses mutations to evolve populations. It is a stochastic optimization strategy similar to Genetic Algorithm, but instead places emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific Genetic Operators as observed in nature. Evolutionary Programming is very similar to Evolution Strategies, although the two approaches developed independently (Beasley, Heitkoetter[9])

EAs seem to offer an economic combination of simplicity and flexibility, and may be the better method for finding quick solutions than the more expensive and time consuming (but higher quality) OR methods.

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[7] A.E. Howe. "Evaluating Planning Through Simulation." AAAI Spring Symposium on Foundations of Automatic Planning. Palo Alto, CA. March 23–25, 1993

[8] http://www.obitko.com/tutorials/genetic-algorithms/

[9] Beasley, Heitkoetter, "The Hitch-Hiker's Guide to Evolutionary Computation" Issue 9.1, released 12 April 2001.

1.3.4 Hybrid System: "Hybrid system uses more than one problem-solving technique in order to solve a problem" (Gray, Kilgour[10] 1997) There is a huge amount of interest in Hybrid Systems, for example: neural-fuzzy, neural-genetic, and fuzzy-genetic hybrid systems. Researchers believe they can capture the best of the methods involved, and outperform the solitary methods.

"Fuzzy Logic & Fuzzy Expert System" and "Data Mining" are placed under the heading of Hybrid System. Fuzzy Logic is a method that is combined with other AI techniques (Hybrid System) to represent knowledge and reality in a better way.

Data mining software most often uses various techniques, including Neural Networks, statistical and visualization techniques, etc., to turn what are often mountains of data into useful information. If Data Mining contains AI techniques than it will become a very useful tool for companies in the competition for market shares.

1.4 Applications of Business Intelligence:

Business intelligence has lot of requirement at different places in an organization, like

- Information Retrieving and Management
- Customer Relationship Management "Behavior Analysis"
- Customer Relationship Management "Support & Marketing"
- Company Management
- Production Management
- Finance Management

[10] Gray, A., Kilgour, R. and Kasabov N., "An agent based framework for modular speech recognition and language processing systems",ICONIP'97, Dunedin, Springer Verlag Singapore (1997) 1076-1079

1.4.1 Information Retrieving and Management:

AI techniques, like data mining can be very useful to discover the useful information from the huge volumes of raw data. It seems that various types of AI solutions to the information problem are slowly penetrating into the business arena. Many people have contact with AI without knowing it (for example, search engines, and knowledge-based systems.) Web Mining will achieve the success like any thing as information retrieval from very huge data source.

1.4.2 Customer Relationship Management "Behavior Analysis":

If information is gathered about customers, and the appropriate tools to analyze the data are used, it will then be able to understand what triggers someone to become a customer or not.

With these tools companies will be able to categorize customers as either non-profitable, or highly profitable. Analyzing customer behavior could also allow a company to identify which customers are open to changes. In other words, the company that can focus on the most profitable customer target group, and reshape customer behavior to be more cost effective, will have a considerable economic advantage over the competition. Evidently AI has penetrated the business of Finance, Collectors, Insurance and Mortgage. In finance the broad application area are Credit card fault detection and in stock market the stocks recommendation based on their transactions like value investors (bargain hunters looking for stocks of high quality companies that are selling for a reasonable price) prefer to buy stocks with low P/Es on the other hand growth investors (aggressive buyers looking for stocks in companies whose sales or earnings are growing rapidly) don't mind buying stocks with high P/Es because they expect the companies' earnings to improve in the future.

1.4.3 Customer Relationship Management "Support & Marketing":

Expert System can provide worldwide knowledge support, around the clock 24x7, and reduce work, phone calls, and e-mail. Advisory Expert Systems have a firm ground in business, and have so had for many years. AI techniques can be used to find patterns that indicate which customers with certain characteristics should be targeted for highly focused marketing.

1.4.4 Company Management:

Managers in companies pray for correct and timely information to support their decisions, instead of having to rely on a gut feeling. Information like faxes, e-mails, commercial information, Intranets (small-scale Internets within a company), the Internet, and corporate databases is now flooding companies. Thus, there is an overwhelming need for intelligent agent software that operates on behalf of humans, processing such information in a highly automated and customized fashion.

1.4.5 Production Management:

Martin & Spears [11] (2000) concludes that the company, which found it difficult to control their inventory, was able to solve their problem by employing Genetic Algorithm (GA) technique that learned to 'breed' factory schedules far better than those humans could. Dr. Martin reports that with help of GA the farm production line is running more smoothly.

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[11] Worthy N. Martin, "William M. Spears Foundations of Genetic Algorithms 6" Morgan Kaufmann, 2000

1.4.6 Finance Management:

Finance services are one of most demanding and growing industry in present decade. Much effort has been devoted over the past decades to the development of time series forecasting models. Still it is impossible to track and predict complex dynamic markets. Many techniques like neural network modeling attempts to predict stock values and make portfolio decisions. AI techniques should catch on in coming years given the growing complexity of the markets, which will require more computing power and analysis to deal with information overload.

1.5 Agent Technology:

The new developments in learning models are based on agent theory. Where,

Agent can be defined to be autonomous, problem solving computational entities capable of effective operation in dynamic and open environments.

Software agents are persistent computations that include percepts, reasoning, action, and communication [Russell & Norvig[12], 1995]

Agents are autonomous in the sense that they perform their tasks regardless of whether they are required or not. Intelligent agents are computational systems that inhabit in a complex dynamic environment and they can act autonomously and have the capacity to reason by themselves in this environment. This environment can be the network, and the intelligent agent can be seen as a software entity that assist people and gathers information or perform some other services without the immediate presence of a human being.

[12] Russell & Norvig, "Artificial Intelligence: A Modern Approach", Prentice Hall 2002.

1.5.1: An Intelligent Distributed Agent Attributes:

An intelligent agent could be characterized by the following attributes: autonomy, Reactivity, pro-activity and social ability, distributed agent have additional attributes Embedded & Distributed.

Autonomy: This attribute is one of the most important characteristics that allow us to distinguish the intelligent agents from other type of software. When we say that an agent must have autonomy, we are talking about the capacity of reacting by them in an environment using their experience. This means; the capacity of observation and operation without the direct intervention of human beings or other agent.

Reactivity: Is the capacity that the agents have to perceive their environment and act depending of the changes that occur in it, in a correct and fast way. Internet can also be one environment where intelligent agents can interact.

Pro-activity: As we had seen before, the agents can react to an environment, but they also have the ability of obtain a goal by taking the initiative. They have a goal-directed behavior without external influences (they are self-sufficient).

Social ability: Sometimes more than one agent is needed to make a task or solve some problems. The social ability is the capacity that one agent have to interact with other agents (or humans), by using some "agent language", for the possibility to cooperate or negotiate.

Embedded: The agent respects the real time of their environment and act depending on this one.

Distributed: Many different kind of agents can work together in the same system and each one of them can be added or removed without interrupting it.

In the environment agent interact, and maybe co-operate with other agents. Agents may have conflicting aims, such a system is known as a multi-agent system.

Agent architecture is the fundamental engines such an autonomous components that support effective behavior in real-world, dynamic and open environments.

In implementing multi-agent system where agents respond in a rational way to their goals and events that occur in their environment. These agents have a specific set of conditions and associated goals, which indicate the events they should respond to. This architecture stresses the problem of heterogeneous information and knowledge sources.

Durfee[13] indicates that the combination of efforts brings:

- Confidence: Independent derived results can be used to corroborate each other, yielding a collective result that has a higher probability of being correct.
- Completeness: The union of the different subtask results can cover a greater proportion of the overall task.
- Precision: To refine its own solution, an agent needs to know more about the solutions that others have formulated.
- Timeliness: Solving subtasks in parallel can yield an overall solution faster

1.6 Business Intelligence in Finance Management: A Magnified View

The wish to derive methods that can predict finance asset returns has engaged the minds of investors and academics since the birth of financial markets. Lot of hypothesis is given to understand the

[13] Edmund H. Durfee, Jeffrey S. Rosenschein, "Distributed problem solving and multi-agent systems", IWDAI-94, 1994

market movement like Random walk hypothesis and efficient market hypothesis. Still it is a great challenge to predict the market. Since 1993, the disciplines like Computational Economics and Computational Finance attract the researchers and occupy their place in field of Artificial Intelligence, Finance Modeling and related research areas. The high-speed computers along with intelligent techniques like Expert Systems, Artificial Neural Networks, and Evolutionary Algorithms make it possible to achieve new milestones. As these methods are utilizing thoughts and reasoning; they have proven far better as compare to traditional statistical and engineering methods. There are so many products available in finance market based on different requirement (need and liquidity), risk and return scenarios. The major Categories are Asset and Liability each have number of products are as categorized below:

Assets:

1) Saving Accounts (Bank and Postal Dept.)
2) Debt Instruments (Govt. Treasury Bonds, Corporate Bonds etc.)
3) Equity Stocks (Common Stock, Preferable Stocks, Mutual Funds, ULIP, Portfolio Management Services, and Derivatives like Futures and Options)
4) Intangibles (Insurance Policies, Medical Policies, Retirement Schemes etc)
5) Provident Fund and Public Provident Fund (PPF)
6) Structured Products
7) Real Estate
8) Gold
9) Antics and Art

Liabilities:

1) Loans: Secured (Home and Durable) and Unsecured (Personal)
2) Credit Card

Process of investment involves setting of Goals, Managing Portfolio, Controlling Liabilities and Tax planning.

We can use of artificial intelligence to make different finance decisions like asset allocation, cash flow management, stock & equity management, prediction of index value, prediction of commodity prices, prediction of foreign exchange rates, prediction and classifications of consumer risk in the credit industry etc.

We have chosen Distributed Co-Operative Multi Agent System for modeling purposes. As it fulfillment of requirement of software with time, technology, User friendly as well as programmer friendly, reusability and supports higher granularity in software development process. The evaluation and invention of the Agent Oriented methodologies is opted as it can better handle application and it's environment issues like heterogeneity, heave interaction, complexity, Distribution ability, openness, dynamics and unpredictability. The comparative study can be referred from "A Comparative Analysis of Programming Methodologies towards Agent Oriented Programming."[14]

We prefer to use the finance dashboard available for reporting purpose. In customized dashboard one can set their preferences, It may include cash flow, profit and loss (P&L), cost center, budget versus actual, as well as regulatory compliance metrics.

Depending on the level and area of an individual's responsibility, the metrics would be presented for that area at appropriate aggregate levels with security to block non-privileged metrics. A typical dashboard is used in many of the financial areas like financial statements: Income sheet, balance sheet, and cash flow, Cost

[14] Satyen M. Parikh, Dr. B. S. Thakkar, Dr. N. N. Jani, "A Comparative Analysis of Programming Methodologies towards Agent Oriented Programming", presented in Conference on Emerging Technologies & Applications ETA-2006 (1st-2nd Oct 2006)

control: budget versus expenses, Expense cycle: Aging, cash out flow, and purchase requisition, Audit control etc.

A finance dashboard may serve as an effective console to manage compliance workflow and processes. It has observed that the use of dashboard kind of tools increases the usability of the software, as it is very powerful reporting tool and it can be easily understand and convey the message to end user which is not necessarily compute expert, which finally enhance the productivity of corporate.

The key benefits of employing a business management process intelligent agent topology are as follows:

- Timeliness of reports
- Automated measurements against planned goals
- Unfiltered information
- Delivery based on the end-user's preference

BI vendors come up with the number of frameworks designed to help in integrate and leverage multiple existing BI systems and analytic capabilities. It empowers the enterprises to keep better track and manage cross-departmental performance. Theoretically, this enables a powerful enterprise-wide management tool for optimizing performance and profits. However, in practice, there are challenges associated with these frameworks that range from data acquisition, cleansing, and metadata management to aligning models and delivering performance management BI capabilities scalable, securely, and flexibly across diverse user interfaces, dashboards, and portals.

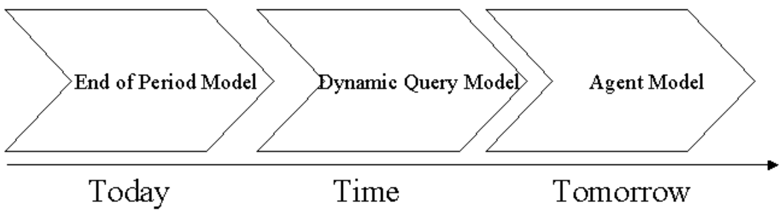

Figure 1.6 Migrations of Reporting Models for Competitive Advantage

To derive business intelligence in financial system the model helps to removing uncertainties, calculating and managing risks and optimizes the returns on investment. We have chosen agent model for business model reporting. In distributed multi agent system model for finance management, all agents' works to achieve a single goal, and all the agents communicate information to each other with out competing for resources. Each type of agent has allocated a job which is helpful to create platform of information to other agent and ultimately all agents may work concurrently for their job. The comparative characteristics of different models are shown in the table[15].

Table 2: Comparative Characteristics of Reporting Models

Sr. No	**Characteristics Of Reporting Model**	**End Of Period Model**	**Dynamic Query Model**	**Agent Model**
1	Timeliness of Data	Stale	Near Real Time	Near Real Time
2	Potential for Managerial Filtering	Yes	Yes	No
3	Delivery Choice	No	Not Typically	Yes
4	Alerts	No	Not Typically	Yes
5	Silo Issue	No	Possible	No

[15] Raisinghani Mahesh, Nugent John H, "Competitive Advantage: Requirements and Issue", Business Intelligence in the Digital Economy: Opportunities,

Multi Agent Systems helps BI applications require complex and sheer volumes of data need to be collecting from multiple, disparate sources, Validating and qualifying the results for accuracy, and performance Improvement Business analytics tools like Traditional query and reporting, OLAP, and Data mining is usable but for effective real time BI solutions include the ability to push information to users. Multi Agent Systems set critical thresholds or triggers and launch a result, report, or note is essential to BI today. The Detail description about topic can be referred in one of my research paper titled "Role of Multi-Agent System in Real Time Business Intelligence."[16]

Limitations and Risk, Idea Group Publication, 2004.

[16] Satyen M. Parikh, J. N. Dharwa, Dr. N. N. Jani, "Role of Multi-Agent System in Real Time Business Intelligence": 83-85 Proceeding of the national conference on Advanced Data Computing Communications & Security at SVICS 14-15 July 2007, ISBN: 978-81-905385-03

Chapter- II

Review of Literature Survey Part-I: Dynamic Market's Investment Vehicles

2.1 Introduction to Investment Problem:

As discussed in our model we have planed to use AI based methods to derive computational intelligence which utilizing thoughts and reasoning and helps to achieve business goal. Our model is supposed to advise process of investment involves setting of Goals, Managing Portfolio, Controlling Liabilities and Tax planning. History is testimony that investors obtained maximum return in stock market, but the risk is also very high. Lot of peoples has booked the loss also, and worst is that some of them became bankrupted. Many investors and academics spent their lives to find methods to predict stock price and stock market since the birth of financial markets. Much effort has been devoted over the past decades to the development of time series forecasting models, still it is impossible to track and predict complex dynamic markets completely.

The capital market behavior has not predicted because of various reasons like:

1) There are large numbers are actors. All have their own mindsets, which is different in many aspects. Even the mind set of one actor react differently in same condition at different time. So that some actors are traders, some are speculators and some are investors.
2) Even same class of investors has different approach of stock picking and exit. Like some prefer the value stocks and some prefer the Growth. Some are greedy and like to trade penny stocks.
3) Different kinds of actors compute risk in different way.

4) Some price of stock can be perceive as good buying opportunity for one trader while for another it may be good selling opportunity. That's way capital market is biggest auction in the world.
5) Actors have different liquidity at different time.
6) Actor's beliefs on different strategies to do analysis like Fundamental, Technical, or Sentimental Analysis. Even some actors throw their money in market on recommendation on another, i.e. on faith.

Overall it is very complex system consists of large number of traders, investors, brokers and corporate persons etc. Which act differently for same conditions.

All works on focusing some hypothesis like Random Walk Behavior of Capital market, Efficient Market Hypothesis

The basic conventional techniques used are

Fundamental Analysis: The fundamental analysis is used to measure quality of stock and it's right valuation, it helps to pick a good stock but it doesn't give any sense how much one has to wait to achieve target price.

Technical Analysis: The technical analysis give lot of sense about market assessment, trend and timing. Conventional technical analysis uses charting approach of parameters of stock. The technical analysis is not useful to find the real valuable stock, as it is very much sensitive about market liquidity, News Announcements and Rumors.

Sentimental Analysis: Sentimental analysis is approach by studying psychological clues, which affects the market.

Computerized modeling of finance market involves basic statistical methods like regression, correlation and other financial econometrics models.

Statistical and Financial Econometric: Econometrics is application of statistical techniques in finance. Economic problems are equal importance in finance applications. Financial econometrics is used to test and establish theories to know effect in finance market with changing economic conditions. Some models are CLRM (Classic Linear Regression Model), Box-Jenkins Modal: ARMA (Auto Regressive Moving Average) or ARIMA (Auto Regressive Integrated Moving Average), Multivariate linear model like VAR (Vector Autoregressive Model), Non-linear models like ARCH (Autoregressive Conditionally Heteroscedastic) Model, GARCH (Generalized Autoregressive Conditionally Heteroscedastic)

Many other techniques like neural network modeling, Genetic Programming has also derived to attempt to predict stock values and make portfolio decisions.

2.2 Fundamental Analysis:

Fundamental analysis is the cornerstone of investing. In fact, it is assumed that every true investment must be followed by fundamental analysis. Fundamental analysis is useful to evaluate the quality of stock, and estimate the true value of stock, also called intrinsic valuation. It is widely used methods that allow the investors to compare similar kind of companies on various fundamental parameters. Basically it is very broad topic and we must need to know all details about the corporation. As every thing is not possible to know and off course company is not providing all it's internal affairs in public, but we can focused on some of available things and try to get the idea of it. Further we can do fundamental analysis on industries or the economy as a whole. Industrial factors like Company Policies and Insiders activity is difficult to know. Most successful investors like billionaire Warren Buffet, CEO of Berkshire

Hathaway, successfully use it. He inherited this skill from broker Benjamin Graham.

Fundamental analysis attempts to find qualitative and quantitative parameters of a company

2.2.1 Qualitative Parameters: Related to or based on the quality or character of something, often as opposed to its size or quantity. Turning to qualitative fundamentals, these are the less tangible factors surrounding a business - things such as the quality of a company's board members and key executives, its brand-name recognition, patents or proprietary technology. We can't ignore the less tangible characteristics of a company. It can further analyse company's Vs industrial aspects. Qualities parameters are common assets in today's marketplace. But they are not listed on company's balance sheets.

- Knowledge and facts: Management Discussion and Analysis
- Business Model: What Company exactly does? How a company makes money? Recession proof, fiscal policy & regulation, economic well being of a company support etc.
- Leadership: Company should be strong-enough position to beat out its competitors in the future.
- Goodwill: Public preference or favors the product of companies, Brand reorganization.
- Management: Executive with their employment history, educational background and any applicable achievements, Conference Calls
- Competitive Advantage: A unique competitive position, Clear tradeoffs and choices vis-à-vis competitors, Activities tailored to the company's strategy, A high degree of fit across activities (it is the activity system, not the parts, that ensure sustainability), A high degree of operational effectiveness

- Corporate Governance: Corporate governance describes the policies in place within an organization denoting the relationships and responsibilities between management, directors and stakeholders. It includes Financial and Information Transparency, Stakeholder Rights, Structure of the Board of Directors.

2.2.2.Quantitative Parameters: Capable of being measured or expressed in numerical terms.

- Financial Health of Company: profit, revenue, expenses, assets, debt etc.
- Future earning estimates: Company’s revenue growth.

To perform quantitative fundamentals, the massive amount of numbers in a company's financial statements can be bewildering and intimidating to many investors. On the other hand, if we know how to analyze them, the financial statements are a gold mine of information.

- The Balance Sheet: The balance sheet represents a record of a company's assets, liabilities and equity at a particular point in time. The balance sheet is named by the fact that a business's financial structure balances in the following manner:

  Assets = Liabilities + Shareholders' Equity
- The Income Statement: While the balance sheet takes a snapshot approach in examining a business, the income statement measures a company's performance over a specific time frame. Technically, we could have a balance sheet for a month or even a day, but we'll only see public companies report quarterly and annually.

  The income statement presents information about revenues, expenses and profit that was generated as a result of the business' operations for that period. For a company, the top line is revenue while the bottom line is net income.

- Statement of Cash Flows: The statement of cash flows represents a record of a business' cash inflows and outflows over a period of time. The cash flow statement is important because it's very difficult for a business to manipulate its cash situation. Typically, a statement of cash flows focuses on the following cash-related activities:

  Operating Cash Flow (OCF): Cash generated from day-to-day business operations

  Cash from investing (CFI): Cash used for investing in assets, as well as the proceeds from the sale of other businesses, equipment or long-term assets

  Cash from financing (CFF): Cash paid or received from the issuing and borrowing of funds

2.2.3 Ratio Analysis:

Financial ratios are mathematical calculations using figures mainly from the financial statements, and they are used to gain an idea of a company's valuation and financial performance.

The calculations produced by the valuation ratios are used to gain some understanding of the company's value. The ratios are compared on an absolute basis, in which there are threshold values. For example, in price-to-book, companies trading below '1' are considered undervalued. Valuation ratios are also compared to the historical values of the ratio for the company, along with comparison to competitors and the overall market itself.

- Quick Ratio: Measure Liquidity: Subtract inventory from current assets and then divide by current liabilities. If the ratio is 1 or higher, it says that the company has enough cash and liquid assets to cover its short-term debt obligations.

$$\text{Quick Ratio} = \frac{\text{Current Assets - Inventories}}{\text{Current Liabilities}}$$

- The Price/Earnings Ratio: Mostly used for valuation of stock
  Many people use the price/earnings ratio (P/E) to get a quick indication of whether the stock price is reasonable given the company's earnings. When we divide the stock price by the company's earnings per share for last one year earning, we end up with a P/E ratio (also known as the multiple), People that can help we determine whether a stock is fairly valued. But it may confuse investor and not always determine true valuation.
  The very well known and successful investor Warren Buffett recommends to buys only companies with trailing P/Es of 10 or less.

- Price/Earnings/Growth: The P/E with growth
  Price/earnings/growth (PEG) ratio is designed to take growth in account along with PE. To calculate the PEG, we divide the P/E by the earnings growth of the company. Many people feel that the PEG is more accurate than the P/E because it takes future growth into account. The problem with the PEG, like that with the forward P/E, is that we are basing our information on earnings estimates, which have historically been unreliable.

- Price-to-Sales Ratio: Effective for Uncovering Revenue
  Because P/E ratios are generally useless with companies that have no earnings, some investors use the price-to-sales ratio

(P/S) to decide whether to buy a stock. The reasoning is that although one can play with earnings, one can't play with revenue. With the P/S ratio, we compare price to sales revenue. To calculate the price-to-sales ratio, we divide the company's total market value by the total sales revenue booked for the previous year. Some people claim that the P/S is more reliable than the P/E or the PEG.

- Return on Equity: Measuring the Financial Health of a Company
  Return on equity (ROE) is a tool that helps us to measure how effectively the company is being managed. Some people consider ROE one of the most important measures of a company's overall financial performance. It is calculated ROE by dividing net income by net worth, although this ratio is not as clear-cut because we must rely on subjective variables to calculate manager efficiency. In general, the higher the ROE, the more effective the company is at using its resources and the more productive the management team.

- Earnings Retention Ratio: The percent of earnings credited to retained earnings. In other words, the proportion of net income that is not paid out as dividends.
  Calculated as:

$$\text{Earnings Retention Ratio} = \frac{\text{Net Income} - \text{Dividends}}{\text{Net Income}}$$

After deduction of all expenses, including taxes, the net profits of a company are split into two parts -- dividends and plough back. Dividend is that portion of a company's profits which is distributed to its shareholders, whereas plough back is the portion that the company retains and gets added to its reserves. The figures for plough back and reserves of any company can be obtained by a cursory glance at its balance sheet and profit and loss account. Plough back is important because it not only increases the reserves of a company but also provides the company with funds required for its growth and expansion. All growth companies maintain a high level of plough back. So if we are looking for a growth company to invest in, we should examine its plough back figures. Companies that have no intention of expanding are unlikely to plough back a large portion of their profits. Reserves constitute the accumulated retained profits of a company. It is important to compare the size of a company's reserves with the size of its equity capital. This will indicate whether the company is in a position to issue bonus shares. As a rule-of-thumb, a company whose reserves are double that of its equity capital should be in a position to make a liberal bonus issue. Retained profits also belong to the shareholders. This is why reserves are often referred to as shareholders' funds. Therefore, any addition to the reserves of a company will normally lead to a corresponding an increase in the price of our shares. The higher the reserves, the greater will be the value of our shareholding. Retained profits (plough back) may not come to us in the form of cash, but they benefit us by pushing up the price of our shares.

- Book value per share: We will come across this term very often in investment discussions. Book value per share indicates what each share of a company is worth according to the company's books of accounts. The company's books of account maintain a record of what the company owns (assets), and what it owes to its creditors (liabilities). If we subtract the total liabilities of a company from its total assets, then what is left belongs to the shareholders, called the shareholders' funds. If we divide shareholders' funds by the total number of equity shares issued by the company, the figure that we get will be the book value per share.

$$\text{Book Value per share} = \frac{\text{Shareholders' funds}}{\text{Total number of equity shares issued}}$$

The figure for shareholders' funds can also be obtained by adding the equity capital and reserves of the company. Book value is a historical record based on the original prices at which assets of the company were originally purchased. It doesn't reflect the current market value of the company's assets. Therefore, book value per share has limited usage as a tool for evaluating the market value or price of a company's shares. It can, at best, give we a rough idea of what a company's shares should at least be worth. The market prices of shares are generally much higher than what their book values indicate. Therefore, if we come across a share whose market price is around its book value, the chances are that it is under-priced. This is one way in which the book value per share ratio can prove useful to we while assessing whether a particular share is over- or under priced.

- Dividend and yield: There are many investors who buy shares with the objective of earning a regular income from their investment. Their primary concern is with the amount that a company gives as dividends and capital appreciation being only a secondary consideration. For such investors, dividends obviously play a crucial role in their investment calculations. It is illogical to draw a distinction between capital appreciation and dividends. Money is money and it doesn't really matter whether it comes from capital appreciation or from dividends. A wise investor is primarily concerned with the total returns on his investment and one doesn't really care whether these returns come from capital appreciation or dividends, or through varying combinations of both. In fact, investors in high tax brackets prefer to get most of their returns through long-term capital appreciation because of tax considerations. Companies that give high dividends not only have a poor growth record but often also poor future growth prospects. If a company distributes the bulk of its earnings in the form of dividends, there will not be enough plough back for financing future growth. On the other hand, high growth companies generally have a poor dividend record. This is because such companies use only a relatively small proportion of their earnings to pay dividends. In the long run, however, high growth companies not only offer steep capital appreciation but also end up paying higher dividends. On the whole, therefore, we are likely to get much higher total returns on our investment if we invest for capital appreciation rather than for dividends. In short, it all boils down to whether we are prepared to sacrifice a part of our immediate dividend income in the expectation of greater capital appreciation and higher dividends in the years to come and the whole issue is basically a trade-off between capital appreciation and income. Investors are not really interested in dividends but in the relationship that dividends bear to the market price of the company's shares. This relationship is best expressed by the ratio called yield or dividend yield:

Yield = (Dividend per share / market price per share) x 100

Yield indicates the percentage of return that we can expect by way of dividends on our investment made at the prevailing market price. The concept of yield is best clarified by the following illustration. Let us suppose we have invested Rs 2,000 in buying 100 shares of XYZ Ltd at Rs 20 per share with a face value of Rs 10 each. If XYZ announces a dividend of 20 per cent (Rs 2 per share), then we stand to get a total dividend of Rs 200. Since we bought these shares at Rs 20 per share, the yield on our investment is 10 per cent (Yield = 2/20 x 100). Thus, while the dividend was 20 per cent; but our yield is actually 10 per cent. The concept of yield is of far greater practical utility than dividends. It gives we an idea of what we are earning through dividends on the current market price of our shares. Average yield figures in India usually vary around 2 percent of the market value of the shares. If we have a share portfolio consisting of shares belonging to a large number of both high-growth and high-dividend companies, then on an average our dividend in-come is likely to be around 2 percent of the total market value of our portfolio.

There are many other fundamental stock measurements, including return on investment (ROI), debt-to-equity ratio, and return on assets (ROA). The purpose of many of these fundamental tools is to determine whether a stock is a good value compared to its price.

2.2.4 The Concept of Value Buying Approach[17]:

The price on the stock market does not fully reflect a stock's "real" value. After all, why would we be doing price analysis if the stock market were always correct? In financial jargon, this true value is known as the intrinsic value.

For example, let's say that a company's stock was trading at Rs. 200. After doing extensive fundamental analysis on the company, we determine that it's intrinsic value of the firm to be Rs. 250. This is clearly relevant because an investor wants to buy stocks that are trading at prices significantly below their estimated intrinsic value.

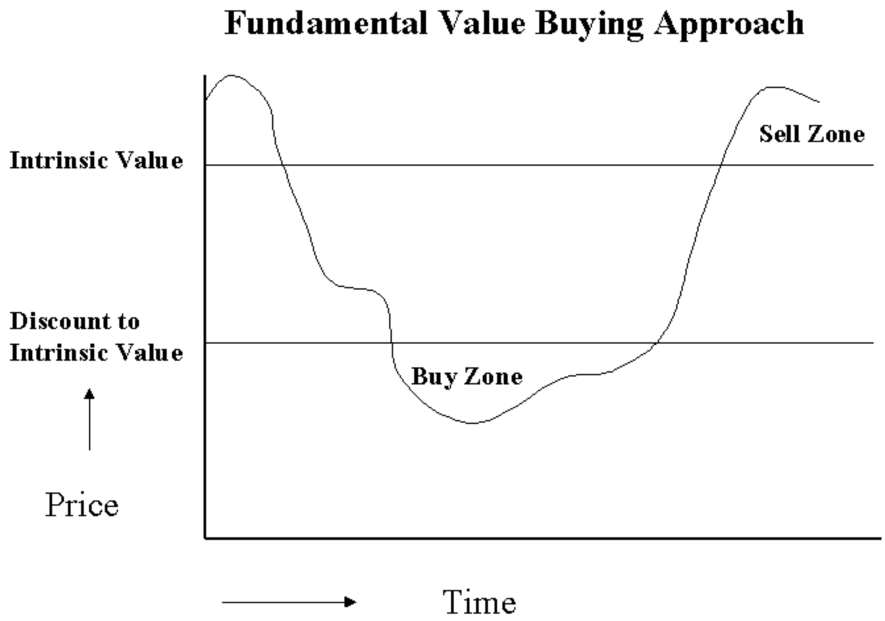

Figure 2.1 Fundamental Value Buying Approach

2.2.5 Criticisms of Fundamental Analysis

The biggest criticisms of fundamental analysis come primarily from two groups: proponents of technical analysis and believers of the "efficient market hypothesis".

The big unknowns in fundamental analysis are:

[17] Charles H Brandes, "Value Investing today" third edition, McGrow-Hill, 2004.

- One doesn't know how long it will take for the intrinsic value to be reflected in the marketplace. It means that fundamental analysis make sure at given point of time the valuation of company is attractive but it not estimate any time when the price will move above the intrinsic value.
- One doesn't know estimate of intrinsic value is correct.
- Fundamental analysis method is based on the information that a corporation provides. If the corporation is manipulating the numbers truthful. One needs the skill and knowledge to uncover such irregularities.
- In fundamental analysis we are making assumptions about a company's future prospects based on past/present performance that are not the true in all cases.
- Qualitative parameter is also very important but we don't have way to calculate or automate such parameter for more accurate estimate the valuation of a company.

2.3 Technical Analysis:

Technical rules are widely used for market assessment and timing, which is the unsupported aspect of fundamental analysis. Technical analysis really an attempt to determine what direction, or trend, by producing trading signal based on the basic parameters like price movement, like open, close, low, and high price for each day and volume information available from market. It is study based on supply and demand phenomena in a market. Similar to the fundamental analysis it has qualitative and quantitative parameters. It is based on different chart like Price chart, Price/Volume chart, Bar chart, Candlestick chart etc.

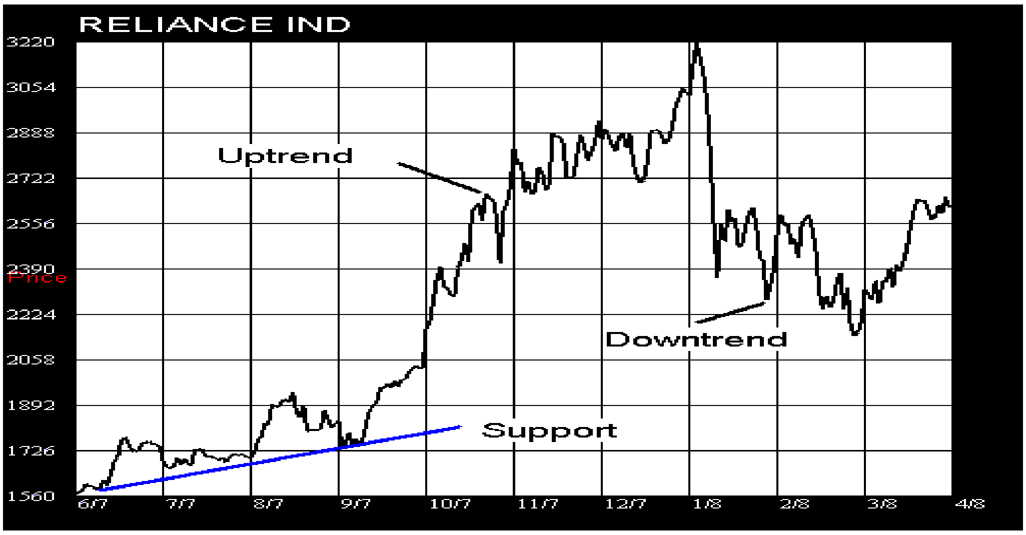

Figure 2.2 Technical Analyses: Trend and Support

The qualitative parameters rely on the interpretation of the form of geometric patterns such as double bottoms, head-and-shoulders, and support and resistance levels. The quantitative parameters create indicators like moving average, relative strength indicators etc. Both parameters can be characterized by appropriate sequences of local minima and/or maxima (Neftci [18]1991).

Figure 2.3 Technical Analyses: Head and Shoulder

[18] Neftci, S.N., "Naïve trading rules in financial markets and Wiener-Kolmogorov prediction theory: A study of 'technical analysis", Journal of Business, 64, (1991), 549-571.

The technical analysis is based on three assumptions:

- The market discounts everything.
- Price moves in trends like Uptrend, Downtrand, Sideways
- History tends to repeat itself.

All technical analysis methods basically predict the price based on the given assumptions and try to interpret the trend, by charting basic trading parameters. Whoever critics of technical analysis say that it is useless as every one can interpret in own way and generally result of interpretation is ambiguous.

One of the most indicators used in technical analysis is moving average used to identify trend more visible by averaging the price for finite past period. In technical analysis timing is very important. There are two types of chart signals reversal and continuation that creates a trading signal.

Some of the widely used patterns are head and shoulders, cup and handle, double tops and double bottom, triangle, Flags and pennants and wedge chart.

A head and shoulders pattern is reversal pattern that signals a security is likely to move against its previous trend. A cup and handle pattern is a bullish continuation pattern in which the upward trend has paused but will continue in an upward direction once the pattern is confirmed. Double tops and double bottoms are formed after a sustained trend and signal to chartists that the trend is about to reverse. The pattern is created when a price movement tests support or resistance levels twice and is unable to break through. A triangle is a technical analysis pattern created by drawing trendlines along a price range that gets narrower over time because of lower tops and higher bottoms. Variations of a triangle include ascending and descending triangles. Flags and pennants are short-term continuation patterns that are formed when there is a sharp price movement followed by a sideways price movement.

The wedge chart pattern can be either a continuation or reversal pattern. It is similar to a symmetrical triangle except that the wedge pattern slants in an upward or downward direction. A rounding bottom (or saucer bottom) is a long-term reversal pattern that signals a shift from a downward trend to an upward trend.

However Mamaysky and Wang[19] (2000) reject this thought and proved, that sophisticated nonparametric statistical techniques can recognize patterns, and indicators/signals used by technical analysts produce incremental information and results are significantly useful. The similar result is produces by Brock, Lakonishok and LeBaron[20] by showing significant improvement in average return by applying moving-average rules.

2.4 Sentiment Analysis:

Sentiment analysis involves studying psychological clues to determine where the market is headed. Sentiment analysis is also important but unfortunately it is not as clear-cut as fundamental or technical analysis. The phenomenon is based on the theory that do opposite than what the average crowds is doing. There are some important psychological indicators that help to determine when the market reverses. The following psychological indicators can be use to perform sentiment analysis.

- Future Options & Exchange Volatility: The more extreme the volatility the more likely it is that the market will reverse direction.

[19] Lo, Andrew W., Harry Mamaysky and Jiang Wang (2000), “Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation,” Journal of Finance, 55, 1705-1765

[20] W. Brock, J. Lakonishok, and B. LeBaron. “Simple technical rules and the stochastic properties of stock returns”, Journal of Finance, 47:1731—1764, 1992.

- Media: The Media In other words, by the time something is reported in the media. Some of the investment and brokerage firms also broadcast their opinion and stock specific grades like Buy/Sell/Hold, under performer/Performers/Outperformers and Bullish rank/ Volatility rank etc for the stock or set of stocks, which finally affects their clients' sentiments.

  Some of the brokerage houses use the thumbnail, which affects sentiments of viewers, some example of these, are: : Confirm Up, : Upside, : Unreliable Up, : Confirm down, : Down side, : Down but little doubtful.
- Mutual Fund Redemptions: Whether individual investors are selling their mutual funds, it gives a clue as to what the crowd is doing.
- Widely used common technical analysis attributes like Exponential Moving Average, Relative Strength Indicators, and Chaikin Money affects sentiments of large numbers of it's users.
- Capitulation: It refers to what happens when everyone in the market panics and immediately sells all of their stocks, causing a stock crash.

Sentiment analysis helps to determine when market hits the bottom or timing for current trend reversal. Research to understand sentiments is gets the successful and few model has been proposed to understand volatility and risk management, Market overreaction, The phenomena of natural and artificially created bubbles and subsequent crashes is explained. (D. Chowdhury, D. Stauffer[21]), the cumulative effect of the consecutive local overreaction pattern is one of the key components of a

[21] D. Chowdhury, D. Stauffer "A generalized spin model of financial markets", The European Physical Journal B - Condensed Matter and Complex Systems Page 477-482. 1434-6028 (Print) 1434-6036 (Online) 2002

financial market bubble (A. Duran and G. Caginalp[22]). Practically history is the testimony that fundamentals and effective market hypothesis challenged by tremendous investor fear especially at the time of crash, and most of the time even fundamentals not taken in account. So sentimental analysis has its own importance over the any other analysis methods.

2.5 Derivatives of Capital Market:

Derivatives are financial contracts whose value/price is dependent on the behavior of the price of one or more basic underlying assets (often simply known as the underlying). These contracts are legally binding agreements, made on the trading screen of stock exchanges, to buy or sell an asset in future.

There are various derivatives of capital market like future & options, equity mutual fund etc. It is worthless to discuss all derivatives in detail. The model developed to ride following derivatives; hence brief discussion is included in order to understand the work carried out in subsequent chapters.

- ULIP (Unit Linked Insurance Policy)
- Equity Mutual Fund

2.5.1 Unit Linked Insurance Policy (ULIP): ULIP is comparatively new investment vehicle approved by Insurance Regulatory and Development Authority (IRDA), and the industry players are unanimous in their opinion that the growth of the overall industry in the future will be led by ULIPs. The investments horizon is comparative long term, as minimum term to take benefits is if five years. Ideally ULIPs are considered for those classes of investors who want to put money in a investment product that earns them

[22] A. Duran and G. Caginalp, "Data Mining for Overreaction in Financial Markets", Proceeding (467) Software Engineering and Applications – 2005 Editor:

decent returns by further investing the money in the market, and at the same time ensure a life cover and tax efficiency. As per guidelines by the IRDA, ULIP allows insurance companies to accept fund switches, by which an investor can switch from liquid fund to an equity fund. The main advantage of ULIP over the other investment instrument is that it provides easy control and switching in various available categories along with the protection. The other advantage is the cheapest switching among the various categories as most of ULIP provides first 4-5 switches per year free and the additional switches can be performed at very low fixed cost irrespective the present valuation of fund.

2.5.2 Mutual Fund:

Mutual Fund is a financial Product, which is categorized as a low risk high return asset. The management of mutual fund is in the hands of experienced and knowledgeable fund managers.

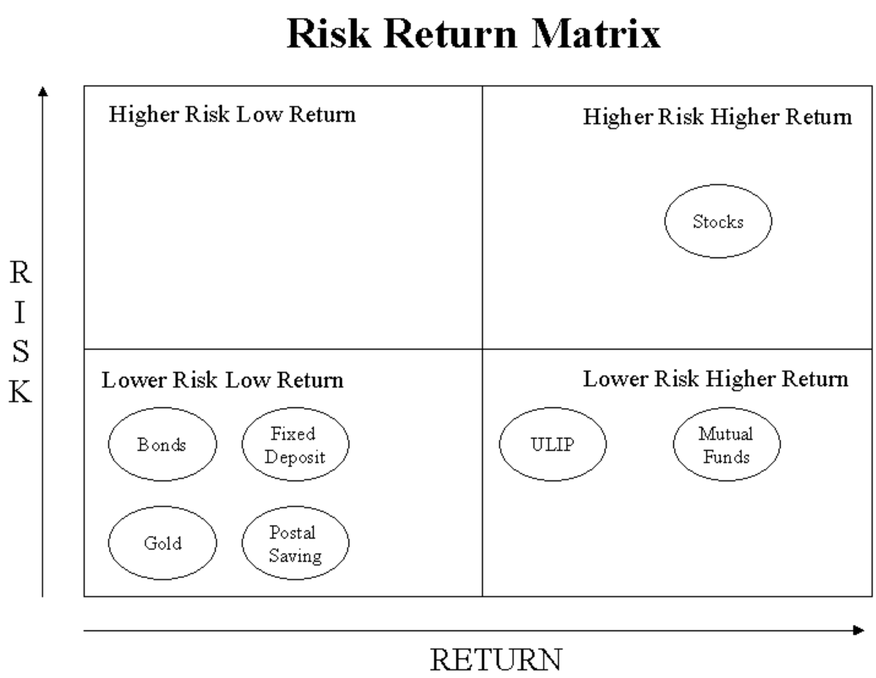

Figure 2.4: Risk Return Matrix

W.-T. Tsai and M.H. Hamza ISBN: 0-88986-529-9 ISSN: 1482-7905 ISBN (CD): 0-88986-531-0 ISSN (CD): 1482-7905

There are various types of mutual fund available. Each one has some special characteristics particularly in assets in their portfolio. Mutual fund by its nature can be classified in to the categories like Equity Fund, Debt Fund and Balanced Fund. One more classification is given by its asset allocation specification like Index Schemes, Sector Specific Schemes. Some of the mutual fund schemes offer tax rebate to its investor and known as tax saving schemes. Another classification is given by the investment objectives like Growth, Income, Balanced schemes etc. The main advantages of mutual fund are Professional Management, Diversification, and Economy-in- operation, Liquidity etc.

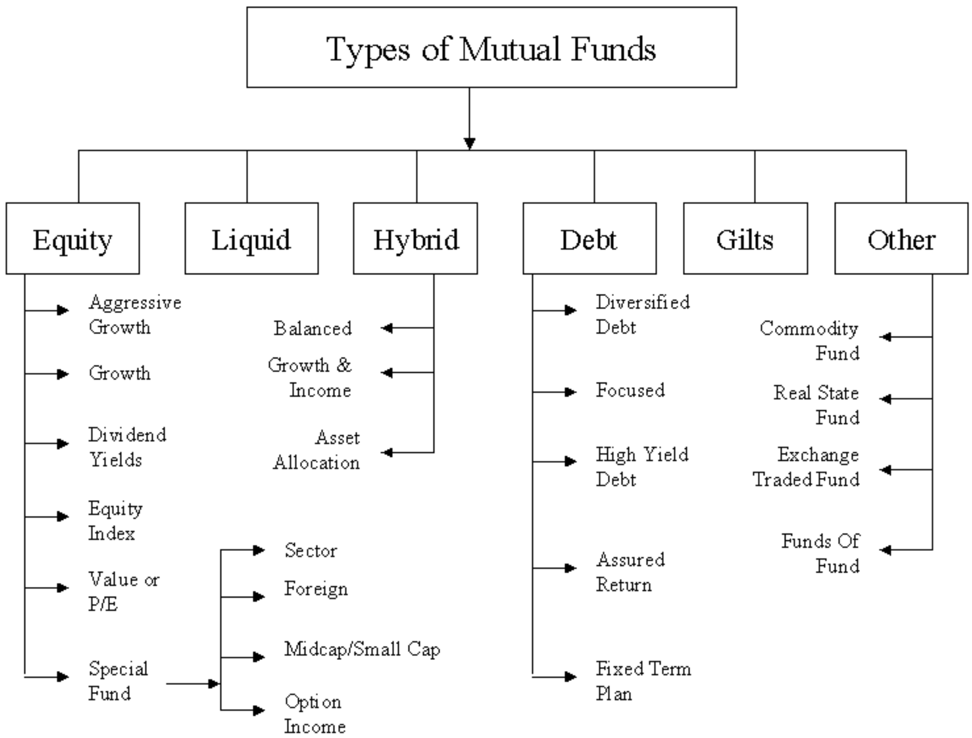

Chart 1: Types of Mutual Fund

Mutual Funds: Benefits

The benefits of investing in mutual funds are as follows:

- Management Techniques: Experienced fund managers using advanced quantitative and mathematical techniques manage your money.
- Diversification: Mutual funds aim to reduce the volatility of returns through diversification by investing in a number of companies across a broad section of industries and sectors.
- Liquidity: Open-ended mutual funds are priced daily and are always willing to buy back units from investors. This mean that investors can sell their holdings in mutual fund investments anytime without worrying about finding a buyer at the right price.
- Tax Efficiency: Currently, dividends are tax-free in the hands of the investor. There is no distribution tax payable by the Mutual Fund on dividends distributed. There is no tax deduction at source on dividends as well. Investments for over 12 months qualify for long-term capital gains. Moreover for resident investors there is no TDS on redemption of the units. The recently introduced Securities Transaction Tax is applicable to equity fund investments.
- Low transaction costs: Since mutual funds are a pool of money of many investors, the amount of investment made in securities is large. This therefore results in paying lower brokerage due to economies of scale.
- Transparency: Prices of open-ended mutual funds are declared daily. Regular updates on the value of your investment are available. The portfolio is also disclosed regularly with the fund manager's investment strategy and outlook.

- Well-regulated industry: All the mutual funds are registered with SEBI and they function under strict regulations designed to protect the interests of investors.
- Convenience of small investments: Under normal circumstances, an individual investor would not be able to diversify his investments (and thus minimize risk) across a wide array of securities due to the small size of his investments and inherently higher transaction costs. A mutual fund on the other hand allows even individual investors to hold a diversified array of securities due to the fact that it invests in a portfolio of stocks. A mutual fund therefore permits risk diversification without an investor having to invest large amounts of money.

Mutual Funds: Risks

Risk is an inherent aspect of every form of investment. For mutual fund investments, risks would include variability, or period-by-period fluctuations in total return.

- Market Risk: At times the prices or yields of all the securities in a particular market rise or fall due to broad outside influences. This change in price is due to "market risk".
- Inflation Risk: Whenever the rate of inflation exceeds the earnings on your investment, you run the risk that you'll actually be able to buy less, not more.
- Credit Risk: Sometime due to instability of the company, it will not be able to pay the interest you are promised, or repay your principal when the investment matures.
- Interest Rate Risk: Changing interest rates affect both equities and bonds in many ways hence affects mutual funds too, thereby to possibly large movements in the net asset value (NAV).

- Investment Risks: In the sectoral or specific type of fund schemes, companies and may be more volatile than a more diversified portfolio of equities.
- Liquidity Risk: Thinly traded securities carry the danger of not being easily saleable at or near their real values. The fund manager may therefore be unable to quickly sell an illiquid bond and this might affect the price of the fund unfavorably
- Changes in the Government Policy: Changes in Government policy especially in regard to the tax benefits may impact the business prospects of the companies leading to an impact on the investments made by the fund.

Efficient management advices are definitely helpful as investors rarely have complete awareness and time to manage.

Chapter- III

Review of Literature Survey Part-II: Financial Models, Hypothesis and Financial Data Forecasting Methods:

3.1 Introduction to Financial Models:

Automation or computerized of financial model incorporates few but relevant attributes of concern finance problem and helps us to do analysis. A good financial model forces the problem solver to state the problem in formal way, so the according to our perception the constraints and objective can be set. A quality model should be flexible enough to experiment with many different course of action, and to do sensitive analysis. Sensitive analysis empowers model to try out the effects of various changes, i.e. effect of changes in one variable to another. This result must be noted quicker than experiments on the system in real life. The main strategies used in financial modeling are optimization and deterministic what-if kind of simulations.

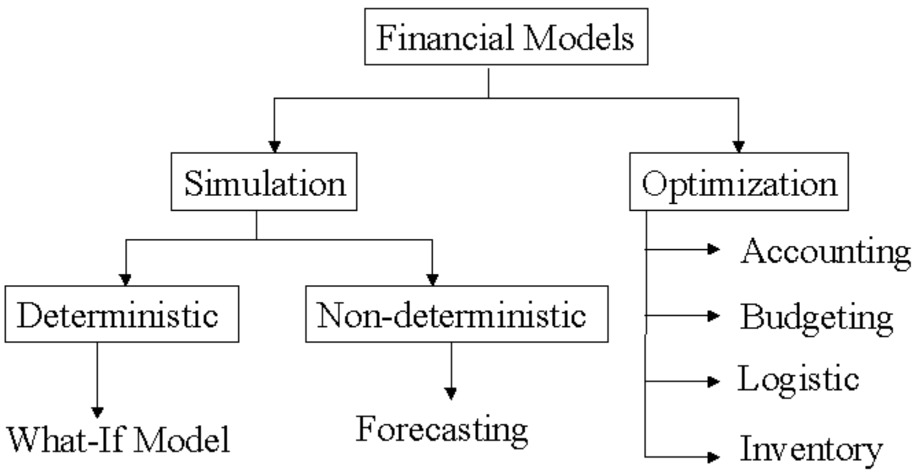

Chart 2: Classification of Financial Models

The financial model is suggested and used everywhere in finance like accounting, capital budgeting, Inventory management. At earlier stage of developing Hirschleifer[23] discussed in details about careful consideration in theoretical models. Miller and Orr[24] suggested model for analogy between cash and inventory management using quality control procedure for investing and disinvesting surplus cash. Morgan[25] describe deterministic accounting model which calculates consolidated income and expense statements, balance sheets, cash flow balances and performance measures for future years, but the main purpose of the model was to test for sensitivity of earning per share to various changes in price, etc.

3.2 Financial Data Classification and Hypothesis:

Financial data is available in different variety, size and shape and forms. In general, it gives the snapshot of trade where price and other related parameters are recorded at the time of trade. As most of the financial data having very high frequency so the number of observations available for analysis is also very large and it implies to use more advanced technique for accurate analysis.

Chris Brooks[26] has broadly divided financial data in following categories:

a) Time Series data: This type of data samples is collected at regular frequencies. Like Company declares their financial result quarterly. Government budget is declared annually.
b) Cross Sectional Data: The data of data where number of variables are collected at a single point in time. Example Stock value returns at Sensex.

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[23] Hirshleifer, J., "On the theory of optimal decision", Journal of Political Economy(1958) Pg. 329-352.
[24] Miller, M., and Orr, D., "A Model of demand for money by firms"
[25] Morgan, J. L., "The Dow Chemicals Corporate Financial Planning Model" In Schreiber (1970), Pg. 374-395
[26] Chris Brooks: "Introductory Econometrics for Finance": Cambridge University Press, 2002.

c) Panel Data: Panel data is the data, which is Time Series as well as Cross Sectional data, example Daily prices of small cap companies for two years.

There are different methods developed to analyze financial data, Capital market is not an exception, different theories & hypothesis are given to understand the return and nature of capital market. We must have to pay attention to the main milestones in the journey of finance market prediction are:

Efficient Market Hypothesis (EMH)

Chaos Theory

3.3 Efficient Market Hypothesis:

The Efficient Market Hypothesis (EMH) given by Fama [27](1965-1970) was most accepted in the financial community (Malkiel[28] 1987, Tisibouris & Zeidenberg[29] 1995). According to EMH, The all traders are using efficiently the information available and all news is promptly incorporated in prices in very short period of time. As it is not possible to predict news by nature, the past prices cannot help in forecasting future price changes (Malkiel[11], 1989). According to EMH the best prediction for a price is the current price and the actual prices follow is called a random walk as new information occurs randomly. Thus, investors cannot devise an investment strategy to yield abnormal profits on the basis of an analysis of past price patterns. Followers of the efficient market hypothesis are usually not agreeing with any kind of fundamental and technical analysts. According to EMH it is impossible to

[27] Fama, Eugene "Efficient Capital Markets: A Review of Theory and Empirical Work", Journal of Finance, 25, 383-417, 1970

[28] Malkiel, B. G., *A Random Walk Down Wall Street*, New York, 1996

[29] Tsibouris G. & Zeidenberg M., *Testing the efficient markets hypothesis with gradient descent algorithms*, 1995

produce consistent long run returns, through either fundamental or technical analysis.

3.3.1 Critics on Efficient Market Hypothesis:

In past decade the efficient market hypothesis has been disregard and contradict by a reasonable studies, Ingber[30], 1996; Taylor[31], Lo and MacKinlay[32], Campbell[33] 1997, Frances and van Dijk[34] (2000); and Tsay[35](2002) some other researchers has proved by statistical models that it is possible to generate consistent long run returns even in today's technical and efficient era, and much evidence suggests that the capital markets are not efficient and facts of predictability of security return from historical price patterns. Most of these studies are based on financial time series and financial econometrics, involving both linear and nonlinear estimation and forecasting methods. As many financial markets are far from perfectly efficient, in the sense that asset prices do not always reflect all available information. This is also acknowledged by the empirical trading activities of many investors. The EMH may be true in the ideal globe with equal information distribution, but in reality today markets retain several players who can do better than the market. Efficient markets hypothesis relevant to perfect knowledge and technology also perfect prediction would only serve to enforce the conditions.

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[30] Ingber, L. (1996). Statistical mechanics of nonlinear non-equilibrium financial markets: Applications to optimized trading. *Mathematical Computer Modelling*.

[31] Taylor, S. J. (Ed.), (1994). *Modelling Financial Time Series*. Chichester: J. Wiley & Sons.

32 Lo, A. W. & MacKinlay, A. C. (1999) 'A Non-Random Walk Down Wall Street. Princeton University Press'

[33] Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay (1997), *The Econometrics of Financial Markets*. Princeton, NJ: Princeton University Press.

[34] Franses, Philip Hans, and Dick van Dijk (2000), *Non-linear Time Series Models in Empirical Finance*. Cambridge, UK: Cambridge University Press.

[35] Tsay, Ruey S. (2002), '*Analysis of Financial Time Series*', New York: John Wiley and Sons, Inc.

3.4 Chaos Theory:

A comparatively innovative advancement to modeling nonlinear dynamic systems like the capital market is chaos theory. Chaos theory is based on the assumption that part of the process is deterministic and part of the process is random. Chaos is a nonlinear process, which appears to be random. Human has limitation to understand such complex process and chaos theory has offered the ways to analyze a process under this assumption. Using concept of chaos theory various theoretical tests have been developed to test if a system is chaotic (has chaos in its time series). Chaos theory is an attempt to show that order does exist in apparent randomness. By implying that the capital market is chaotic and not simply random, chaos theory contradicts the EMH. A very similar concept to chaos theory was the rational expectation equilibrium (REE), introduced by Muth[36], 1961. Similar to chaos the rational expectations model makes two assumptions (Sargent[37] 1986). First market representative are rational and are able to optimize an objective function. Second the same information is available to all market representatives. Therefore agents are expected to be fully informed and to know all equations of the economic model. Perfectly rational agents maximize their utility function and are able to solve complicated optimization problems. This seems to be highly demanding, and therefore bounded rationality models have been proposed. The models with agents being bounded rational and having access to different information

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[36] Muth, J.F., (1961) "Rational expectations and the theory of price movements", Econometrica 29, 315-335.

[37] Sargent, T. (1986), 'Rational Expectations and Inflation', Harper and Row, New York

Sargent, T. (1993), "Bounded Rationality in Macroeconomics", Oxford University Press,
Oxford, UK.

sets may still converge to the rational expectation equilibrium. Therefore these two markets may be indistinguishable on a macro-level. F. Van Der Ploeg[38] presented a model for bond pricing equilibrium by taking assumption that bond market is nonlinear and he shows that equlibrium in bond pricing is obtained where expectations are self fulfiling in both the mean and variance and it can be obtaind by appliying rational expectation equilibrium.

We have limitations in attention because of conventional process, which presents of deterministic nonlinear systems dynamics that appear random. The conclusion rendered linear processes as a unique case in a huge spectrum of possible deterministic systems. Analyzing nonlinear phenomena quickly became particularly important for those of us who have to forecast real world data. Opportunity are in the form of chaotic and anybody who is able to model the price structure and make convincing predictions using that model will have access to information, which are hidden or directly unavailable. In recent decade many academicians and researchers has try to identify the chaos or non-linear patterns from the time series data. One of such basic study was proposed by Brock, Deckert, and Scheinkman[39] (1987), further elaborated in Brock, Deckert, Scheinkman, and LeBaron[40] (1996), propose a test for detecting nonlinear patterns in time series. Following Kocenda[41] (2001), the null hypothesis is that the data are independently and identically distributed processes. This test, known as the BDS test,

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[38] F. Van Der Ploeg, "Rational Expectations, Risk and Chaos in Financial Markets", *The Economic Journal*, Vol. 96, Supplement: Conference Papers (1986), pp. 151-162 publication: Blackwell Publishing for the Royal Economic Society.

[39] Brock, W., W. Deckert, and J. Scheinkman (1987), "A Test for Independence Based on the Correlation Dimension," Working Paper, Department of Economics, University of Wisconsin at Madison.

[40] Brock, W., W. Deckert, J. Scheinkman and B. LeBaron (1996), "A Test for Independence Based on the Correlation Dimension." *Econometric Reviews* 15: 197–235.

[41] Kocenda, E. (2001) "An Alternative to the BDS Test: Integration Across the Correlation Integral", Econometric Reviews 20, 337–351

is unique in its ability to detect non-literalities independently of linear dependencies in the data. The test rests on the correlation integral, developed to distinguish between chaotic deterministic systems and stochastic systems.

One immediately realizes that the underlying data generating process of any observed phenomenon is unknown and that the chances are unlimited. The oversimplifying assumptions underlying linear models that we build quickly render such models as obsolete.

The efficient markets hypothesis will no longer valid in present state. In another way, chances of superior profits occur when one set their stock prices incorrectly because of chaos and another investors are able to perceive the difference before it is corrected. Accurate forecasting for all would eliminate these discrepancies and with them the prospect for enhanced profit.

In favor of chaos theory in finance market the work is produce by Savit[42], Peter[43], Deboeck[44]. The research in non-linear chaotic time series analysis Principe & Kuo[45], Mukherjee, Osuna & Girosi[46] also applicable to analyze finance market data.

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[42] Savit, R. (1989), 'Nonlinearities and Chaotic Effects in Option Prices', Journal of Futures Markets 9, 507-518.
Savit, R. (1988), 'When Random Is Not Random: An Introduction to Chaos in Market Prices', Journal of Futures Markets 8, 271-290.

[43] Peters, E. (1991). Chaos and order in the capital markets. John Wiley & Sons

[44] Deboeck GJ (ed) Trading on the edge: neural, genetic and fuzzy systems for chaotic financial markets, New York:148–173
Deboeck GJ (1994) Using GAs to optimize a trading system. In: Deboeck GJ (ed) Trading on the edge: neural, genetic and Fuzzy Systems for chaotic financial markets. John Wiley & Sons:174–188

[45] Principe, J. C.&Kuo, J.-M. (1995). Dynamic modelling of chaotic time series with neural networks In Advances in Neural Information Processing Systems (Vol. 7, pp. 311–318), MIT Press

[46] Mukherjee, S., Osuna, E., & Girosi, F. (1997). Nonlinear prediction of chaotic time series using support vector machines. In J. Principe, L. Giles, N. Morgan, & E. Wilson, (Eds.), IEEE Workshop on Neural Networks forSignal Processing VII (p. 511), IEEE Press.

3.5 Time Series Data Modeling:

Time series modeling approach is one of the major techniques widely used in practice. Time series approach has the advantage of easier data collection and modeling groundwork compared to another major forecasting approach underlying method where a number of advisory or contributory variables have to be identified and predicted. In time series forecasting the following steps is performed during the modeling.

1. Historical data of the prediction variable are collected.
2. Analyze the contributory variables and relationship among the variables in time series observations.
3. Develop a model that acquires the core relationships identified in step 2.

The model is then used to extrapolate the time series into the future for forecasting.

Data generating processes can be categorized broadly into one or more in the following:

a) Linear deterministic
b) Nonlinear deterministic
c) Linear-stochastic
d) Nonlinear-stochastic
e) Random.

In real world it is most of the financial data patterns are nonlinear, nonlinear-stochastic, and random systems while it is very rare to find simple linear or linear-stochastic systems. Different econometrics and artificial intelligence methods have been developed to predict time series future values for both linear and non-linear pattern of data.

3.6 Financial Data Forecasting Methods: Financial data forecasting methods are developed for time series data. The initial work is based on statistical and econometric methods; Armstrong[47] provided the survey of research needs of forecasting. Development of artificial intelligent methods like Artificial Neural Networks, and Genetic Program the non-linearity can be modeled forecasting in an efficient way. The latest models are based on the combination of previously available methods. Improvement in forecasting is clearly visible but still perfect ness is not achieved.

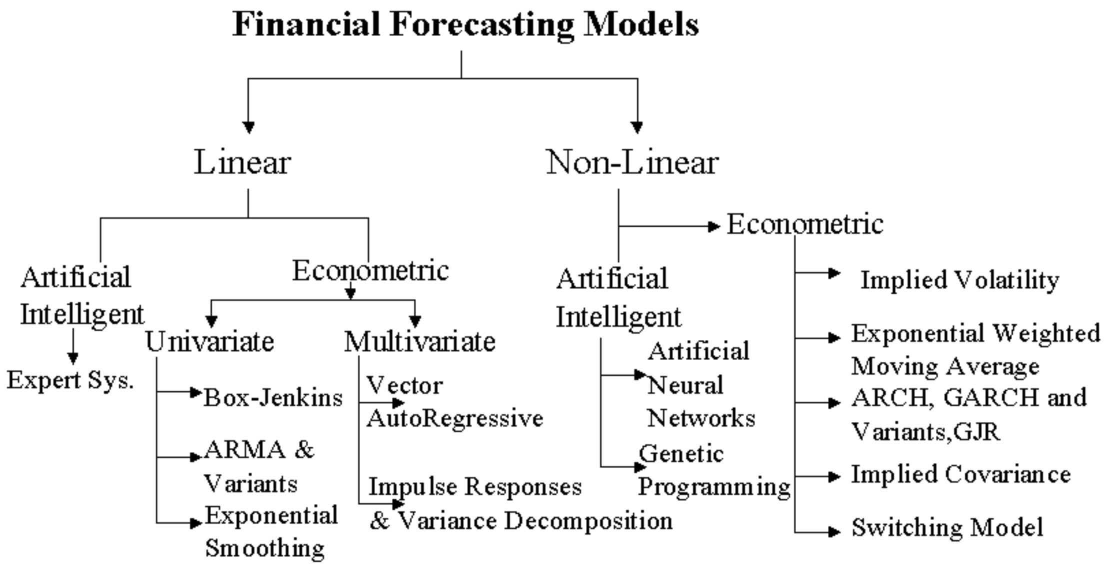

Chart 3: Classifications of Financial Forecasting Models

3.6.1 Linear Finance Data Forecasting:

Linear time series modeling techniques are further having two categories based on number of variables, Univariate Time Series Modeling and Forecasting and Multivariate Time Series Modeling and Forecasting. Univariate Tome Series Modeling and Forecasting involves basic models like: Box-Jenkins-ARMA, ARIMA and its variants, Exponential Smoothing etc.

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[47] Armstrong, J. S. (1988). Research needs in forecasting. *International Journal of Forecasting*, 4, 449–465.

3.6.2 Box-Jenkins Model: A very influential time series forecasting model was described by statisticians George Box and Gwilym Jenkins[48] in 1970 called Box-Jenkins model. The original Box-Jenkins modeling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. The advancement model of (Box, Jenkins, and Reinsel[49], 1994) was proven a powerful tool and has found wide applications of forecasting in modeling dynamic processes encountered in finance, economics, business, engineering, and many other fields. Box-Jenkins model are often called ARMA (Autoregressive Moving Average) model.

Given a time series of data Xt, the ARMA model is a tool for understanding and predicting future values in this series. The model consists of two parts, an autoregressive (AR) Model and a moving average (MA) Model. The model is usually then referred to as the ARMA (p,q) model where p is the order of the autoregressive part and q is the order of the moving average part.

Autoregressive Model: The notation AR(p) refers to the autoregressive model of order p. The AR(p) model is written

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t.$$

Where $\varphi_1, \ldots, \varphi_p$ are the parameters of the model, c is a constant and ε_t is an error term. An autoregressive model is essentially an infinite impulse response filter with some additional interpretation placed on it. Some constraints are necessary on the values of the parameters of this model in order that the model remains stationary.

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[48] BOX, G.E.P. and G.M. JENKINS (1970) Time series analysis: Forecasting and control, San Francisco: Holden-Day

Moving average Part: The notation MA (q) refers to the moving average model of order q:

$$X_t = \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

where the θ1, ..., θq are the parameters of the model and the εt, εt-1,... are again, the error terms. The moving average model is essentially a finite impulse response filter with some additional interpretation placed on it.

Autoregressive moving average model: The notation ARMA (p, q) refers to the model with p autoregressive terms and q moving average terms. This model contains the AR(p) and MA(q) models,

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

The error terms εt are generally assumed to be independent identically distributed random variables (i.i.d.) sampled from a normal distribution with zero mean: εt ~ N(0,σ2) where σ2 is the variance. These assumptions may be weakened but doing so will change the properties of the model.

One of the most important and popular linear models is the autoregressive integrated moving average (ARIMA), As the model was inhabited from Box-Jenkins Model, Often times, ARIMA is also called the Box-Jenkins model.

Autoregressive integrated moving average (ARIMA) model is a generalisation of an autoregressive moving average or (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series. The model is generally referred to as an ARIMA (p, d, q) model where p, d, and q are integers greater than or equal to zero and refer to the

[49] Box, G. E. P., Jenkins, G. M., and Reinsel, G. C. (1994), *Time Series Analysis: Forecasting and Control*, 3rd Ed., Prentice-Hall, Inc., New Jersey.

order of the autoregressive, integrated, and moving average parts of the model respectively.

Given a time series of data Xt where t is an integer index and the Xt are real numbers, then an ARMA (p, q) model is given by

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right) X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

Where L is the lag operator, the φi are the parameters of the autoregressive part of the model, the θi are the parameters of the moving average part and the ε_t are error terms. The error terms ε_t are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero mean.

An ARIMA (p, d, q) process is obtained by integrating an ARMA (p, q) process. That is,

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

Where d is a positive integer that controls the level of differencing (or, if d = 0, this model is equivalent to an ARMA model). Conversely, applying term-by-term differencing d times to an ARMA (p, q) process gives an ARIMA (p, d, q) process. Note that it is only necessary to difference the AR side of the ARMA representation, because the MA component is always I (0).

It should be noted that not all choices of parameters produce well-behaved models. In particular, if the model is required to be stationary then conditions on these parameters must be met.

A special case, an ARIMA (0,1,0) model is given by:

$$X_t = X_{t-1} + \varepsilon_t$$

Which is simply a random walk.

The linear approach assumes a linear underlying data generating process. Linear models have been used for a long time and are still very useful, but the linear assumption underlying these models may be too restrictive.

3.6.2.1 <u>Limitations of Box-Jenkins Model:</u>

- Although Box-Jenkins and ARIMA models are quite flexible in modeling a wide range of time series patterns; their major limitation is the accepted linear form of data generating process to the model. That is, a linear autocorrelation structure is assumed before the model is fitted to the data. In real world it is most of the financial data patterns are nonlinear, nonlinear-stochastic, and random systems while it is very rare to find simple linear or linear-stochastic systems.
- Jenkins technique demands a substantial amount of manual work by visually checking the correlograms of the time series. It is in this step that subjective judgment and preference are incorporated and that it is made extremely difficult to automate the model building process.
- Box-Jenkins technique is applicable for short term forecasting. Box-Jenkins is good for short -term forecasting. It requires enough number of data, and then determines the appropriate model equations and parameters. It is not able to forecast if number of casual factors affects the behavior of data.

Qiang Song and Augustine O. Esogbue[50] eliminates the limitation of manual work required by automation, they develop an algorithm to identify p or q from the autocorrelation plots, and the other to

[50]Qiang Song and Augustine O. Esogbue 'A New Algorithm for Automated Box-Jenkins ARMA Time Series Modeling Using Residual Autocorrelation/Partial Autocorrelation Functions' IEMS Vol. 5, No. 2, December 2006

automate the modeling process by means of inspecting residual correlograms.

The limitation of forecast if more than one variable affect the behavior of data is over come by multivariate models. Vector Auto Regression (VAR) model and Support Vector Machines (SVM) are used for the forecasting of time series if one variable is responsible to affect the behavior. The VAR model has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting. It is a natural extension of the Univariate autoregressive model to dynamic multivariate time series. Vector Auto Regression (VAR) model in economics were made accepted by Sims[51] (1980). The ultimate technical reference for VAR models is given by Lutkepohl[52] (1991), and updated review of VAR techniques are given in Watson[53] (1994), Lutkepohl[54] (1999), Waggoner and Zha[55] (1999). Applications domain of VAR models to financial data covered by Hamilton[56] (1994), Campbell, Lo and MacKinlay[57] (1997), Cuthbertson[58] (1996), Mills[59] (1999) and Tsay[60] (2001).

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[51] Sims, C.A. (1980). "Macroeconomics and Reality," Econometrica, 48, 1-48.
52 Lutkepohl, H. (1991). Introduction to Multiple Time Series Analysis, Springer-Verlag, Berlin
[53] Watson, M. (1994). "Vector Autoregressions and Cointegration," in Handbook of Econometrics, Volume IV. R.F. Engle and D. McFadden (eds.). Elsevier Science Ltd., Amsterdam.
[54] Lutkepohl, H. (1999). "Vector Autoregressions," unpublished manuscript, Institute for Statistics und Econometrics, Humboldt-University at zu Berlin. (1999).
[55] Waggoner, D. F., and Zha, T. (1999). "Conditional Forecasts in Dynamic Multivariate Models," Review of Economics and Statistics, 81 (4), 639-651.
[56] Hamilton, J.D. (1994). Time Series Analysis. Princeton University Press, Princeton.
[57] Campbell, J. A. Lo and C. MacKinlay (1997). The Econometrics of Financial Markets. Princeton University Press, New Jersey.
[58] Culbertson, K. (1996), Quantitative Financial Economics: Stocks, Bonds and Foreign Exchange, John Wiley and Sons, Chichester.
[59] Mills, T.C. (1999), The Econometric Modeling of Financial Time Series, Second Edition, Cambridge University Press, Cambridge.
[60] Tsay, R. (2001). Analysis of Financial Time Series. John Wiley & Sons. New York.

Support Vector Machine (SVM) is also powerful to deals with multidimensional instances, having attractive characteristics for time series prediction (Muller[61] et al., 1997). SVM has few parameters, thus finding optimal settings can be easier, one of the parameters referring to noise level the system can handle. It is remarkable that SVM generalization depends on the geometrical characteristics of the training data, not on the dimensions of the input space. Vapnik[62] shows how training a SVM for the pattern recognition problem.

There are a large number of linear forecasting models use concepts of moving average, exponential smoothing, time series regression, and time series decomposition but such a models are not able to capture nonlinear patterns that are commonly seen in many business and economic time series. The approximation of linear models to complex real-world problems is not always satisfactory as evidenced by the well-known M-competition in the early 1980s (Makridakis[63] et al., 1982). M-competition data has been used by hundreds of researchers. In M-Competition majority of commonly used linear methods were tested with more than 1,000 real time series. The mixed results show that no single linear model is globally the best, which may be interpreted as the failure of linear modeling in accounting for a varying degree of non-linearity that is common in real world problems. Groups of researchers performed analysis and compare the various time series forecasting methods over the past two decades.

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[61] Muller, K.-R., Smola, A., Rtsch, G., Schlkopf, B., Kohlmorgen, J., & Vapnik, V. (1997). Using support vector machines for time series prediction.

[62] V. Vapnik. *The Nature of Statistical Learning Theory*, Springer-Verlag, New York, 1995.

[63] Makridakis S, Wheelright S (1978) Forecasting methods and applications. John Wiley & Sons, New York, USA

3.6.3 Non-Linear Finance Data Forecasting:

Generally there are two approaches to time series modeling and forecasting: linear approach and nonlinear approach. VAR and SVM having their limitation is because of their linear assumption of financial time series data. As in real world it has observed that most of the financial data patterns contains non-linearity, The nonlinear approach to time series modeling is perhaps more appropriate for most real world problems. But, the nonlinear world is much more complex than the linear world since there are so many possible nonlinear relationships or structures. Non-linear processes in the data, introduces slow upward movements in stock prices followed by sudden collapses, or slow downward or linear movement followed by surges. Because of such non-linearity, linear model may fail to capture or forecast well sharp turning points in data, and motivated to turn nonlinear forecasting techniques. Most nonlinear models built-up during the last twenty years are based on data characteristics. These models are useful if the data characteristic matches the model assumptions otherwise models are restrictive to application in nature. Many nonlinear models try to capture the effects of nonlinear processes through parametric assumptions with specific nonlinear functional forms. Examples of such models are Generalized Autoregressive Conditional Heteroskedasticity (GARCH) by Engel[64] (1982) and it's variants. The GARCH models are capable to capture patterns of volatility. Means periods of high volatility are followed by high volatility and periods of low volatility are followed by similar periods, and we can predict the volatility up to a very good extends using GARCH.

One limitation of the GARCH model is minimization of the log-likelihood functions is often very difficult to achieve. Another

[64] Robert F. Engle. "Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation", *Econometrica* 50:987-1008, 1982.

limitation of model is parametric approach of GARCH to the specification of model form before use, it makes model restricted.

GJR Model given by Glosten, Jagannathan, and Runkle is extension of GAR75CH model and incorporated support for possible asymmetries.

The further development in nonlinear time series forecasting noticed by Threshold Autoregressive model contributed by Tong[65](1983,1990) and Markov Regime Switching model by Hamilton[66](1989,1990). The Motivation of switching models is structure break behavior of in a time series data. If this behavior change may revert back in to the previous behavior of series, it is known switching; else it may initiate another style of behavior known as 'regime shift' or 'regime switch'.

Brooks and Persand[67] model tested switching model for more than 22 years period from January 1975 to August 1997, for three countries UK, US and Germany. They have used dividend yields and index values of the FTSE 100 (UK), the S&P 500 (US) and the DAX (Germany). The statistics of their results are represented in the table given below. The lower standard deviation as compare to equity shows less risk, so model generates good return for same amount of risk.

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[65] Tong, H (1983) Threshold Model in Nonlinear Time Series Analysis, Springer-Verlag, New York
(1990) Nonlinear Time Series: A Dynamical Systems Approach, Oxford University Press, Oxford

[66] Hamilton, J.D. (1989) A New Approach to the Economic Analysis of Non-stationary Time Series and Business Cycle, Econometrica 57, 357-84
(1990) Analysis of Time Series Subject to Changes in Regime, Journal of Ecometrics 45, 39-70

[67] Brooks C., Persand G., "The Trading Profitability of Forecast of the Gilt-Equity Yield Ratio", International Journal of Forecasting v17, 11-29, 1997

Table 3: Result of Brooks C., Persand G. Switching Portfolio Model

	Buy & Hold Bonds Portfolio	Buy & Hold Equity Portfolio	Switching Portfolios	Number of Switches
Panel A: UK, Average Return	0.4303	0.6223	0.6893	16
Panel A: UK, Standard deviation of Return	0.8977	2.1449	1.5820	
Panel B: US, Average Return	0.0506	0.4660	0.3259	4
Panel B: US, Standard deviation of Return	1.0971	1.7254	1.0723	
Panel C: Germany, Average Return	0.0243	0.3762	0.1661	6
Panel B: Germany, Standard deviation of Return	0.7385	2.1112	.8445	

It has noted by Campbell, Lo, and MacKinlay68 (1997) that economic theories are not specific about non-linear function forms. The economists have rarely had proper theoretic reason for expecting to find one form of non-linearity rather than another. Several efforts have been committed to evolving the time series forecasting methods and also improving it. A more flexible nonlinear model is the artificial neural networks (ANNs), which have received more attentions recently (Zhang[69] et al., 1998).

[68] Campbell J, Lo A, MacKinlay C (1997) The econometrics of financial markets. Princeton University Press, NJ
[69] Zhang, G. P. & Hu, M. Y. (1998). Neural network forecasting of the British Pound/US dollar exchange rate. *Omega*, 26(4), 495–506.

Realization of non-linearity motivates the use of computation artificial intelligence techniques for data mining like Decision Tree, Artificial Neural Networks and Genetic Programming and K-means algorithm.

The artificial neural networks and genetic programming are non-parametric and hence are quite flexible to different functional forms. Techniques contributed in the modeling of non-linear data forecasting include fuzzy logic, neural networks, nonlinear principle components analysis, k-mean clustering, instant-based techniques, genetic programming, and hybrid agent-based modeling. Principle component analysis (PCA) is a technique used to reduce multidimensional data sets to lower dimensions for analysis. Depending on the field of application both artificial neural networks (ANN), and genetic programming (GP) are good choices to modeling non-linear time series data modeling. We have presented a comparative study to select algorithms mentioned above suitable to application nature in one of our paper "A Comparative Study of Data Mining Techniques and its Selection Issue[70]".

Many researchers have been proven the artificial neural network, particularly the recurrent neural network, as an extension of linear time series modeling, the self-associative neural network as an extension of linear principle components analysis. Neural network offer a powerful alternative to linear models for forecasting, classification, and risk assessment in finance and economics. As we know the limitations of the linear model with normally generated disturbances may lead to serious misspecification and mispricing of risk if the real world deviates significantly from these

[70] Dharwa J. N.,Parikh Satyen M., Patel A. R.(Dr.). "A Comparative Study of Data Mining Techniques and its Selection Issues" 61-65 Proceeding of the national conference on IDBIT-2008, 23-24 February 2008 at SRIMCA, ISBN: 978-81-906446-0-0.

assumptions of linearity and normality. This limitation is overcome up to great extend by using the artificial neural network. The major advantage of artificial neural networks is that they are data driven and do not require restrictive assumptions about the form of the underlying model. Artificial neural networks have proven best candidature in various applications like powerful pattern classification and prediction capabilities because of their unique features and attributes like data driven, self-adaptability, and support for non-linear data generating processes.

This flexible nonparametric approach is fairly appropriate for many problems with complex nonlinear structures, but there is a lack of theory to suggest a specific form of the structure. Neural nets have proven to be very effective classifiers—better than the state-of-the-art methods based on classical statistical methods. Neural networks are more versatile methods as compare to any other method as it can forecast linear and non-linear data. Neural networks have universal functional approximating capability, so numerous types of complex functional relationships in that they can accurately approximated by neural network forecasting. In brief Artificial Neural Network works best in situations where financial theory has virtually nothing to say about the likely functional form for the relationship between the set of variables. The ability of neural network to work better and manage with far less information than any other rule based expert system, as in finance it is not always possible to have known rule, as the possibilities are exhaustive, make neural network very effective and useful.

The limitation of neural network is the risks of obtain local optimal solution rather to finding global optimal solution for crucial problems. Fortunately we can overcome this limitation of neural network by involving the use of other strategies like evolutionary computing methods or econometrics forecasting methods.

One of such study uses a combined approach of linear ARIMA and nonlinear artificial neural networks models for time series forecasting (Zhang[71], 2003). The idea is based on the fact that no single model is the best for any situation. Therefore, if we can use each model's unique features and strengths, we are able to better capture the patterns in the data. There are many contrasting features in ARIMA and artificial neural networks. First, ARIMA is linear and artificial neural networks are inherently nonlinear. ARIMA is a very comprehensive linear model and can represent many types of linear relationships, such as autoregressive (AR), moving average (MA), and mixed AR and MA time series structures. In addition, some exponential smoothing models can be represented by ARIMA models (Mckenzie[72], 1984). On the other hand, artificial neural networks are universal functional approximators and can model any type of nonlinear relationship. Second, ARIMA is essentially parametric while artificial neural networks are non-parametric in nature. Thus, in using ARIMA, the general model form is known while in using artificial neural networks, we don't need to specify a particular model form. Of course, linear ARIMA is relatively simple to understand and implement compared to artificial neural networks. Finally, ARIMA models are developed based on formal statistical theory and statistical techniques are often used for model development and adequacy checking. Neural network model building and artificial neural networks are often treated as black boxes but as they are

[71] Zhang GP (2003) Time series forecasting using a hybrid ARIMA and Neural Network Model, Neuro-computing 50:159–175

[72] Mckenzie, E. (1984). General exponential smoothing and the equivalent ARMA process, *Journal of forecasting*, 3, 333–344

universal functional approximators and can model any type of nonlinear relationship, It is preferable to use the application of dynamic prediction applications in finance where we have no proven statistical method available. Let give a brief look to neural network, as it has a vital role in our model.

3.6.4 Neural Networks for Data Forecasting:

In biological term neuron is one of the primary cell types in the nervous system; a neural network is a network of interconnected networks of neurons. Study of neural networks includes the brain adaptability to acquire knowledge, i.e. learning process.

There are mainly three components in biological neurons.

a) Soma: Soma is main body of neuron; it is pyramidal or cylindrical in shape. It processes the all-incoming signals and fires a signal, when sufficient input is received.

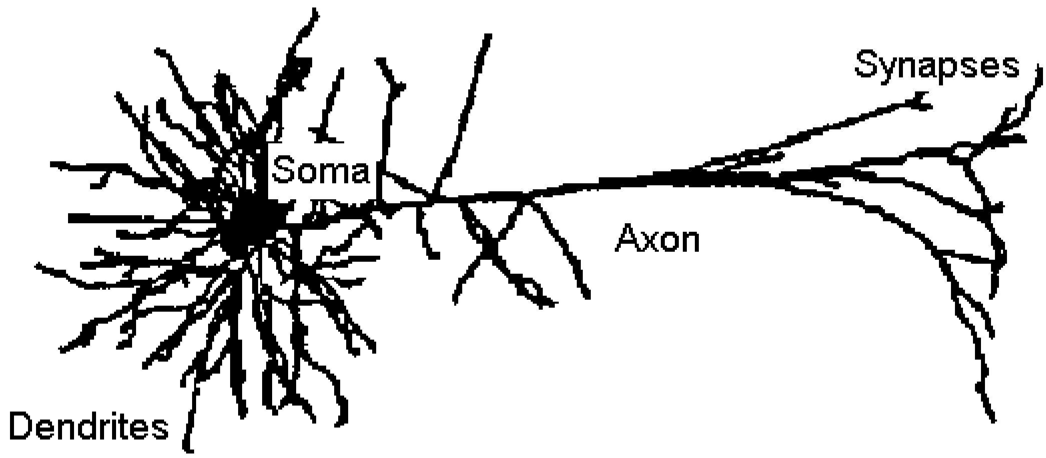

Figure 3.1 Biological Neural Networks

b) Dendrites: Dendrites receives the signals from other neurons and connected with Soma.

c) Axon: axon or nerve fiber is an output area; it transmitted the impulse signal triggered by one cell to other.

As neurons are typically composed of a soma, dendrites tree and an axon, The contact between one neuron's axon to another neuron's dendrite. The majorities of vertebrate neurons receive input on the cell body and dendritic tree, and transmit output via the axon. Neurons communicate via chemical and electrical synapses, in a process known as synaptic transmission. The fundamental process that triggers synaptic transmission is the action potential, a propagating electrical signal that is generated by exploiting the electrically excitable membrane of the neuron. There are 10^{14} neurons in a human brain; each neuron in the human brain connects to 10,000 other neurons. Hence, the human brain is a complicated network of neurons with roughly 10^{18} connections.

3.6.4.1 Artificial Neural Networks: Warren McCulloch and Walter Pitts[73] (1943) proposed threshold logic unit the first artificial neuron. The artificial neuron receives one or more inputs (representing the one or more dendrites) and sums them to produce an output (synapse). Usually the sums of each node are weighted, and the sum is passed through a non-linear function known as an activation function or transfer function. The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions.

Input Signals, Xi is the data set come from environment, or any other neurons. Typical inputs are discrete, or real numbers.

Weights, w^i, the set of real values describes connection strengths.

An activation level $\sum w^i X_i$, is cumulative strength of input signals, computed by summing up the weighted inputs.

[73] Warren McCulloch , Walter Pitts 1943. "A Logical Calculus of the Ideas Immanent in Nervous Activity". In: *Bulletin of Mathematical Biophysics* Vol 5, pp 115-133.

A threshold function *f*, computes the neurons final output state on the basis of activation level and threshold value.

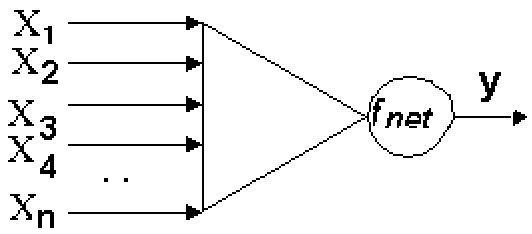

Figure 3.2 Node of Artificial Neural Network

When number of such neurons is interconnected, they form artificial neural networks, the aspects that we have to consider when to build artificial neural networks:

- Network Topology: Collection pattern between the neurons, It gives the structure of network and tell us how many layers are there in the network, and what their functions are, such as for input, for output, or for pattern reorganization.
- Encoding Scheme: Interpretation placed on data to the networks and the result of it's processing. In simple words it's refer the value of weight change between connections of neurons. The process of encoding is required at the time of training of neural networks, once the training is over, weight will be fixed and further encoding is not required.
- Learning Algorithm: The way to make network intelligent. It enables the neural network to provide desired output for the given set of input.

3.6.4.2 Types of Artificial Neural Network:

Fundamentally, there are two different types of artificial neural networks

- Feed-forward neural network: There are three layers of nodes: The lowest layer is called the input layer, as these nodes accept the input values; the middle layer is called the hidden layer, as all the activity there remains hidden, there may be number of hidden layer possible in a artificial neural network; and the top layer is called the output layer, as the activity that traversed the network finally arrives here. However feed forward Artificial Neural Network with no hidden layer is simply a standard linear regression model. Feed forward neural network has no recurrent connections between nodes and so the activity flows in one direction (i. e., the activity is fed forward step-by-step from the input nodes toward the output nodes). This type of neural network is most often used for function approximation and classification.

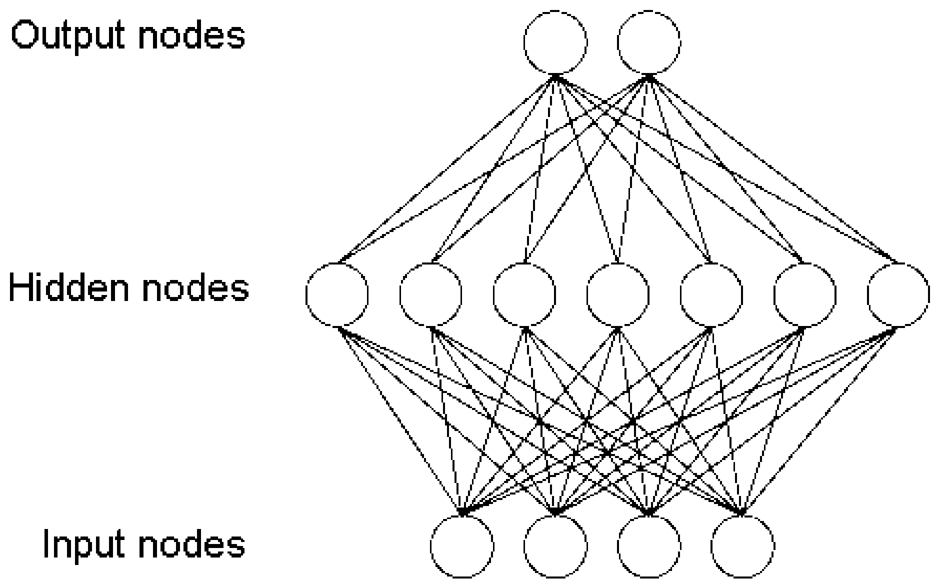

Figure 3.3 Feed-forward Artificial Neural Network Model

- Recurrent neural networks have recurrent links between nodes, so activity can be circulate around the network. Recurrent neural networks can create a situation where the activity never settles down. Recurrent neural networks also open the door for the concept of memory. There are couples of recurrent neural network structures; here we look for Elman recurrent neural networks and Jordan recurrent neural networks.

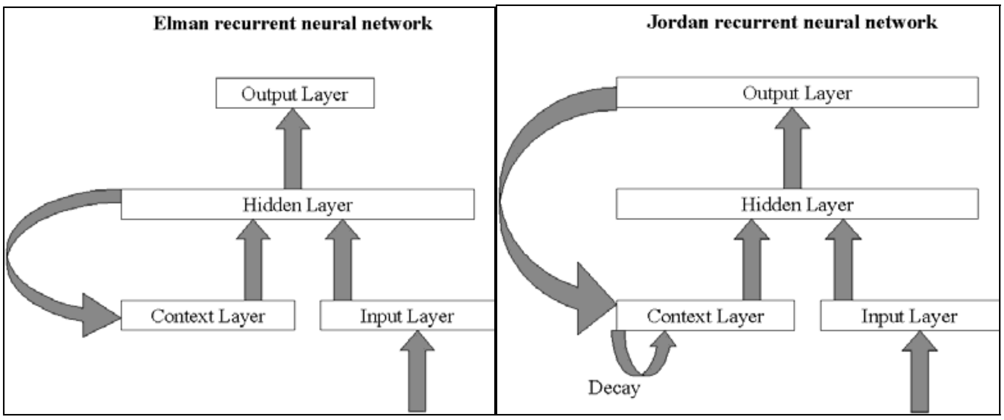

Figure 3.4 Recurrent Artificial Neural Network Models

Many other structures of recurrent neural networks are introduced using one or more context layers. The memory in these neural networks is based on the decay of information using a decay rate. This decay of information allows recurrent neural networks to correlate two or more patterns that are separated in time. Using the well-known back-propagation learning described by Werbos[74](1974) and Rumelhard[75] (1986) widely used for training of such recurrent neural networks.

3.6.4.3 Evaluation Criteria for Artificial Neural Network:

Any Artificial Neural Networks are evaluated by the

- **Network Environment:** It refers the network architecture used to develop the Artificial Neural Network. Number of layers in Artificial Neural Network, number of neurons in

[74] Werbos, P. (1974). Beyond regression: New tools for prediction and analysis in the behavioral sciences. *Ph.D. thesis,* Harvard University

[75] Rumelhard, D. E.,McClelland, J. L. and the PDP Research Group. (1986). *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Volume 1: Foundations*. Cambridge, MA: MIT Press.

each type of layer and their connection and connection weights etc. for example in Hopfield network, every neuron was connected to every other in the one layer that was present in the network and in the Perceptron, neurons within the same layer were not connected with one another, but the connections were between the neurons in one layer and those in the next layer. Different environment represent differences between the models lie in their architecture, encoding, and recall learning.

- **Network Training:** Neural network training generally require number of iterations, meaning that the learning procedure is repeated a certain number of times referred as cycles. After each cycle, the input used may remain the same or change, or the weights may remain the same or change. Such change is based on the output of a completed cycle.
- **Network Performance:** A network's performance is often measured on how well the system predicts the output according to the set of inputs given. Ideally, the system should predict output with less error.

3.6.4.4 Modeling Consideration of Neural Networks:

- **Adaptive:** Ability to change the architecture (mainly in hidden layer) itself.
- **Stability:** Stability refers to occurrence of convergence to identify the end to the iterative process during network training. If any two consecutive cycles produce result in the same output and no change in weight for any node in the network, then there may be no need to further iteration.
- **Plasticity:** Plasticity refers the ability to retain the learning or training of Artificial Neural Network. A good plasticity

enables Artificial Neural Network to modify weights and learn new patterns without much affecting stored pattern already in the networks.

- **Over-fitting Vs Generalization:** Neural network may suffer form the danger of over-fitting. Over-fitting can occur during network training. The over-fitting is unfavorable because the network will not only learn the relationships inherent in data, but will also learn the noise existing in the data. Over-fitted network predictions well for within-sample data, makes false predictions for out-of-sample data. It is suggestible to have enough data for training as well as for testing of network.

Adaptive Resonance Theory for neural networks developed by Gail Carpenter[76] and Stephen Grossberg[77]. This theory was developed to address the stability–plasticity problem. The Artificial Neural Network is supposed to be plastic enough to learn an important pattern, but at the same time it should remain stable when, it encounters some distorted versions of the same pattern during training.

[76] Carpenter, Gail A., and Ross, William D., "ART-EMAP: A Neural Network Architecture for Object Recognition by Evidence Accumulation," *IEEE Transactions on Neural Networks*, Vol. 6., No. 4, July 1995, pp. 805–818.
[77] Grossberg, Stephen, et al., Introduction and Foundations, Lecture Notes, Neural Network Courses and Conference, Boston University, May 1992.

Chapter- IV

Architecture and Design of Integrated Intelligent Advisory Model (IIAM)

4.1 Introduction to A Multi Agent Business Intelligence Model For Finance Management:

The model is designed to achieve optimized net worth growth and perform better finance management. The core technical part of model is based on Business Intelligence for financial modeling. Which provides the capability to model to act as an expert finance advisor as well as assistant. According to personal preferences and finance knowledge attributes model helps in Asset Allocation, Asset Management, Controlling liabilities, and off course managing risks, all with taking care of cash flow. The models' Business Intelligence (BI) applicability is confined to finance management. Model disregards and contradict to efficient market hypothesis.

The main components in the model proposed are

- **Financial Data Depository:** Financial Data Depository contains all details of historical financial data. The main categories including Financial Stock market data, Finance news database, Tax-benefit policies, Mutual fund data, and ULIP data.
- **Personal Portfolio:** It includes the personal details of Assets/Liabilities/Intangibles holding, Income, Expense, and Goals.
- **Finance Data Fetcher Agents:** The regular updating activity of financial depository is carried out through different finance data fetcher agents. The main data fetcher agents include Daily Stock Data Fetcher, Quarterly Financial Result Fetcher, Mutual Fund Data Fetcher, and ULIP Data Fetcher.

- **Knowledge Discovery Agents:** Computational Intelligent agents discover the knowledge using supervised learning through existing financial depository. In our model knowledge feed forward artificial neural networks through back propagation algorithm do discovery. The knowledge discovery process involve the analysis techniques of financial market data through non- linear data forecasting includes fuzzy logic, artificial neural networks, principle components analysis and hybrid agent-based modeling. As already stated the major advantage of artificial neural networks is that they are data driven and do not require restrictive assumptions about the form of the underlying model. Artificial neural networks have proven best candidature in various applications like powerful pattern classification and prediction capabilities because of their unique features and attributes like data driven, self-adaptability, and support for non-linear data generating processes.
- **Knowledge Base:** The knowledge base contains knowledge discovered through Artificial Neural Network. Knowledge base contains the static rules for different financial product behavior based on basic analysis techniques like fundamental analysis, technical analysis, and sentimental analysis. The applicability of fundamental analysis is for stock identification and technical analysis in the model is limited to trend analysis and identification of evidence for history repetition. The rules based on Sentiment analysis are used to identify bubble and protect the investments from sudden loss.
- **Portfolio Management Agents:** The agents' uses the personal details and verify through knowledgebase. This

agent generates the recommendations and alerts for portfolio holder.

- **Communication Agents:** This agent passes the generated recommendations and alerts to portfolio holder.

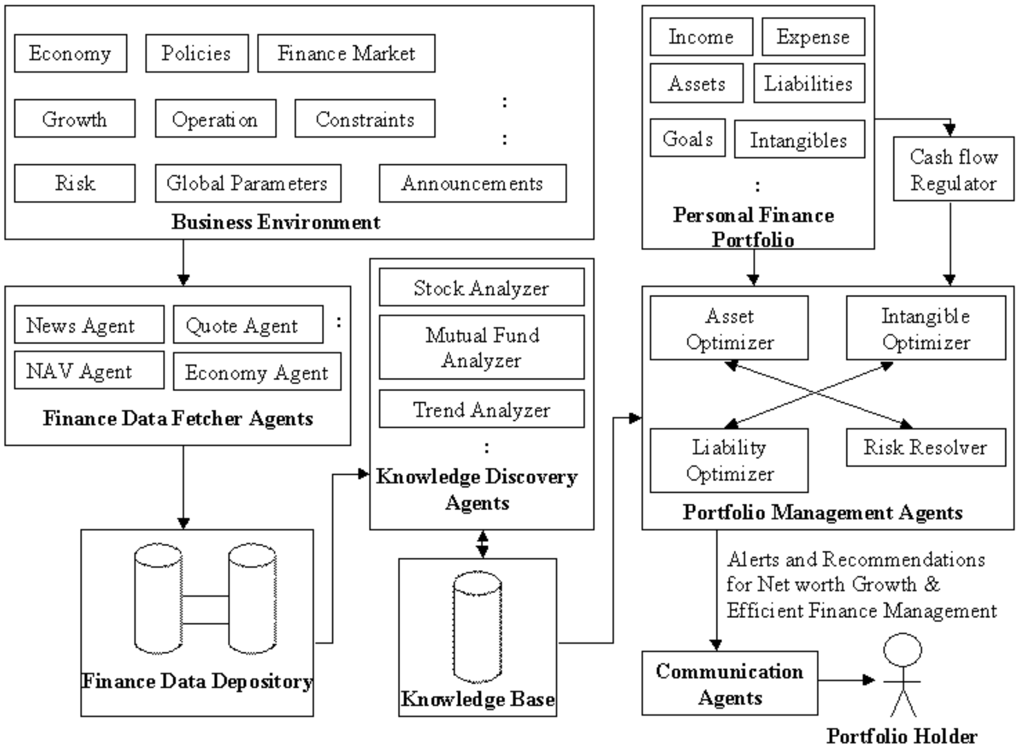

Figure 4.1 Architecture of Multi Agent Business Intelligence Model For Finance Management

The functionality of complete model is carried out by cooperation of different agents engaged in different activities, and they may work concurrently and communicates with each other in order to achieve the goal. Knowledge discovery agents are most complex part and supports analysis work of financial data. Knowledge Discovery Agents are the core part of the model and designed as a hybrid System involving different computational intelligent methods like Artificial Neural Network and Expert System. All agents' works to achieve a common goal but design to work in distributed manner. Portfolio management works on the basis of finance and optimization principles and does not apply any intelligence algorithms directly. Communication Agents perfumes the job to communicate recommendations and alerts independently as portfolio management agents generate it. Different agents are allowed to work or access different application module and database schema according to their rights, hence there is no competition in between the agents, however different agents can communicate together by sharing the information, if required and free to take decision based on that. It makes model distributed co-operative and efficient.

4.2 Selection of Software Environment for Development of IIAM (Integrated Intelligent Advisory Model):

As part of the research work presented in this thesis some of software components have been developed and tested individually to in order to confirm functionality on different asset categories. The programming efforts have been spent on specialized tasks, as well as few general-purpose tools. We will discusses a few general guidelines and design principles, and then provides a brief and non-technical description of the parts that constitute the environment. The final objective of Networth growth in the portfolio is achieved at the end by combining the entire modules. It has been to simplify and improve the development and evaluation cycle when working with knowledge discovery algorithms for financial markets. Activities needed to perform at one point of time for efficient finance management and confirmed by knowledge based on historical data patterns is termed as recommendation.

Development work is carried out in Microsoft Visual Studio 2008 and Data depository is in Microsoft SQL server, and some knowledge discovery Artificial Neural Network algorithms are in

C++. Presently neural network based on backpropagation algorithm is implemented and use for forecasting.

The .Net Platform is chosen as lot of support for Business Objects and presenting tools are available in it. As Microsoft SharePoint Server and Microsoft Office PerformancePoint Server incorporated Business Intelligent and support is also available to develop web part development for SharePoint agents in Microsoft Visual Studio, So finally it can help to implement Multi Agent Business Intelligence Model For Finance Management. According to Craig Utley[78] "*PerformancePoint Server 2007 represents an attempt by Microsoft to bring together tools that provide companies with greatly enhanced business intelligence capabilities. Two of the pillars of PerformancePoint Server provide tools that support different types of users, such as analysts and business decision makers, while the third pillar moves beyond delivering data to the organization to supporting the planning, budgeting, and forecasting efforts of the organization. The budgeting and forecasting data can become part of the process, so that actual performance is compared to the forecasts and so that the health of the business can be monitored. Variances in performance from the plan can be easily analyzed in detail to determine the source of any variances.*"

John C. Hancock, Roger Toren[79] greatly explained about to use Business Intelligence Technologies with SQL server for solving real world problems. Microsoft is supposed to remain leader in future in the area of business intelligence development tools and compatible to existing Microsoft technologies. It assures us to fast and easy development and easy up gradation in future needs.

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[78] Craig Utley, "Business Intelligence With Microsoft Office Performance Point Server 2007", McGraw Hill 2008

[79] John C. Hancock, Roger Toren, "Practical Business Intelligence with SQL Server", Addison Wesley, 2006

No doubt there are different platform based on Java like Jade, Jack etc. are also available which provides features required for Agent Oriented Programming, which can be use to development of model alternatively.

Our present model implementation is not indented to generate spontaneous recommendations for day trading activity, such an activities require more computing power and real time performance, which can be achieve by load balancing and fine grain parallel processing on specialized hardware. In future the design can be easily scale for Multi Computer or Multi Processor distributed computing for performance optimization.

4.3 Software Components of Integrated Intelligent Advisory Model:

The main software component of Multi Agent Business Intelligence Model For Finance Management can be classified in to the following categories:

- Data Capturing Agents:
- Financial Knowledge Discovery Simulators:
- Communication Agents:
- Software Interface:

- **4.3.1 Data Capturing Agents:** Data capturing or Data fetcher agents update the financial data depository by fetching the required latest interested information from financial market resources through Internet. Agents are very useful to retrieve regular financial data. Now stock exchanges are providing the live quotes in the form of web services, Agents uses that and bring the quotes and then it stored in to financial data depository for further processing. This approach makes data capturing very easy completely automated and time efficient. Also for other financial assets data is captured either through company web site in which the particular product of interest belongs or any other financial product specific website resources. The frequency of different data capturing agents is based on availability of data; Quote fetcher agents fetches the quote during the market working hours when a transaction is performed in scripts of interest, News fetcher agent fetches the news when any new news is announced, Economy agent normally fetches the data one in a week, when inflation rate is declared, it also fetches the data when ever new credit policy is announced or policy change trigger fired by news agent, and NAV agent fetches the NAV of mutual funds and ULIP at the end of market working day.

- **4.3.2 Financial Knowledge Discovery Simulators:** These are the most important components of the model. As we are working with different assets and liabilities and each of having there own characteristics, and with the help of existing statistical, and finance analysis technique it is still not possible to find out the function with relates finance market based asset growth with different parameters. As finance market data patterns are nonlinear, nonlinear-stochastic, and random systems and there is very difficult to find simple linear relationship for the moderate period of investment. In present research the work has been carried out to develop knowledge discovery simulators (KDS) based on neural network for mainly three class of dynamic capital market based investments:
    - Unit Link Insurance Policies
    - Mutual Fund
    - Stocks Investment in Capital Market

All knowledge discovery agents update the knowledge base on continuously basis, as they will find the interested set of pattern from finance data depository. The process of knowledge discovery require couple of steps on data preprocessing before performing training and testing.

4.3.2.1 KDS for Switching in Unit Link Insurance Policies**:**

In our model we have recommended the fund switching in different categories by analyzing market fundamental and technical parameters. The inspiration of switching model is taken from Brooks and Persand[80] model. The implementation of model involves the integration of Expert System, Data Mining, financial econometrics and Agent Technology. In our KDS the switching is recommended on the probability of future trend of market by studying market parameters. As market moves in a trend, switching in safe mode helps to protect continue loss, when market moves in negative trend, and when market trend is positive, the switching in equity mode assure that return is almost in comparable to return of benchmark.

Dimensional modeling empowered the process in a way that information can be organized and enables it to easily formulate. Expert system uses the backward chaining through rule-based data mining to take decisions from its knowledge base. Finally Agent technology can make model self sustainable as data mining agent functions within a data warehouse structure to discover changes in business trends of potential interest, and other agent keeps data warehouse up to date by retrieving and filtering required data, and communicate the recommendations to intended user group.

[80] Brooks C., Persand G., "The Trading Profitability of Forecast of the Gilt-Equity Yield Ratio", International Journal of Forecasting v17, 11-29, 1997

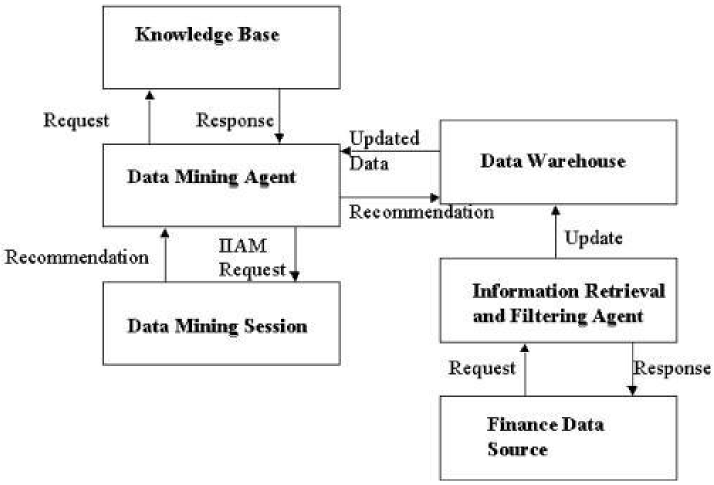


Figure 4.2: Design Principle of ULIP KDS

It gives the evidence that market technical and fundamentals can be use to track the trend, and investment strategies based on trend maximizes the ROI.

The complete description of work is given in the paper "Data Mining Supported Integrated Intelligent Advisory Model (IIAM) For Financial Growth".

4.3.2.2 KDS for Asset Allocation in Mutual Fund:

Switching models also inspire our model for mutual fund asset allocation. Before a year in India Government has given approval for especial class of mutual fund named Fund of Funds. Our model can be very useful for these types of funds. It has observed that in bullish trend equity based mutual fund gives good return while in bearish trend mutual fund based on arbitrage objective performs better.

Our model generates the asset allocation recommendations by analyzing the financial market at various dimensions like Indices trend, Inflation Rate, Market breath, Volatility, Market turnover, Currency exchange trend etc. All these parameters determined by analyze the huge finance and economy data generated over different periods.

Applying concepts of financial econometrics, market technical and fundamentals can perform this analysis. According to trend of market the decision for allocate money in to equity index growth or arbitrage kind of equity fund with the objective to seek long-term capital appraisal.

The complete description of model is given in the paper "Deriving Business Intelligence Through Collaborative Cooperative Multi Agent Model For Mutual Fund Asset Allocation".

4.2.2.3 KDS for Capital Market:

To discover knowledge from finance market data we have followed the following steps.

Data Preparation: The data fetcher agents stored the data in to data depository, It will accomplish most important activity of data preparation but to discover knowledge some pre-processing is required so we can compare the performance of different stocks one to one at least for most common parameters. This requirement of preprocessing on the data existing in the data depository to get the uniformity, in preprocessing we have transformed the relative change in data, either in percentage or in normalized value.

Training Parameter Considerations (Inputs to be considered in modeling, Data Smoothing, Data Scaling, PCA (Principle Component Analysis) to reduce the dimensionality, over fitting Vs generalization.

We will train the train the neural network with data from data depository. We have uses 3 layers feed forward neural network architecture, means one layer for input, one for output and one in hidden layer.

We have taken the following parameters during the learning:

- Sales (Revenue Growth): This parameter is very important as it is not possible to manipulate sales growth up to a great extend as profit can be manipulate but quarterly sale growth is not.
- Net profit Growth: This parameter is indicating company performance as a present and continuous basis. Quarter-to-quarter and year-to-year net profit growth is considered as training parameters.
- Reserves/Net profit: This parameter is considered, as it is retained profits of a company, which form part of its capital. It gives a sense, about the financial strength to handle tuff time or capacity to repay liabilities. The existence of such a reserve informs readers of the firm's financial statements that at least a part of the retained earnings will not be available to the stockholders. A very high value of the ratio shows inability to use the fund available.
- PE Ratio: This parameter is considered to find out the how much stock is costly. For high growth companies the value of PE can be high.
- Operating Profit/ Equity value ratio: This parameter is considered as it gives the earnings before interest and taxes because companies operate with different levels of debt and differing tax rates. Using operating earnings before interest and taxes, or operating profit allowed us to view and compare the operating earnings of different companies without the distortions arising from differences in tax rates and debt levels.

- Holding Pattern: This parameter is considered to know how to percentage of stock owned by the public. It is also one of the important fundamental parameter.
- Technical Parameters (Price and Turnover): Moving average for price volumes and indices are considered, as it is very important technical parameter.

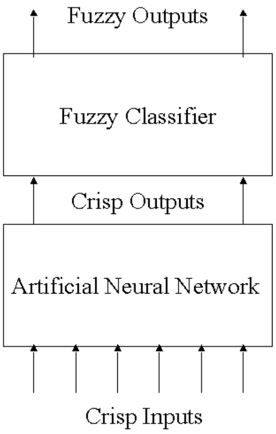


Figure 4.3: Post-Processing by Fuzzy Classifier

Knowledge base for stocks updated as any new stock pattern is obtained in finance data depository. Once the knowledge base is updated portfolio management can access it and they compare all high growth stocks with the updated pattern and based on that they generate recommendation for sell, hold or switch the particularly high growth segment stock.

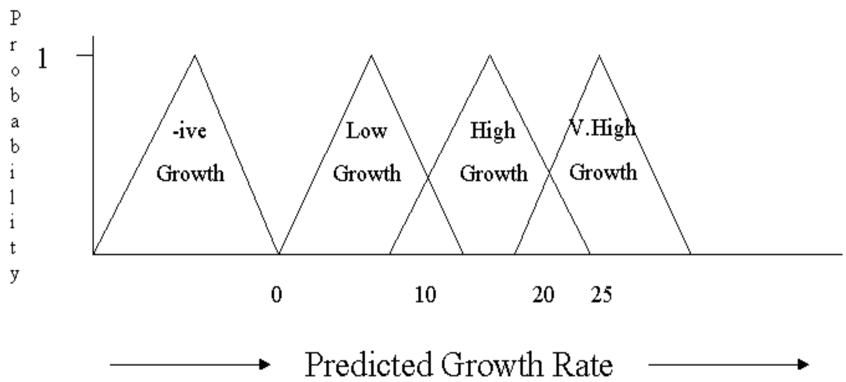


Figure 4.4: Fuzzy Classifier

The further details are discussed under the topic Research Methodology.

- **4.3.3 Communication Agents:** As name indicates communication agent performs the job of communication. Timely communication is very much essential in Finance market based investment products, so a communication agent uses the latest communication techniques like SMS, E-mail to communicate all the recommendations and alerts to the portfolio holder. Recommendations generated either to initiate action based on dynamic behavior of market or to manage the portfolio with updated knowledge base. Alerts generating process are basically not uses the knowledgebase and either indicate time base information like Maturity of Fixed Deposit, Due date of insurance policy, or Due date for credit card payment etc.
- **4.3.4 Software Interface:** This interface provides access to software components. Administrator can use interface to update user, company or sector information. User can use the interface to view/update portfolio transaction information or to view financial data information. The main functions of software interface can be further divided in the following categories:

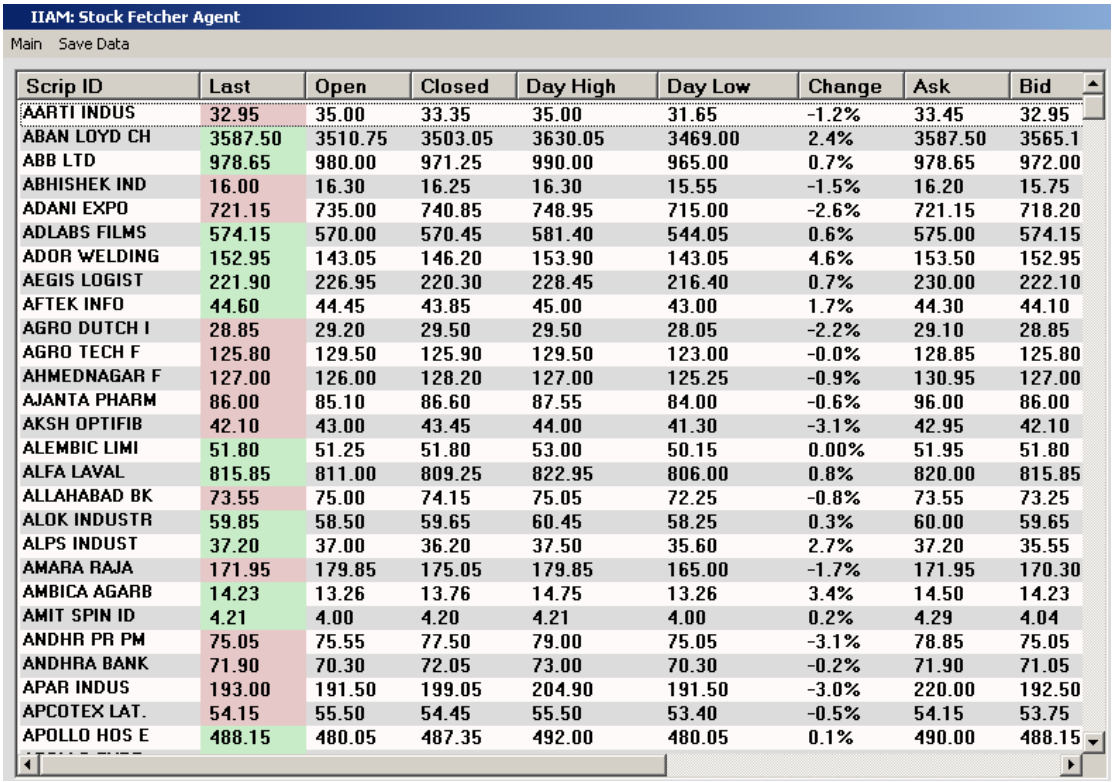
  Users Personal Activity: Login-password and personal information management, Profile evaluation and management, Setting Preferences etc.

  Portfolio Activities: Create Portfolio, Add transactions details for accounts created for Asset/Liabilities/Intangibles/Goals,

  View the performances of existing investment products with benchmark, Viewing Fundamental Details of Stock and Draw the Technical charts and indicators for Stock etc.

News Activities and Management: The one important activity is the news management. Financial sites provide RSS feeds for the financial news. So the news can be gathered and it can analyze and with the time the effect of news can be noted. As the different news can be classified in to the different categories and generally history repeats itself and news so. Once we train the expert system over the period of time, it can be used as a one important component in knowledge discovery activity.

4.3.4.1 Screen Snaps of Software Interfaces:

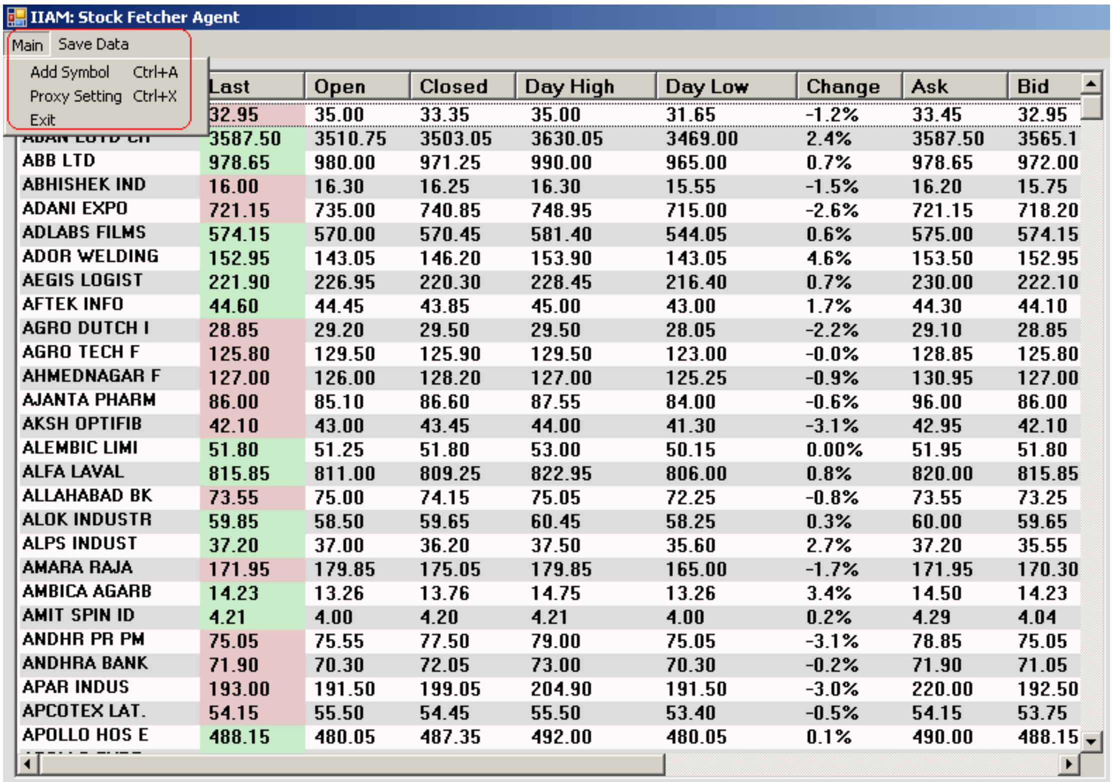

IIAM: Stock Fetcher Agent

Main Save Data

Scrip ID	Last	Open	Closed	Day High	Day Low	Change	Ask	Bid
AARTI INDUS	32.95	35.00	33.35	35.00	31.65	-1.2%	33.45	32.95
ABAN LOYD CH	3587.50	3510.75	3503.05	3630.05	3469.00	2.4%	3587.50	3565.1
ABB LTD	978.65	980.00	971.25	990.00	965.00	0.7%	978.65	972.00
ABHISHEK IND	16.00	16.30	16.25	16.30	15.55	-1.5%	16.20	15.75
ADANI EXPO	721.15	735.00	740.85	748.95	715.00	-2.6%	721.15	718.20
ADLABS FILMS	574.15	570.00	570.45	581.40	544.05	0.6%	575.00	574.15
ADOR WELDING	152.95	143.05	146.20	153.90	143.05	4.6%	153.50	152.95
AEGIS LOGIST	221.90	226.95	220.30	228.45	216.40	0.7%	230.00	222.10
AFTEK INFO	44.60	44.45	43.85	45.00	43.00	1.7%	44.30	44.10
AGRO DUTCH I	28.85	29.20	29.50	29.50	28.05	-2.2%	29.10	28.85
AGRO TECH F	125.80	129.50	125.90	129.50	123.00	-0.0%	128.85	125.80
AHMEDNAGAR F	127.00	126.00	128.20	127.00	125.25	-0.9%	130.95	127.00
AJANTA PHARM	86.00	85.10	86.60	87.55	84.00	-0.6%	96.00	86.00
AKSH OPTIFIB	42.10	43.00	43.45	44.00	41.30	-3.1%	42.95	42.10
ALEMBIC LIMI	51.80	51.25	51.80	53.00	50.15	0.00%	51.95	51.80
ALFA LAVAL	815.85	811.00	809.25	822.95	806.00	0.8%	820.00	815.85
ALLAHABAD BK	73.55	75.00	74.15	75.05	72.25	-0.8%	73.55	73.25
ALOK INDUSTR	59.85	58.50	59.65	60.45	58.25	0.3%	60.00	59.65
ALPS INDUST	37.20	37.00	36.20	37.50	35.60	2.7%	37.20	35.55
AMARA RAJA	171.95	179.85	175.05	179.85	165.00	-1.7%	171.95	170.30
AMBICA AGARB	14.23	13.26	13.76	14.75	13.26	3.4%	14.50	14.23
AMIT SPIN ID	4.21	4.00	4.20	4.21	4.00	0.2%	4.29	4.04
ANDHR PR PM	75.05	75.55	77.50	79.00	75.05	-3.1%	78.85	75.05
ANDHRA BANK	71.90	70.30	72.05	73.00	70.30	-0.2%	71.90	71.05
APAR INDUS	193.00	191.50	199.05	204.90	191.50	-3.0%	220.00	192.50
APCOTEX LAT.	54.15	55.50	54.45	55.50	53.40	-0.5%	54.15	53.75
APOLLO HOS E	488.15	480.05	487.35	492.00	480.05	0.1%	490.00	488.15

Figure 4.5 IIAM Stock Fetcher Agent Interface

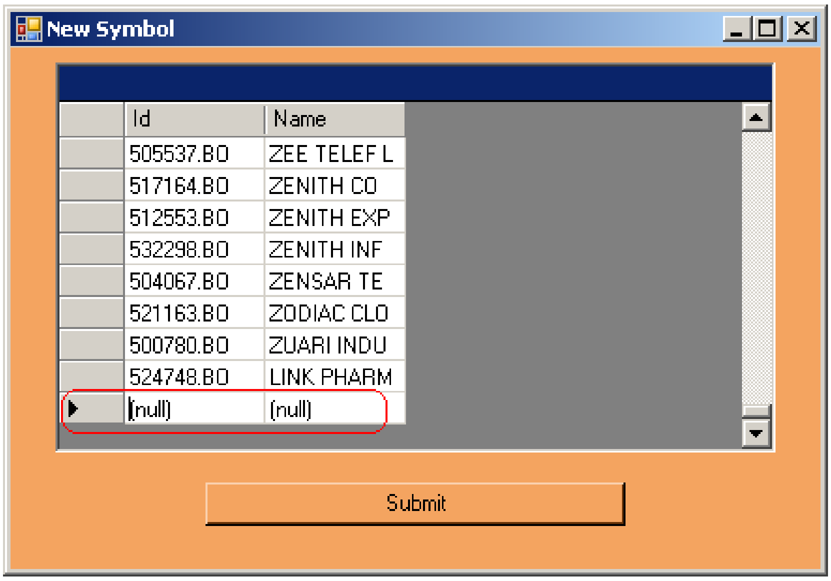
The Stock Fetcher Agent work on server side and fetches capital market recent data. Data Fetched updates the data depository also it can be exported in to different format like xls, or csv by selecting save data from the menu.



	Last	Open	Closed	Day High	Day Low	Change	Ask	Bid
	32.95	35.00	33.35	35.00	31.65	-1.2%	33.45	32.95
[illegible]	3587.50	3510.75	3503.05	3630.05	3469.00	2.4%	3587.50	3565.1
ABB LTD	978.65	980.00	971.25	990.00	965.00	0.7%	978.65	972.00
ABHISHEK IND	16.00	16.30	16.25	16.30	15.55	-1.5%	16.20	15.75
ADANI EXPO	721.15	735.00	740.85	748.95	715.00	-2.6%	721.15	718.20
ADLABS FILMS	574.15	570.00	570.45	581.40	544.05	0.6%	575.00	574.15
ADOR WELDING	152.95	143.05	146.20	153.90	143.05	4.6%	153.50	152.95
AEGIS LOGIST	221.90	226.95	220.30	228.45	216.40	0.7%	230.00	222.10
AFTEK INFO	44.60	44.45	43.85	45.00	43.00	1.7%	44.30	44.10
AGRO DUTCH I	28.85	29.20	29.50	29.50	28.05	-2.2%	29.10	28.85
AGRO TECH F	125.80	129.50	125.90	129.50	123.00	-0.0%	128.85	125.80
AHMEDNAGAR F	127.00	126.00	128.20	127.00	125.25	-0.9%	130.95	127.00
AJANTA PHARM	86.00	85.10	86.60	87.55	84.00	-0.6%	96.00	86.00
AKSH OPTIFIB	42.10	43.00	43.45	44.00	41.30	-3.1%	42.95	42.10
ALEMBIC LIMI	51.80	51.25	51.80	53.00	50.15	0.00%	51.95	51.80
ALFA LAVAL	815.85	811.00	809.25	822.95	806.00	0.8%	820.00	815.85
ALLAHABAD BK	73.55	75.00	74.15	75.05	72.25	-0.8%	73.55	73.25
ALOK INDUSTR	59.85	58.50	59.65	60.45	58.25	0.3%	60.00	59.65
ALPS INDUST	37.20	37.00	36.20	37.50	35.60	2.7%	37.20	35.55
AMARA RAJA	171.95	179.85	175.05	179.85	165.00	-1.7%	171.95	170.30
AMBICA AGARB	14.23	13.26	13.76	14.75	13.26	3.4%	14.50	14.23
AMIT SPIN ID	4.21	4.00	4.20	4.21	4.00	0.2%	4.29	4.04
ANDHR PR PM	75.05	75.55	77.50	79.00	75.05	-3.1%	78.85	75.05
ANDHRA BANK	71.90	70.30	72.05	73.00	70.30	-0.2%	71.90	71.05
APAR INDUS	193.00	191.50	199.05	204.90	191.50	-3.0%	220.00	192.50
APCOTEX LAT.	54.15	55.50	54.45	55.50	53.40	-0.5%	54.15	53.75
APOLLO HOS E	488.15	480.05	487.35	492.00	480.05	0.1%	490.00	488.15

Figure 4.6 IIAM Stock Fetcher Agent: Menus

Add Symbol allows user to add any number of script required to be fetch by agent. Same scripts listed on different index have different extension. All the script added to be fetch is stored in XML file (Script.xml)



Id	Name
505537.BO	ZEE TELEF L
517164.BO	ZENITH CO
512553.BO	ZENITH EXP
532298.BO	ZENITH INF
504067.BO	ZENSAR TE
521163.BO	ZODIAC CLO
500780.BO	ZUARI INDU
524748.BO	LINK PHARM
(null)	(null)

Figure 4.7 IIAM Stock Fetcher Agent: Add New Symbol

On a first run Internet settings may required to configure. The main menu allows user to do this configuration.

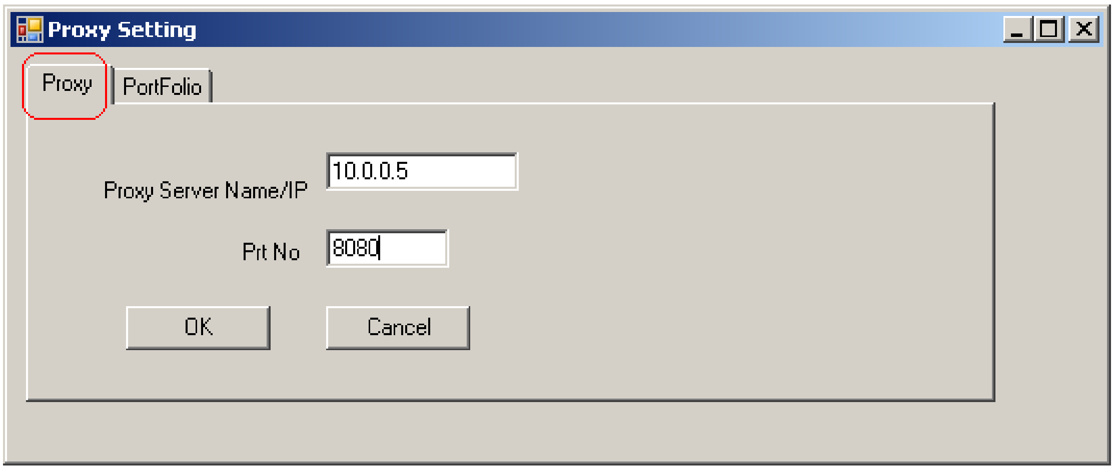


Figure 4.8 IIAM Stock Fetcher Agent: Proxy Setting

The scripts to be fetch by agent is determined by file name given in Portfolio tab of the Proxy Setting, The file is in XML format. It can be located by Open button.

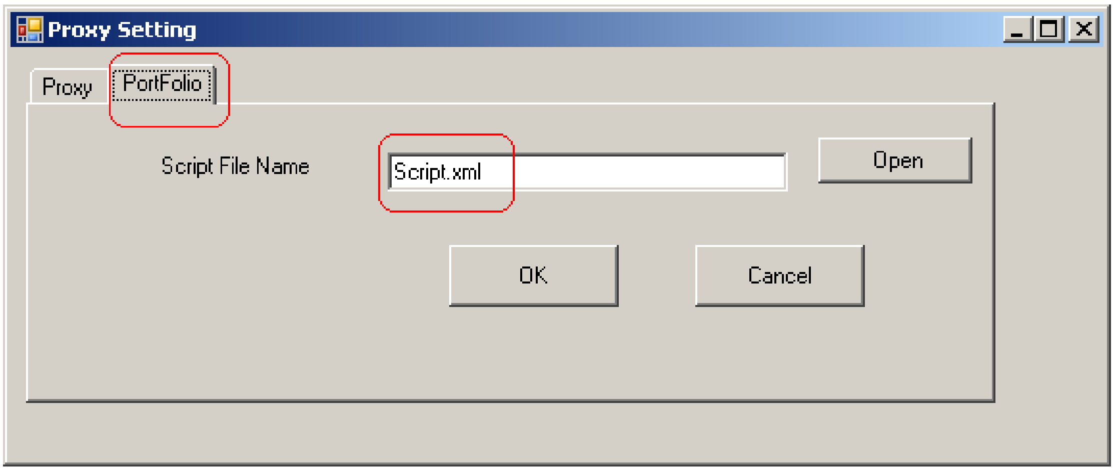
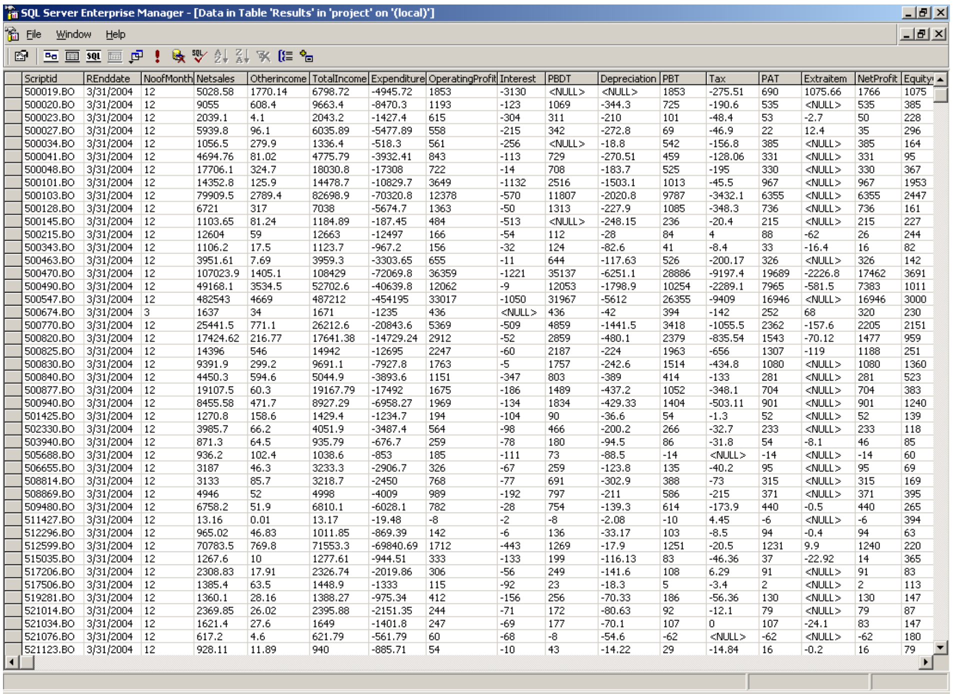


Figure 4.9 IIAM Stock Fetcher Agent: Portfolio Script File

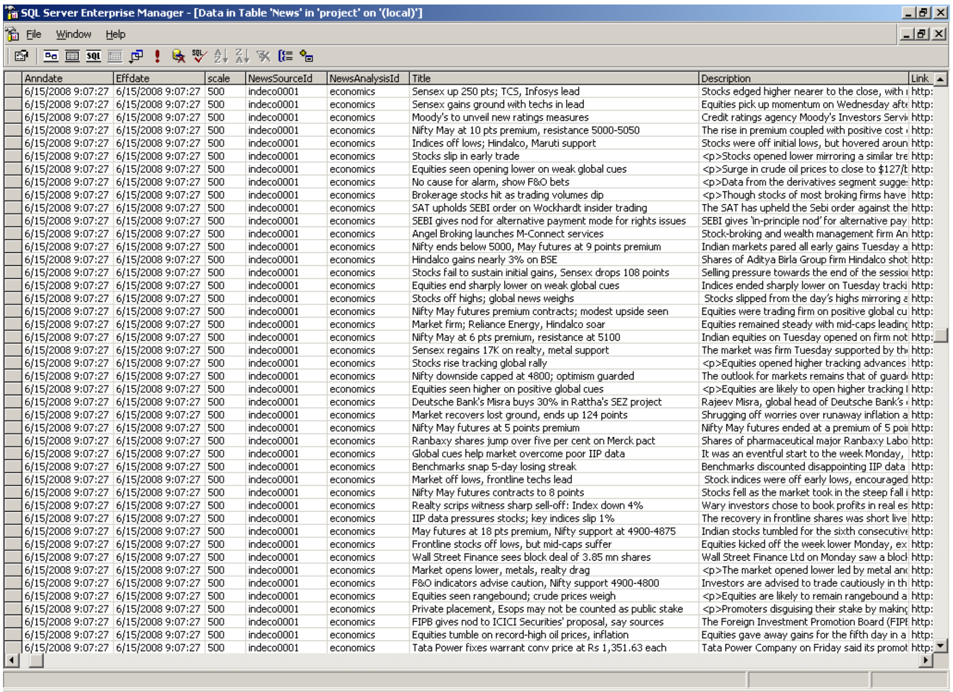
Stock Result Fetcher Agent informs to update the Result table of data depository as new result announced. Program modules of IIAM user interface modules can access it either pick stock matched with fundamental criteria given by user or to evaluate the fundamental strength of stocks by knowledge discovery simulator.



Scriptid	REnddate	NoofMonth	Netsales	Otherincome	TotalIncome	Expenditure	OperatingProfit	Interest	PBDT	Depreciation	PBT	Tax	PAT	Extraitem	NetProfit	Equity
500019.BO	3/31/2004	12	5028.58	1770.14	6798.72	-4945.72	1853	-3130	<NULL>	<NULL>	1853	-275.51	690	1075.66	1766	1075
500020.BO	3/31/2004	12	9055	608.4	9663.4	-8470.3	1193	-123	1069	-344.3	725	-190.6	535	<NULL>	535	385
500023.BO	3/31/2004	12	2039.1	4.1	2043.2	-1427.4	615	-304	311	-210	101	-48.4	53	-2.7	50	228
500027.BO	3/31/2004	12	5939.8	96.1	6035.89	-5477.89	558	-215	342	-272.8	69	-46.9	22	12.4	35	296
500034.BO	3/31/2004	12	1056.5	279.9	1336.4	-518.3	561	-256	<NULL>	-18.8	542	-156.8	385	<NULL>	385	164
500041.BO	3/31/2004	12	4694.76	81.02	4775.79	-3932.41	843	-113	729	-270.51	459	-128.06	331	<NULL>	331	95
500048.BO	3/31/2004	12	17706.1	324.7	18030.8	-17308	722	-14	708	-183.7	525	-195	330	<NULL>	330	367
500101.BO	3/31/2004	12	14352.8	125.9	14478.7	-10829.7	3649	-1132	2516	-1503.1	1013	-45.5	967	<NULL>	967	1953
500103.BO	3/31/2004	12	79909.5	2789.4	82698.9	-70320.8	12378	-570	11807	-2020.8	9787	-3432.1	6355	<NULL>	6355	2447
500128.BO	3/31/2004	12	6721	317	7038	-5674.7	1363	-50	1313	-227.9	1085	-348.3	736	<NULL>	736	161
500145.BO	3/31/2004	12	1103.65	81.24	1184.89	-187.45	484	-513	<NULL>	-248.15	236	-20.4	215	<NULL>	215	227
500215.BO	3/31/2004	12	12604	59	12663	-12497	166	-54	112	-28	84	4	88	-62	26	244
500343.BO	3/31/2004	12	1106.2	17.5	1123.7	-967.2	156	-32	124	-82.6	41	-8.4	33	-16.4	16	82
500463.BO	3/31/2004	12	3951.61	7.69	3959.3	-3303.65	655	-11	644	-117.63	526	-200.17	326	<NULL>	326	142
500470.BO	3/31/2004	12	107023.9	1405.1	108429	-72069.8	36359	-1221	35137	-6251.1	28886	-9197.4	19689	-2226.8	17462	3691
500490.BO	3/31/2004	12	49168.1	3534.5	52702.6	-40639.8	12062	-9	12053	-1798.9	10254	-2289.1	7965	-581.5	7383	1011
500547.BO	3/31/2004	12	482543	4669	487212	-454195	33017	-1050	31967	-5612	26355	-9409	16946	<NULL>	16946	3000
500674.BO	3/31/2004	3	1637	34	1671	-1235	436	<NULL>	436	-42	394	-142	252	68	320	230
500770.BO	3/31/2004	12	25441.5	771.1	26212.6	-20843.6	5369	-509	4859	-1441.5	3418	-1055.5	2362	-157.6	2205	2151
500820.BO	3/31/2004	12	17424.62	216.77	17641.38	-14729.24	2912	-52	2859	-480.1	2379	-835.54	1543	-70.12	1477	959
500825.BO	3/31/2004	12	14396	546	14942	-12695	2247	-60	2187	-224	1963	-656	1307	-119	1188	251
500830.BO	3/31/2004	12	9391.9	299.2	9691.1	-7927.8	1763	-5	1757	-242.6	1514	-434.8	1080	<NULL>	1080	1360
500840.BO	3/31/2004	12	4450.3	594.6	5044.9	-3893.6	1151	-347	803	-389	414	-133	281	<NULL>	281	523
500877.BO	3/31/2004	12	19107.5	60.3	19167.79	-17492	1675	-186	1489	-437.2	1052	-348.1	704	<NULL>	704	383
500940.BO	3/31/2004	12	8455.58	471.7	8927.29	-6958.27	1969	-134	1834	-429.33	1404	-503.11	901	<NULL>	901	1240
501425.BO	3/31/2004	12	1270.8	158.6	1429.4	-1234.7	194	-104	90	-36.6	54	-1.3	52	<NULL>	52	139
502330.BO	3/31/2004	12	3985.7	66.2	4051.9	-3487.4	564	-98	466	-200.2	266	-32.7	233	<NULL>	233	118
503940.BO	3/31/2004	12	871.3	64.5	935.79	-676.7	259	-78	180	-94.5	86	-31.8	54	-8.1	46	85
505688.BO	3/31/2004	12	936.2	102.4	1038.6	-853	185	-111	73	-88.5	-14	<NULL>	-14	<NULL>	-14	60
506655.BO	3/31/2004	12	3187	46.3	3233.3	-2906.7	326	-67	259	-123.8	135	-40.2	95	<NULL>	95	69
508814.BO	3/31/2004	12	3133	85.7	3218.7	-2450	768	-77	691	-302.9	388	-73	315	<NULL>	315	169
508869.BO	3/31/2004	12	4946	52	4998	-4009	989	-192	797	-211	586	-215	371	<NULL>	371	395
509480.BO	3/31/2004	12	6758.2	51.9	6810.1	-6028.1	782	-28	754	-139.3	614	-173.9	440	-0.5	440	265
511427.BO	3/31/2004	12	13.16	0.01	13.17	-19.48	-8	-2	-8	-2.08	-10	4.45	-6	<NULL>	-6	394
512296.BO	3/31/2004	12	965.02	46.83	1011.85	-869.39	142	-6	136	-33.17	103	-8.5	94	-0.4	94	63
512599.BO	3/31/2004	12	70783.5	769.8	71553.3	-69840.69	1712	-443	1269	-17.9	1251	-20.5	1231	9.9	1240	220
515035.BO	3/31/2004	12	1267.6	10	1277.61	-944.51	333	-133	199	-116.13	83	-46.36	37	-22.92	14	365
517206.BO	3/31/2004	12	2308.83	17.91	2326.74	-2019.86	306	-56	249	-141.6	108	6.29	91	<NULL>	91	83
517506.BO	3/31/2004	12	1385.4	63.5	1448.9	-1333	115	-92	23	-18.3	5	-3.4	2	<NULL>	2	113
519281.BO	3/31/2004	12	1360.1	28.16	1388.27	-975.34	412	-156	256	-70.33	186	-56.36	130	<NULL>	130	147
521014.BO	3/31/2004	12	2369.85	26.02	2395.88	-2151.35	244	-71	172	-80.63	92	-12.1	79	<NULL>	79	87
521034.BO	3/31/2004	12	1621.4	27.6	1649	-1401.8	247	-69	177	-70.1	107	0	107	-24.1	83	147
521076.BO	3/31/2004	12	617.2	4.6	621.79	-561.79	60	-68	-8	-54.6	-62	<NULL>	-62	<NULL>	-62	180
521123.BO	3/31/2004	12	928.11	11.89	940	-885.71	54	-10	43	-14.22	29	-14.84	16	-0.2	16	79

Figure 4.10: IIAM Result Data Fetch

Similarly New Fetcher Agent fetch the news from RSS feed and stored it in to data depository, which can be further access by the different modules of software.



Anndate	Effdate	scale	NewsSourceId	NewsAnalysisId	Title	Description	Link
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Sensex up 250 pts; TCS, Infosys lead	Stocks edged higher nearer to the close, with i	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Sensex gains ground with techs in lead	Equities pick up momentum on Wednesday afte	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Moody's to unveil new ratings measures	Credit ratings agency Moody's Investors Servi	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Nifty May at 10 pts premium, resistance 5000-5050	The rise in premium coupled with positive cost	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Indices off lows; Hindalco, Maruti support	Stocks were off initial lows, but hovered aroun	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Stocks slip in early trade	<p>Stocks opened lower mirroring a similar tre	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Equities seen opening lower on weak global cues	<p>Surge in crude oil prices to close to $127/t	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	No cause for alarm, show F&O bets	<p>Data from the derivatives segment sugge:	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Brokerage stocks hit as trading volumes dip	<p>Though stocks of most broking firms have	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	SAT upholds SEBI order on Wockhardt insider trading	The SAT has upheld the Sebi order against the	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	SEBI gives nod for alternative payment mode for rights issues	SEBI gives 'in-principle nod' for alternative pay	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Angel Broking launches M-Connect services	Stock-broking and wealth management firm An	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Nifty ends below 5000, May futures at 9 points premium	Indian markets pared all early gains Tuesday a	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Hindalco gains nearly 3% on BSE	Shares of Aditya Birla Group firm Hindalco shot	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Stocks fail to sustain initial gains, Sensex drops 108 points	Selling pressure towards the end of the sessio	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Equities end sharply lower on weak global cues	Indices ended sharply lower on Tuesday tracki	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Stocks off highs; global news weighs	Stocks slipped from the day's highs mirroring a	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Nifty May futures premium contracts; modest upside seen	Equities were trading firm on positive global cu	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Market firm; Reliance Energy, Hindalco soar	Equities remained steady with mid-caps leadinç	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Nifty May at 6 pts premium, resistance at 5100	Indian equities on Tuesday opened on firm not	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Sensex regains 17K on realty, metal support	The market was firm Tuesday supported by th	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Stocks rise tracking global rally	<p>Equities opened higher tracking advances	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Nifty downside capped at 4800; optimism guarded	The outlook for markets remains that of guard	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Equities seen higher on positive global cues	<p>Equities are likely to open higher tracking l	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Deutsche Bank's Misra buys 30% in Rattha's SEZ project	Rajeev Misra, global head of Deutsche Bank's	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Market recovers lost ground, ends up 124 points	Shrugging off worries over runaway inflation a	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Nifty May futures at 5 points premium	Nifty May futures ended at a premium of 5 poi	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Ranbaxy shares jump over five per cent on Merck pact	Shares of pharmaceutical major Ranbaxy Labo	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Global cues help market overcome poor IIP data	It was an eventful start to the week Monday,	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Benchmarks snap 5-day losing streak	Benchmarks discounted disappointing IIP data	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Market off lows, frontline techs lead	Stock indices were off early lows, encouraged	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Nifty May futures contracts to 8 points	Stocks fell as the market took in the steep fall i	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Realty scrips witness sharp sell-off: Index down 4%	Wary investors chose to book profits in real es	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	IIP data pressures stocks; key indices slip 1%	The recovery in frontline shares was short live	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	May futures at 18 pts premium, Nifty support at 4900-4875	Indian stocks tumbled for the sixth consecutive	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Frontline stocks off lows, but mid-caps suffer	Equities kicked off the week lower Monday, ex	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Wall Street Finance sees block deal of 3.85 mn shares	Wall Street Finance Ltd on Monday saw a block	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Market opens lower, metals, realty drag	<p>The market opened lower led by metal anc	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	F&O indicators advise caution, Nifty support 4900-4800	Investors are advised to trade cautiously in th	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Equities seen rangebound; crude prices weigh	<p>Equities are likely to remain rangebound a	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Private placement, Esops may not be counted as public stake	<p>Promoters disguising their stake by makinç	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	FIPB gives nod to ICICI Securities' proposal, say sources	The Foreign Investment Promotion Board (FIPE	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Equities tumble on record-high oil prices, inflation	Equities gave away gains for the fifth day in a	http:
6/15/2008 9:07:27	6/15/2008 9:07:27	500	indeco0001	economics	Tata Power fixes warrant conv price at Rs 1,351.63 each	Tata Power Company on Friday said its promot	http:

Figure 4.11: IIAM News Data Fetch

ULIP NAV Fetcher Agents fetch the NAV and store it in to data depository, which can be further access by the ULIP knowledge discovery simulators or any module of software required ULIP data.

SQL Server Enterprise Manager - [Data in Table 'UlipTransection' in 'project' on '(local)']

File Window Help

ScriptID	Udate	Mode1	Mode2	Mode3	Mode4
000001.UL	6/23/2006	10.13	10.0703	9.66	9.2
000001.UL	6/26/2006	10.14	10.0749	9.54	8.91
000001.UL	6/27/2006	10.14	10.0759	9.57	9
000001.UL	6/28/2006	10.14	10.0738	9.57	9
000001.UL	6/29/2006	10.14	10.0755	9.58	9.01
000001.UL	6/30/2006	10.15	10.0767	9.73	9.4
000001.UL	7/3/2006	10.15	10.0826	9.76	9.46
000001.UL	7/4/2006	10.15	10.0826	9.75	9.45
000001.UL	7/5/2006	10.16	10.0844	9.82	9.63
000001.UL	7/6/2006	10.17	10.1375	9.86	9.55
000001.UL	7/7/2006	10.17	10.1383	9.78	9.33
000001.UL	7/10/2006	10.18	10.1416	9.84	9.47
000001.UL	7/11/2006	10.18	10.1432	9.81	9.39
000001.UL	7/12/2006	10.18	10.1448	9.89	9.59
000001.UL	7/13/2006	10.18	10.1465	9.86	9.52
000001.UL	7/14/2006	10.19	10.1484	9.81	9.39
000001.UL	7/17/2006	10.19	10.1535	9.69	9.07
000001.UL	7/18/2006	10.19	10.1554	9.66	8.99
000001.UL	7/19/2006	10.19	10.1576	9.58	8.77
000001.UL	7/20/2006	10.2	10.1601	9.7	9.06
000001.UL	7/21/2006	10.2	10.1634	9.62	8.85
000001.UL	7/24/2006	10.21	10.169	9.65	8.92
000001.UL	7/25/2006	10.21	10.1705	9.72	9.08
000001.UL	7/26/2006	10.21	10.1701	9.79	9.26
000001.UL	7/27/2006	10.21	10.1705	9.83	9.37
000001.UL	7/28/2006	10.21	10.1738	9.83	9.33
000001.UL	7/31/2006	10.22	10.1791	9.86	9.4
000001.UL	8/1/2006	10.22	10.1803	9.87	9.43
000001.UL	8/2/2006	10.23	10.184	9.93	9.57
000001.UL	8/3/2006	10.23	10.186	9.94	9.59
000001.UL	8/4/2006	10.23	10.1884	9.91	9.53
000001.UL	8/7/2006	10.23	10.1946	9.9	9.47
000001.UL	8/8/2006	10.23	10.198	9.96	9.62
000001.UL	8/9/2006	10.23	10.2043	10.01	9.75
000001.UL	8/10/2006	10.24	10.2068	10.02	9.75
000001.UL	8/11/2006	10.24	10.2081	10.04	9.81
000001.UL	8/14/2006	10.24	10.2136	10.09	9.94
000001.UL	8/16/2006	10.25	10.2177	10.14	10.07
000001.UL	8/17/2006	10.25	10.221	10.15	10.07
000001.UL	8/18/2006	10.25	10.2218	10.14	10.05
000001.UL	8/21/2006	10.26	10.2273	10.17	10.12
000001.UL	8/22/2006	10.26	10.2291	10.17	10.1
000001.UL	8/23/2006	10.26	10.2328	10.13	10.01
000001.UL	8/24/2006	10.26	10.2374	10.17	10.12
000001.UL	8/25/2006	10.27	10.2371	10.2	10.19
000001.UL	8/28/2006	10.27	10.2427	10.22	10.24

Figure 4.12: IIAM ULIP NAV Fetch

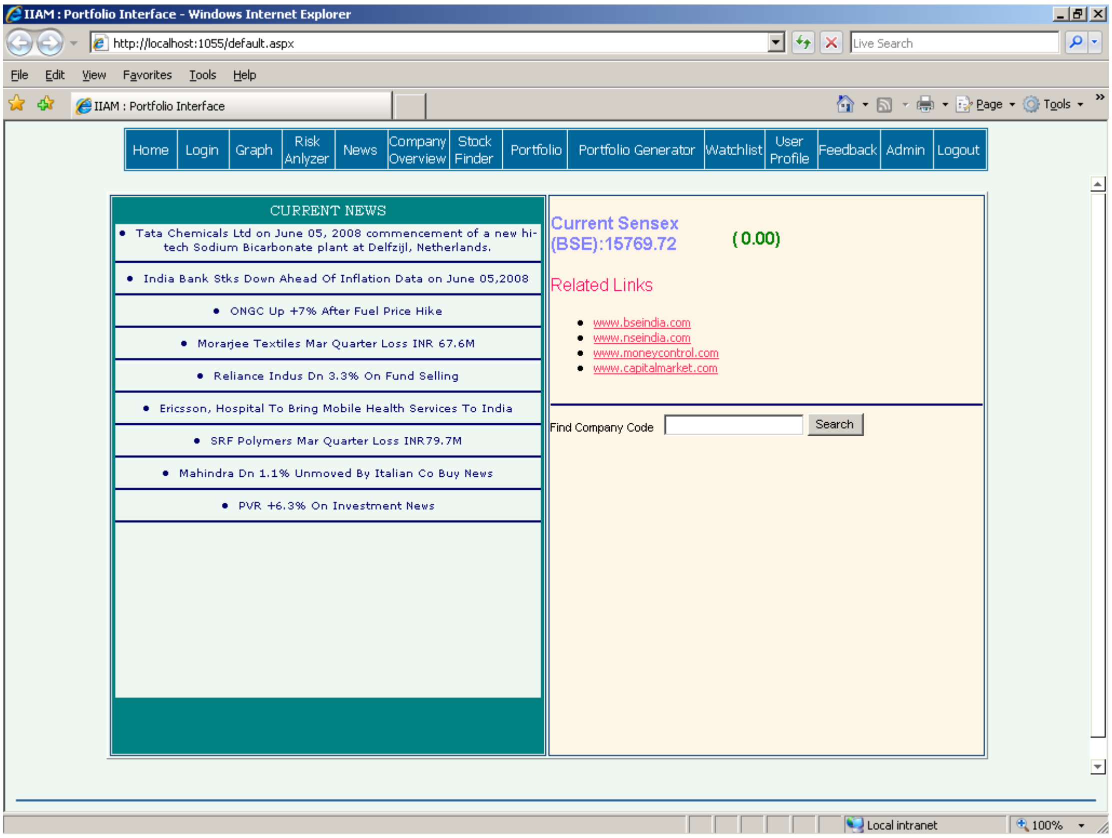


Figure 4.13: IIAM User Interface Home Page

Home Page contains current market news, Sensex details, interface to search company code, and menu for navigation, like the News menu navigates to the detail news information. The interface contains number of modules, we can assign different privileges to different class of users, so it can possible that the visitors only access the general information, and restricted to the modules having use of knowledge discovery activity.

User can retrieve the list of scripts and their code by searching the database by keyword.

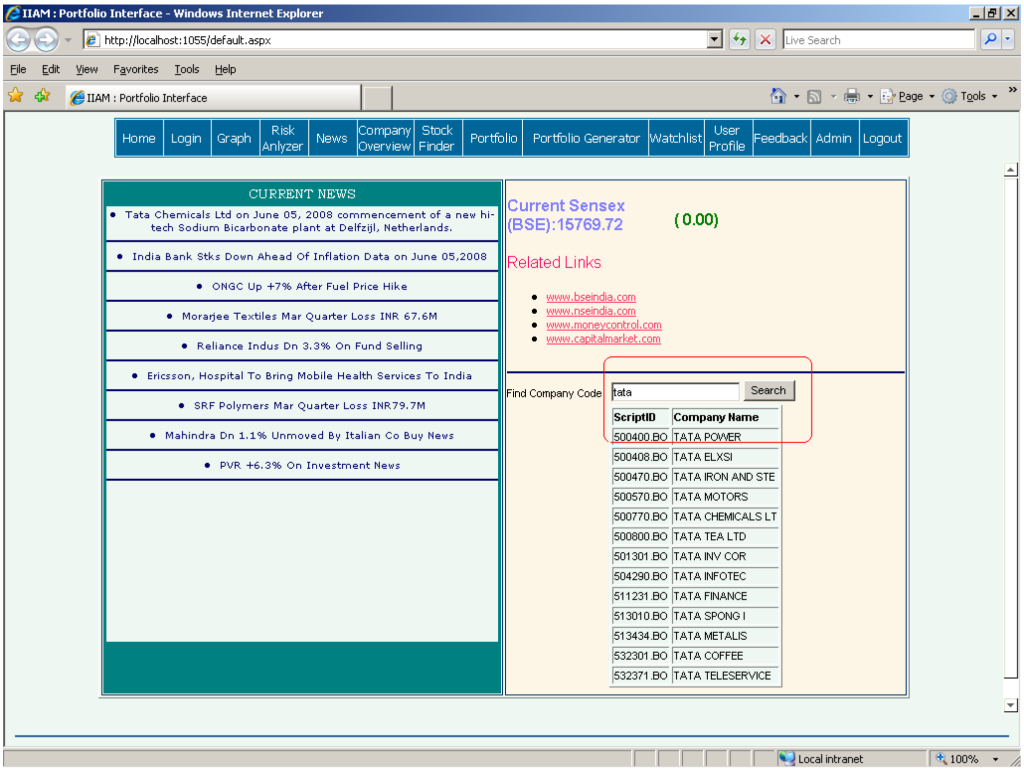


Figure 4.14: IIAM User Interface Find Company

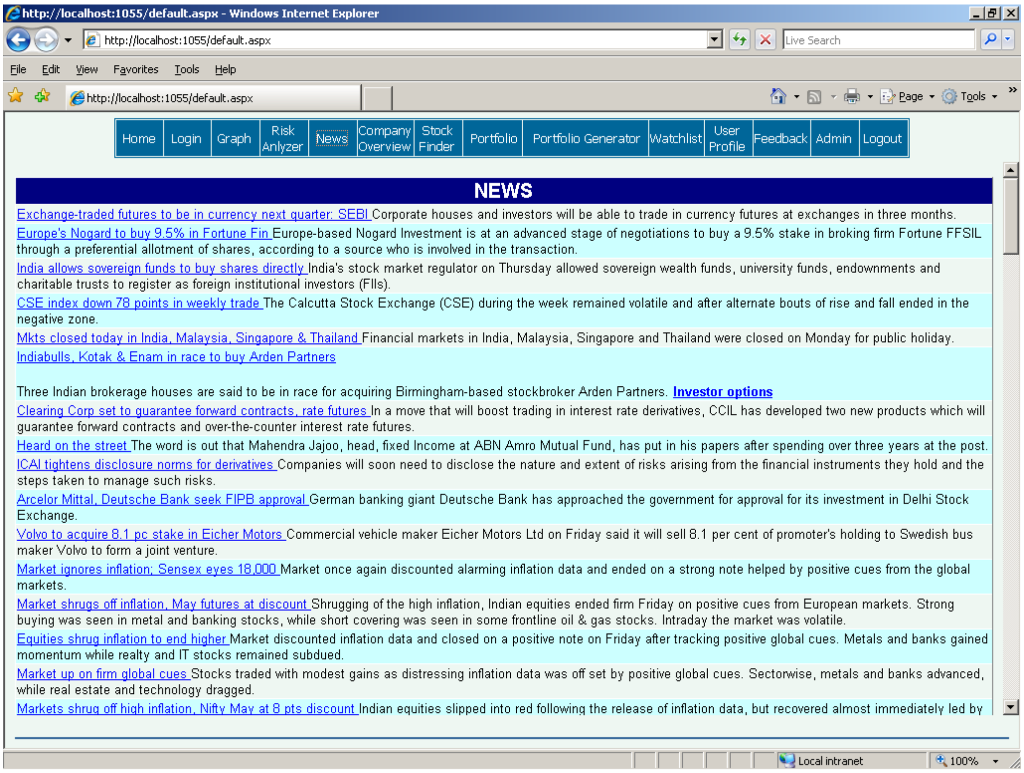


Figure 4.15: IIAM - NEWS User Interface

The news section displays the latest news heading and description fetched by News Fetcher Agent and details news from the RSS feeds.

Graph Menu allows user to access stock data from data depository in graphical form for analysis. So user can get quick idea about stock price trend over any desired period of time.

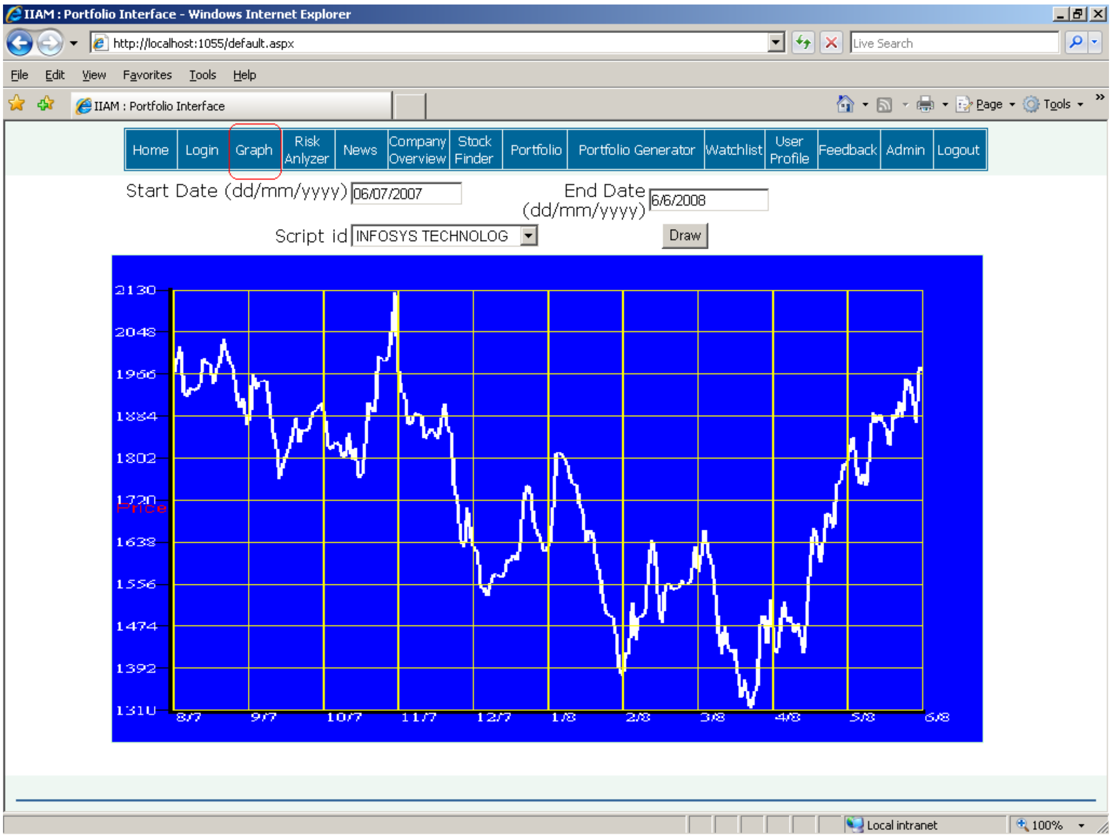


Figure 4.16: IIAM - Graph User Interface

The interface company overview generates fundamental parameters using this information or to list the stocks matches the certain fundamental criteria given by user. Stock Finder menu offer this facility.

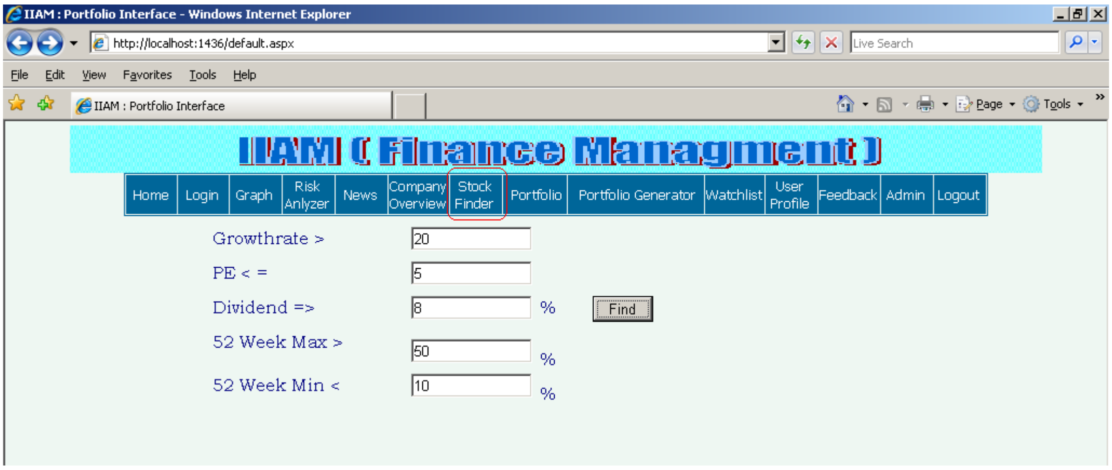


Figure 4.17: IIAM – Stock Filter Interface

There is a separate account for each user, when user enters correct login information, system allows user to create account, perform transactions in account, and view all the details in summarized form as a portfolio.

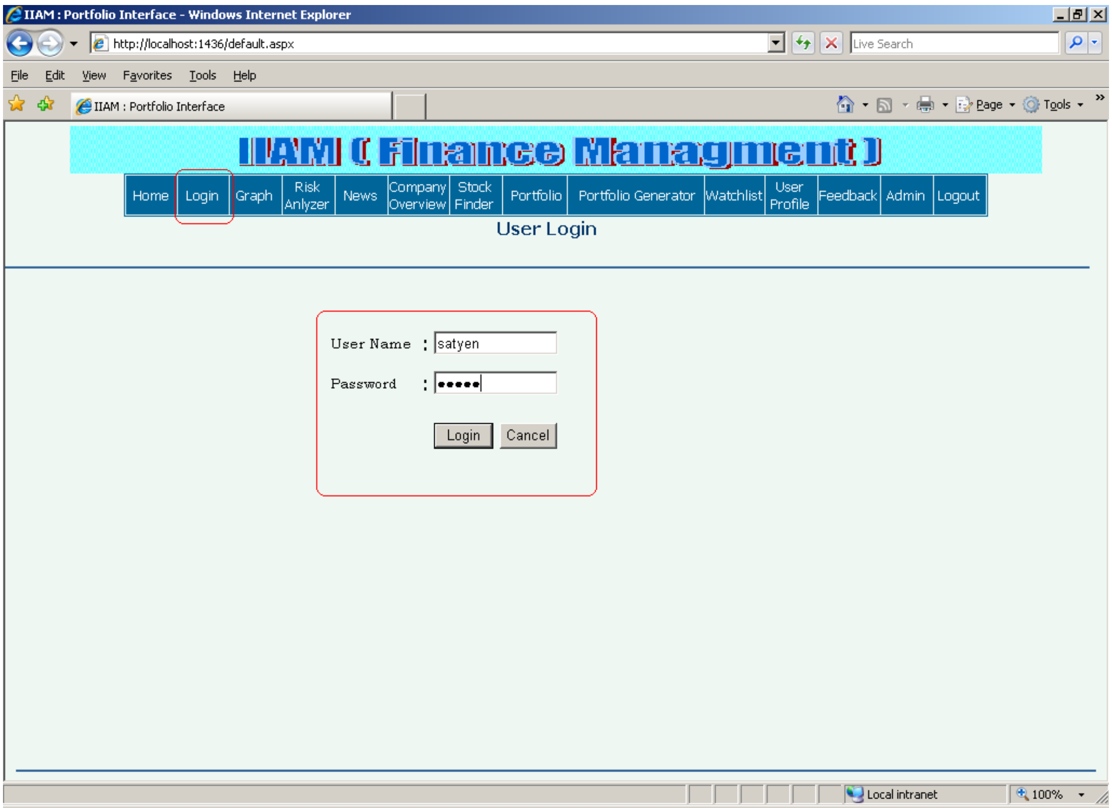


Figure 4.18: IIAM – User Login Interface

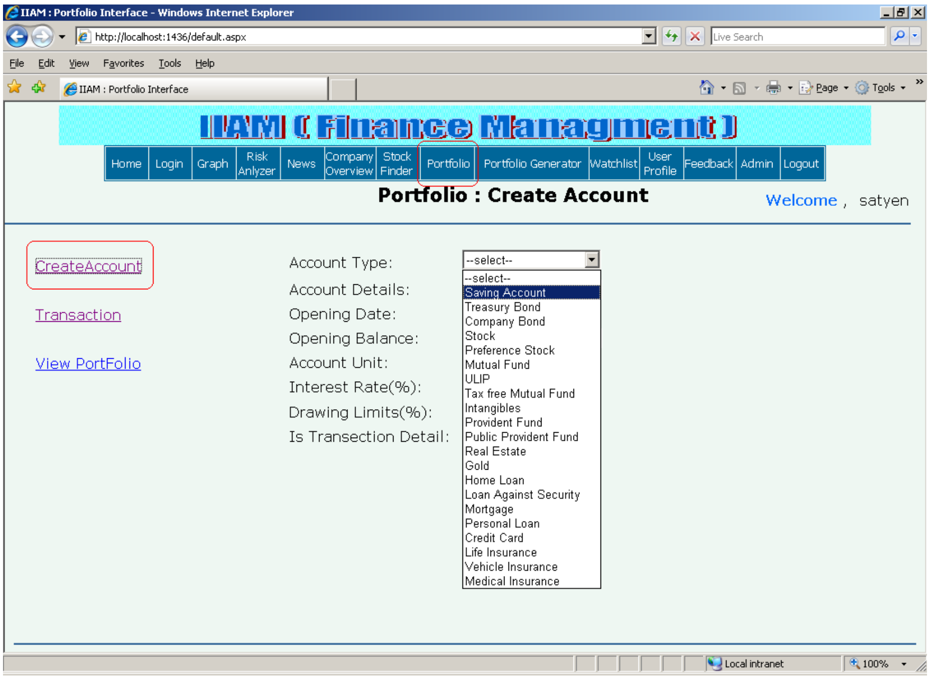


Figure 4.19: IIAM Portfolio-Create Account

The account information will gets vary for different asset categories, for example ULIP and Life insurance polices have additional attributes for locking period and loan eligibility based on account value.

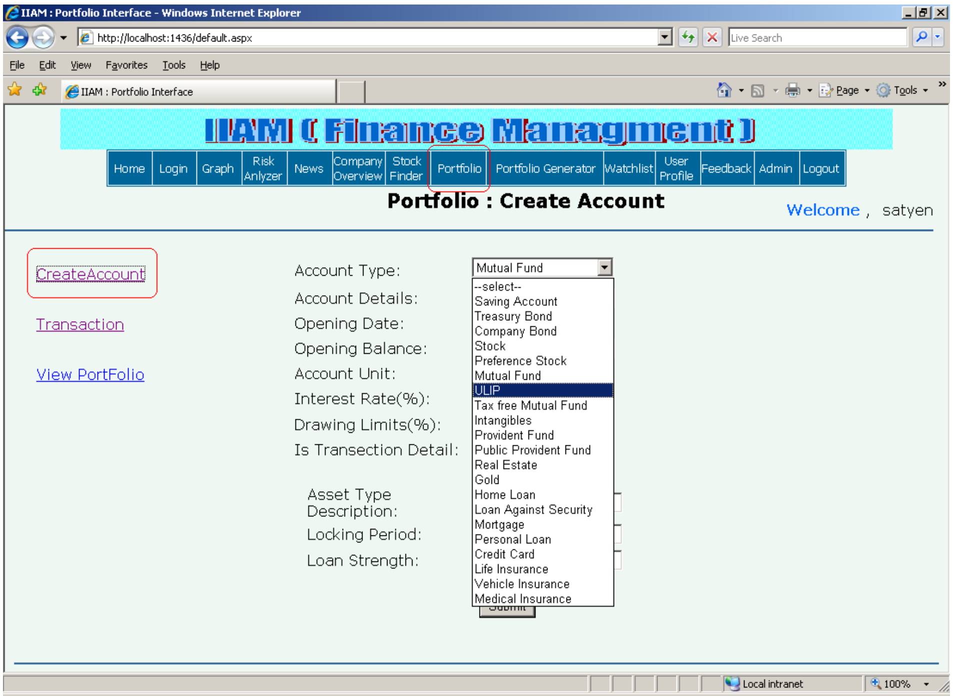


Figure 4.20: IIAM Portfolio-Create Account Detail

Once account is created, user can perform transactions in its account after selecting the available accounts. Transaction of one account may affect another account. For example when we buy stock, and pay the price of stock from saving account, the balance of saving account reduces by the stock price and balance of stock account will increase by the quantity of stock purchased.

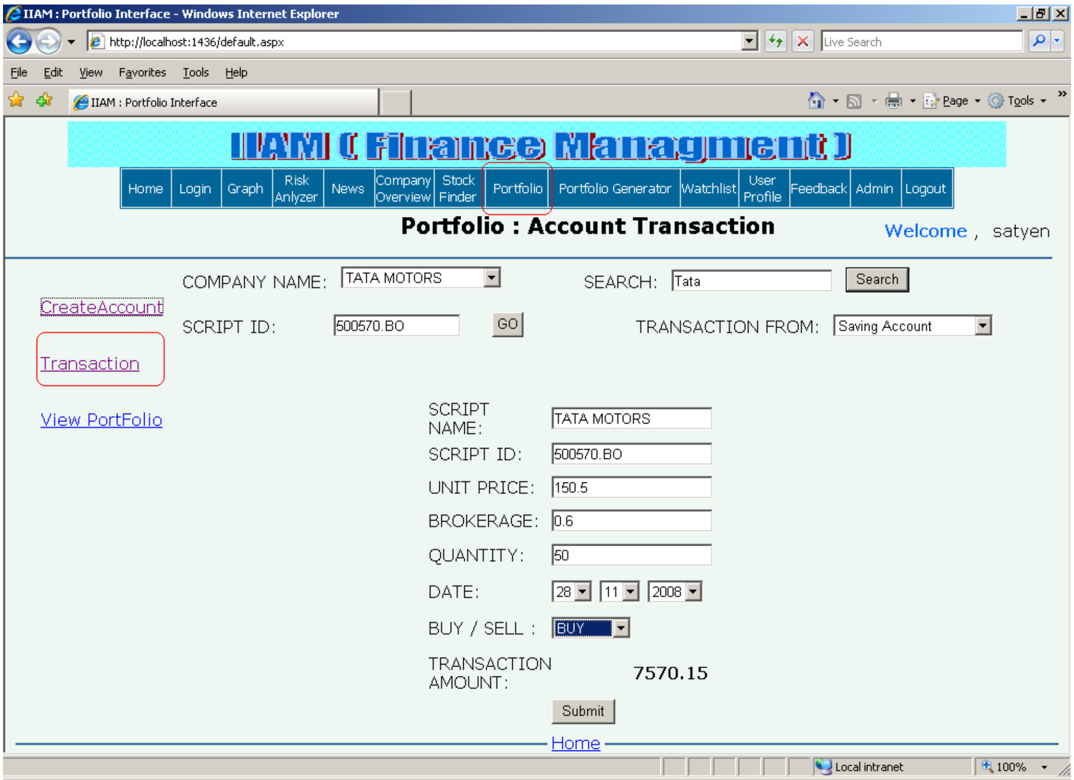


Figure 4.21: IIAM Portfolio- Account Transaction

User can view complete portfolio net worth by selecting View Portfolio option from portfolio. As overall growth is very imported. User can analyze his different allocations at a glance, and can decide future action plan.

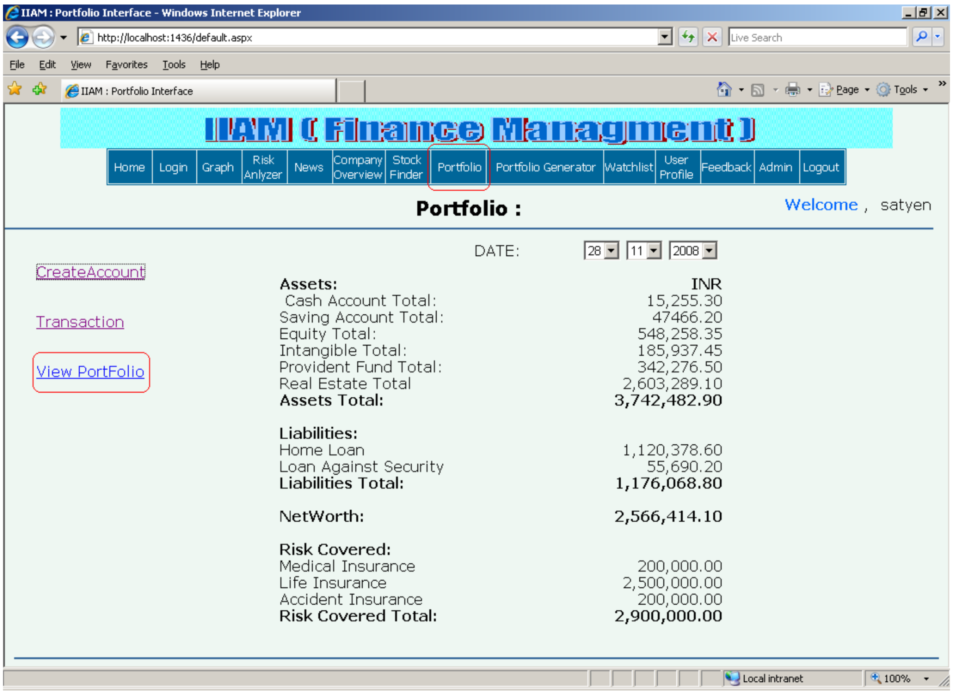


Figure 4.22: IIAM Birds Eye Portfolio View

There is a provision for analyze the user profile and risk taking ability along with the safety principles should be recommended. The purpose is achieved by analyzing the answers from a questionnaire from the user.

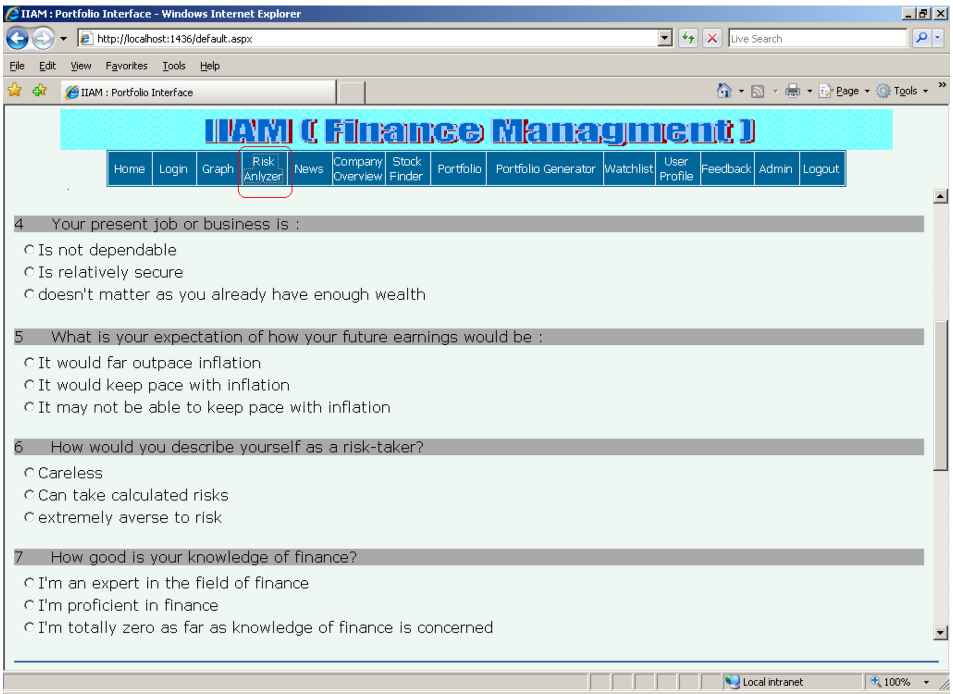


Figure 4.23: IIAM Risk Analyzer

User can submit suggestion by selecting feedback option and then providing the detailed information.

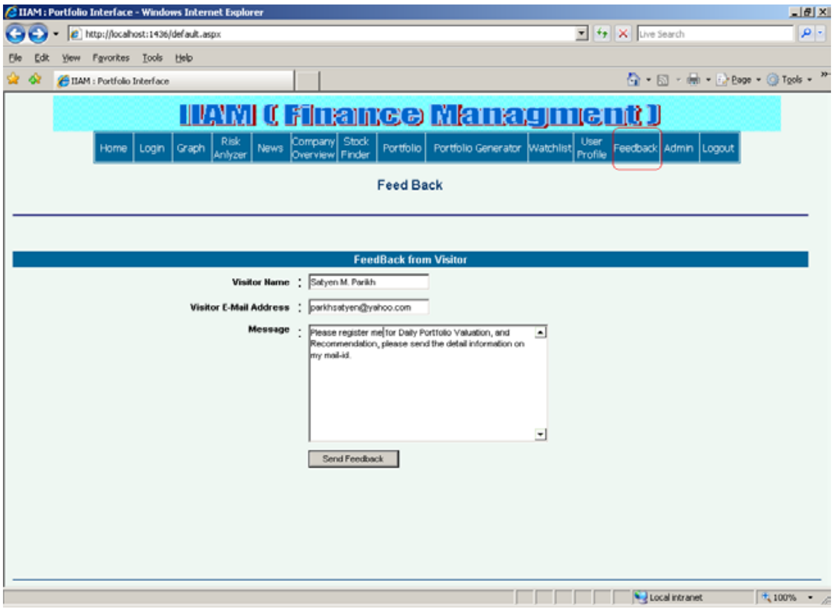


Figure 4.24: IIAM User Feedback

As discussed earlier that some intelligent models has developed for providing recommendations. The following report generated by ULIP (Unit Link Insurance Plan) financial knowledge discovery simulator.

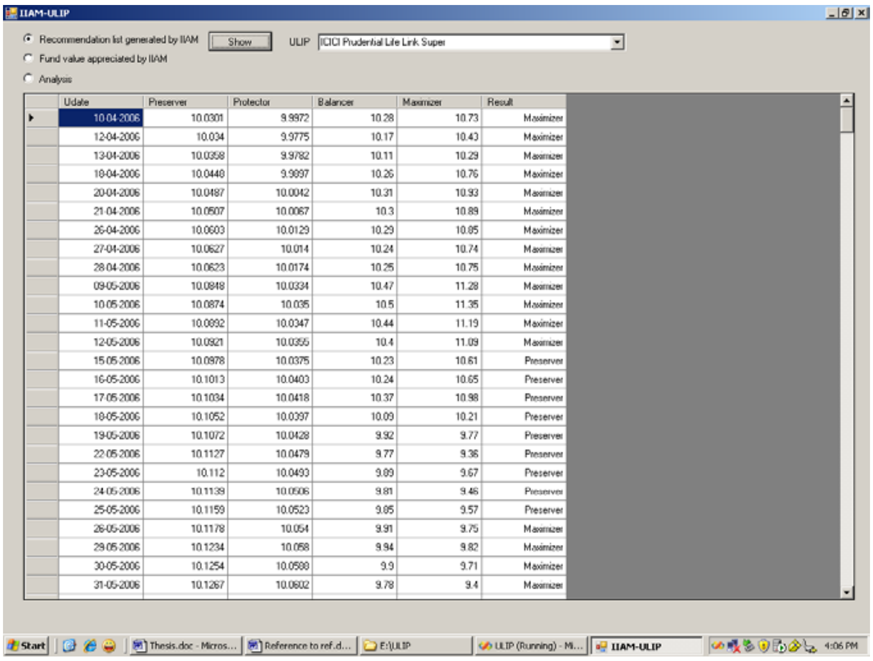
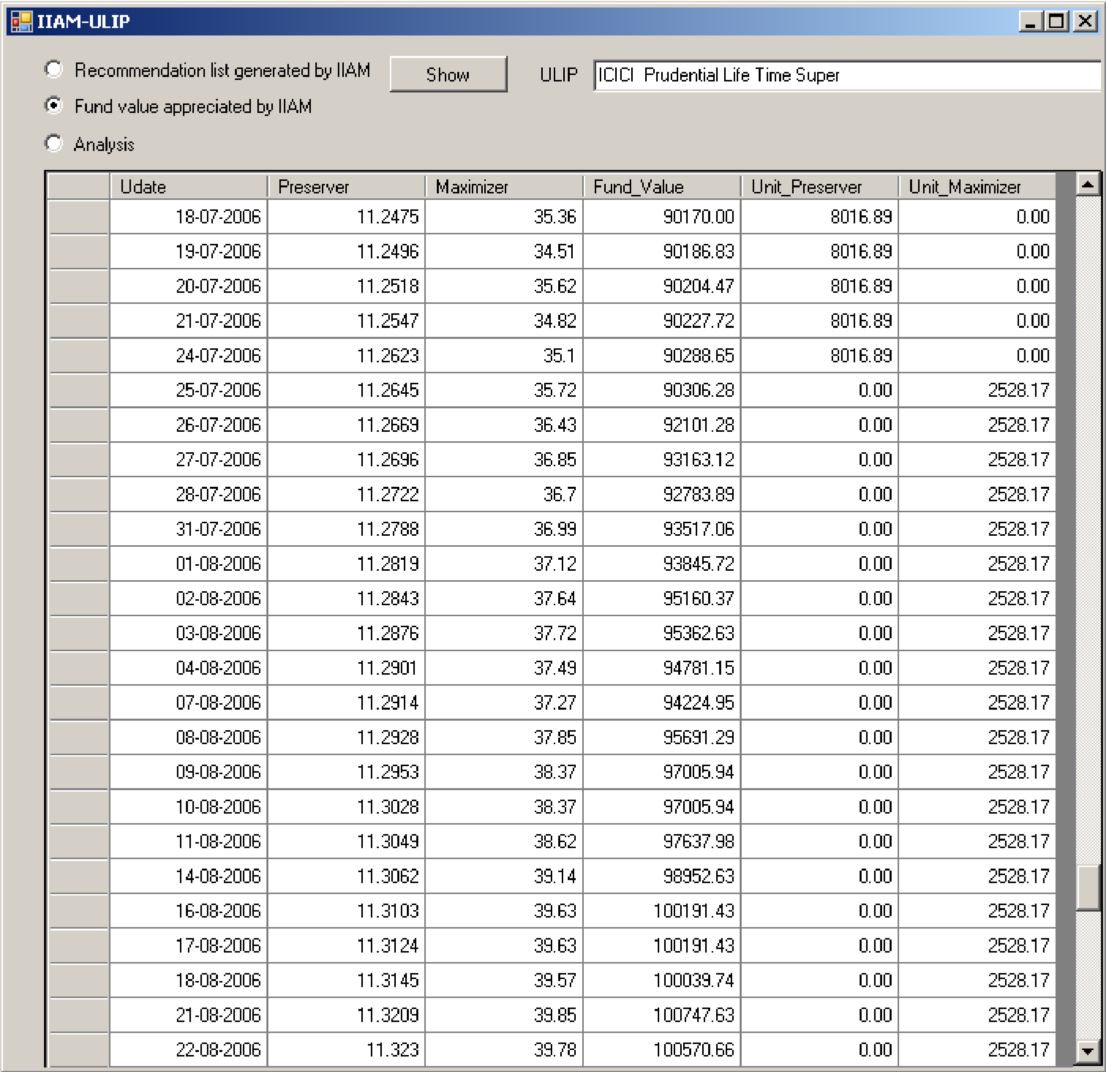


Figure 4.25: IIAM ULIP Recommendation

The model suggests the switching, be analyzing the different parameters. The object of switching is to grab the advantage of equity growth in good market time and protect the capital with debt/bond class of investment in tuff market time.

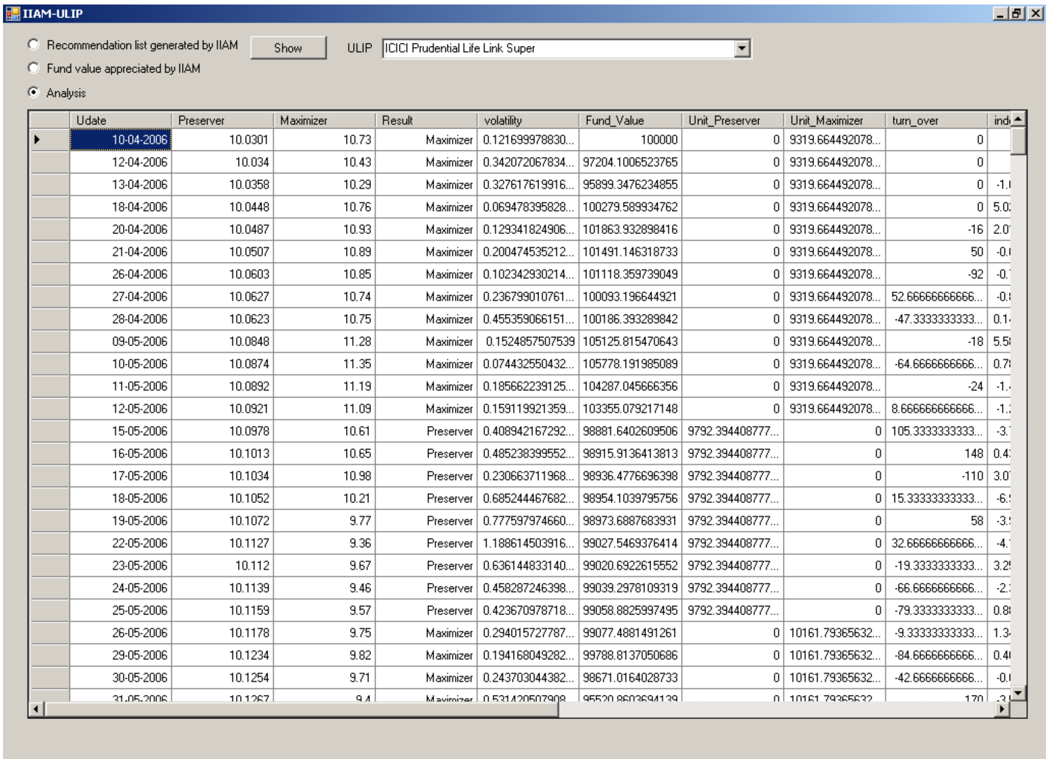
The Fund Value Appreciated by IIAM model option will give complete detail of number of unit converted in the switching mode recommended by model along with fund value.



Udate	Preserver	Maximizer	Fund_Value	Unit_Preserver	Unit_Maximizer
18-07-2006	11.2475	35.36	90170.00	8016.89	0.00
19-07-2006	11.2496	34.51	90186.83	8016.89	0.00
20-07-2006	11.2518	35.62	90204.47	8016.89	0.00
21-07-2006	11.2547	34.82	90227.72	8016.89	0.00
24-07-2006	11.2623	35.1	90288.65	8016.89	0.00
25-07-2006	11.2645	35.72	90306.28	0.00	2528.17
26-07-2006	11.2669	36.43	92101.28	0.00	2528.17
27-07-2006	11.2696	36.85	93163.12	0.00	2528.17
28-07-2006	11.2722	36.7	92783.89	0.00	2528.17
31-07-2006	11.2788	36.99	93517.06	0.00	2528.17
01-08-2006	11.2819	37.12	93845.72	0.00	2528.17
02-08-2006	11.2843	37.64	95160.37	0.00	2528.17
03-08-2006	11.2876	37.72	95362.63	0.00	2528.17
04-08-2006	11.2901	37.49	94781.15	0.00	2528.17
07-08-2006	11.2914	37.27	94224.95	0.00	2528.17
08-08-2006	11.2928	37.85	95691.29	0.00	2528.17
09-08-2006	11.2953	38.37	97005.94	0.00	2528.17
10-08-2006	11.3028	38.37	97005.94	0.00	2528.17
11-08-2006	11.3049	38.62	97637.98	0.00	2528.17
14-08-2006	11.3062	39.14	98952.63	0.00	2528.17
16-08-2006	11.3103	39.63	100191.43	0.00	2528.17
17-08-2006	11.3124	39.63	100191.43	0.00	2528.17
18-08-2006	11.3145	39.57	100039.74	0.00	2528.17
21-08-2006	11.3209	39.85	100747.63	0.00	2528.17
22-08-2006	11.323	39.78	100570.66	0.00	2528.17

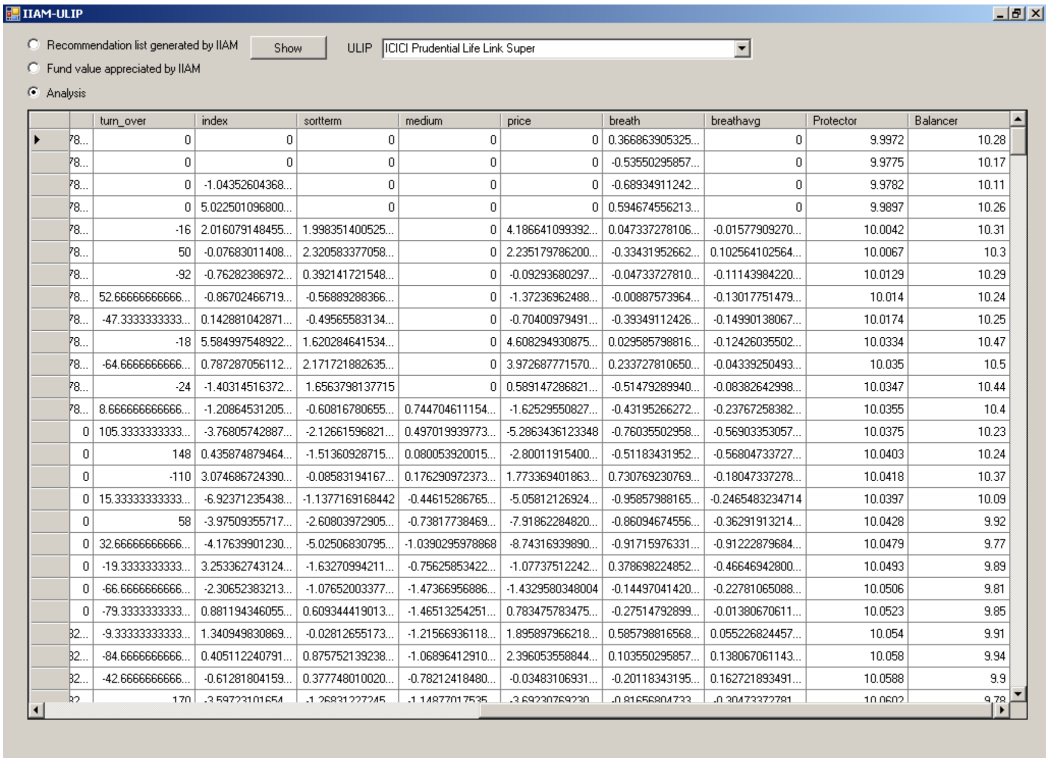
Figure 4.26: IIAM ULIP Fund Value Appreciation Report

The model simulator also generates the details of parameters and its value considered for recommendation.



Udate	Preserver	Maximizer	Result	volatility	Fund_Value	Unit_Preserver	Unit_Maximizer	turn_over
10-04-2006	10.0301	10.73	Maximizer	0.121699978830...	100000	0	9319.664492078...	0
12-04-2006	10.034	10.43	Maximizer	0.342072067834...	97204.1006523765	0	9319.664492078...	0
13-04-2006	10.0358	10.29	Maximizer	0.327617619916...	95899.3476234855	0	9319.664492078...	0
18-04-2006	10.0448	10.76	Maximizer	0.069478395828...	100279.589934762	0	9319.664492078...	0
20-04-2006	10.0487	10.93	Maximizer	0.129341824906...	101863.932898416	0	9319.664492078...	-16
21-04-2006	10.0507	10.89	Maximizer	0.200474535212...	101491.146318733	0	9319.664492078...	50
26-04-2006	10.0603	10.85	Maximizer	0.102342930214...	101118.359739049	0	9319.664492078...	-92
27-04-2006	10.0627	10.74	Maximizer	0.236799010761...	100093.196644921	0	9319.664492078...	52.66666666666...
28-04-2006	10.0623	10.75	Maximizer	0.455359066151...	100186.393289842	0	9319.664492078...	-47.3333333333...
09-05-2006	10.0848	11.28	Maximizer	0.1524857507539	105125.815470643	0	9319.664492078...	-18
10-05-2006	10.0874	11.35	Maximizer	0.074432550432...	105778.191985089	0	9319.664492078...	-64.6666666666...
11-05-2006	10.0892	11.19	Maximizer	0.185662239125...	104287.045666356	0	9319.664492078...	-24
12-05-2006	10.0921	11.09	Maximizer	0.159119921359...	103355.079217148	0	9319.664492078...	8.66666666666...
15-05-2006	10.0978	10.61	Preserver	0.408942167292...	98881.6402609506	9792.394408777...	0	105.3333333333...
16-05-2006	10.1013	10.65	Preserver	0.485238399552...	98915.9136413813	9792.394408777...	0	148
17-05-2006	10.1034	10.98	Preserver	0.230663711968...	98936.4776696398	9792.394408777...	0	-110
18-05-2006	10.1052	10.21	Preserver	0.685244467682...	98954.1039795756	9792.394408777...	0	15.33333333333...
19-05-2006	10.1072	9.77	Preserver	0.777597974660...	98973.6887683931	9792.394408777...	0	58
22-05-2006	10.1127	9.36	Preserver	1.188614503916...	99027.5469376414	9792.394408777...	0	32.6666666666...
23-05-2006	10.112	9.67	Preserver	0.636144833140...	99020.6922615552	9792.394408777...	0	-19.3333333333...
24-05-2006	10.1139	9.46	Preserver	0.458287246398...	99039.2978109319	9792.394408777...	0	-66.6666666666...
25-05-2006	10.1159	9.57	Preserver	0.423670978718...	99058.8825997495	9792.394408777...	0	-79.3333333333...
26-05-2006	10.1178	9.75	Maximizer	0.294015727787...	99077.4881491261	0	10161.79365632...	-9.33333333333...
29-05-2006	10.1234	9.82	Maximizer	0.194168049282...	99788.8137050686	0	10161.79365632...	-84.6666666666...
30-05-2006	10.1254	9.71	Maximizer	0.243703044382...	98671.0164028733	0	10161.79365632...	-42.6666666666...

Figure 4.27: IIAM ULIP Detailed Analysis-I



	turn_over	index	sortterm	medium	price	breath	breathavg	Protector	Balancer
78...	0	0	0	0	0	0.366863905325...	0	9.9972	10.28
78...	0	0	0	0	0	-0.53550295857...	0	9.9775	10.17
78...	0	-1.04352604368...	0	0	0	-0.68934911242...	0	9.9782	10.11
78...	0	5.022501096800...	0	0	0	0.594674556213...	0	9.9897	10.26
78...	-16	2.016079148455...	1.998351400525...	0	4.186641099392...	0.047337278106...	-0.01577909270...	10.0042	10.31
78...	50	-0.07683011408...	2.320583377058...	0	2.235179786200...	-0.33431952662...	0.102564102564...	10.0067	10.3
78...	-92	-0.76282386972...	0.392141721548...	0	-0.09293680297...	-0.04733727810...	-0.11143984220...	10.0129	10.29
78...	52.66666666666...	-0.86702466719...	-0.56889288366...	0	-1.37236962488...	-0.00887573964...	-0.13017751479...	10.014	10.24
78...	-47.3333333333...	0.142881042871...	-0.49565583134...	0	-0.70400979491...	-0.39349112426...	-0.14990138067...	10.0174	10.25
78...	-18	5.584997548922...	1.620284641534...	0	4.608294930875...	0.029585798816...	-0.12426035502...	10.0334	10.47
78...	-64.6666666666...	0.787287056112...	2.171721882635...	0	3.972687771570...	0.233727810650...	-0.04339250493...	10.035	10.5
78...	-24	-1.40314516372...	1.6563798137715	0	0.589147286821...	-0.51479289940...	-0.08382642998...	10.0347	10.44
78...	8.66666666666...	-1.20864531205...	-0.60816780655...	0.744704611154...	-1.62529550827...	-0.43195266272...	-0.23767258382...	10.0355	10.4
0	105.3333333333...	-3.76805742887...	-2.12661596821...	0.497019939773...	-5.2863436123348	-0.76035502958...	-0.56903353057...	10.0375	10.23
0	148	0.435874879464...	-1.51360928715...	0.080053920015...	-2.80011915400...	-0.51183431952...	-0.56804733727...	10.0403	10.24
0	-110	3.074686724390...	-0.08583194167...	0.176290972373...	1.773369401863...	0.730769230769...	-0.18047337278...	10.0418	10.37
0	15.33333333333...	-6.92371235438...	-1.1377169168442	-0.44615286765...	-5.05812126924...	-0.95857988165...	-0.2465483234714	10.0397	10.09
0	58	-3.97509355717...	-2.60803972905...	-0.73817738469...	-7.91862284820...	-0.86094674556...	-0.36291913214...	10.0428	9.92
0	32.66666666666...	-4.17639901230...	-5.02506830795...	-1.0390295978868	-8.74316939890...	-0.91715976331...	-0.91222879684...	10.0479	9.77
0	-19.3333333333...	3.253362743124...	-1.63270994211...	-0.75625853422...	-1.07737512242...	0.378698224852...	-0.46646942800...	10.0493	9.89
0	-66.6666666666...	-2.30652383213...	-1.07652003377...	-1.47366956886...	-1.4329580348004	-0.14497041420...	-0.22781065088...	10.0506	9.81
0	-79.3333333333...	0.881194346055...	0.609344419013...	-1.46513254251...	0.783475783475...	-0.27514792899...	-0.01380670611...	10.0523	9.85
32...	-9.33333333333...	1.340949830869...	-0.02812655173...	-1.21566936118...	1.895897966218...	0.585798816568...	0.055226824457...	10.054	9.91
32...	-84.6666666666...	0.405112240791...	0.875752139238...	-1.06896412910...	2.396053558844...	0.103550295857...	0.138067061143...	10.058	9.94
32...	-42.6666666666...	-0.61281804159...	0.377748010020...	-0.78212418480...	-0.03483106931...	-0.20118343195...	0.162721893491...	10.0588	9.9

Figure 4.28: IIAM ULIP Detailed Analysis-II

Chapter- V

Data Management, Research Methodology, Results

5.1 Data Sources:

The Ultimate sources for most of Index data are stock exchanges. The data generated by exchanges are provided in the form of data feed.

We have collected data from different sources; the stock transaction data is available in the form of 10 min delayed quote from xignite.com.

Web link http://xignite.com/Products/ProductDirectory.aspx contains the details to access all available data through web services.

The data requested are return in the form of XML, so it can be incorporate in the application and then we can store it for further use.

The news data is available in the form of RSS feed from various sources like

http://economictimes.indiatimes.com/rssfeedsdefault.cms

Provides the latest feed, that can be process further for intended use of application, there are number of other sources to get the similar financial news like www.cnbc.com, www.businessweek.com, www.sify.com etc.

Communication of corporate and BSE are available in BSE Xplorer, It is excellent software allows us to download, open, save, search and print kind of facilities for notices.

Now BSE is also providing the RSS feed for various product the details are available at http://bseindia.com/about/datapdcts.asp. We have collected the corporate financial results from BSE India.

The lot of historical data is available at yahoo.com, the index volume and details are collect from the link

http://finance.yahoo.com/q/hp?s=%5EBSESN

The ULIP and mutual fund Net Asset values are announced regularly on their portals, we have collected ULIP NAV value from https://www.iciciprulife.com/ipru/unitvalue.jsp and mutual funds NAV is collected from http://www.amfiindia.com

In summary the following table present list of major data sources used in research.

Table 4: List of Data Sources

Sr No	Data Type	Data Source
1	Stock Quotes	http://xignite.com
2	Index Data	http://finance.yahoo.com/q/hp?s=%5EBSESN
3	ULIP NAV	https://www.iciciprulife.com/ipru/unitvalue.jsp
4	Mutual Fund NAV	http://www.amfiindia.com
5	Corpor -ate Results	http://bseindia.com
6	Notices	http://bseindia.com
7	News	http://economictimes.indiatimes.com/rssfeedsdefault.cms

5.2 Data Depository Structure Design: The following table incorporates in IIAM Data Storage.

1. AccountMaster
2. AccountTransaction
3. AccountTransactionDetail
4. AssetMaster
5. Company
6. FinanceALGI
7. FinancialHealth
8. IntangibleMaster
9. LiabilityGoalMaster
10. Login
11. MFNature
12. MFNAV
13. MFSchemeDetail
14. MFSchemeNature
15. MFType
16. Mtranscation
17. News
18. NewsAnalysis
19. NewsApplicable
20. NewsSource
21. Portfolio
22. PortfolioTransaction
23. Register
24. Results
25. ReturnType
26. Script
27. Sector
28. Index
29. TaxBenifit
30. UlipMaster
31. UlipTransaction
32. Watchlist

5.2.1 Table: AccountMaster

Description: Accounts used to store financial information for a portfolio holder. Every instance of Asset, Liability, Intangible, or financial goal need to be creates new account. For example Saving Account, Loan Account, Credit Card Account, Mutual Fund etc. One portfolio holder may hold number of accounts, which construct portfolio for the user. In model we have taken account for AccountMaster table holds details of accounts.

Table 5: AccountMaster [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Accountid	int	Yes		Unique key for each account
AccountDesc	varchar(50)			Description of Account
Userid	int			Users Identification
AccountClassId	varchar(10)		Yes	Account Class for ALGI, Ref FinanceALGI
Balance	float			Balance in Account
Unit	char(10)			INR or Quantity
IntersestRate	float			Interest Rate Applicable to Account
DrawingLimit	money		Yes	Maximum Drawing Limit of Account
IsDetailedTransaction	binary(1)		Yes	1 in case of more details required

Table 6: AccountMaster [Foreign Keys]

Name	Foreign Table	Primary Key
FK_AccountTransaction_Account-Master	AccountTransaction	PK_AccountMaster
FK_AccountMaster_FinanceALGI	AccountMaster	PK_FinanceALGI

Table 7: AccountMaster [Indexes]

Name	Unique	Clustered	Type	Collation
PK_AccountMaster	Yes	Yes	BTREE	ASCENDING

5.2.2 Table: AccountTransaction

Description: The Transaction detail information for Account is stored in to this table.

Table 8: AccountTransaction [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
TransactionId	int	Yes		Unique Id for each transaction
AccountId	int			Account Identification for transaction
TransactionDate	datetime			Transaction Date & Time
OpeningBalance	float			Balance before Transaction
TransactionData	float			Quantity of Data in Transaction
TransactionType	int			Type of Transactions
ClosingBalance	float			Balance after Transaction
Notes	varchar(7000)		Yes	Any Note related to transaction
TransactionDesc	varchar(50)		Yes	Description about Transaction

Table 9: AccountTransaction [Foreign Keys]

Name	Foreign Table	Primary Key
FK_AccountTransaction-Detail_AccountTransaction	AccountTransactionDetail	PK_AccountTransaction
FK_AccountTransaction-_AccountMaster	AccountTransaction	PK_AccountMaster

Table 10: AccountTransaction[Indexes]

Name	Unique	Clustered	Type	Collation
PK_AccountTransaction	Yes	Yes	BTREE	ASCENDING

5.2.3 Table: AccountTransactionDetail

Description: Some Assets need additional information for transaction. This table will take care for such details. Stock account and Mutual fund account often require detailed transaction information.

Table 11: AccountTransactionDetail [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
TransactionDetailId	int	Yes		Unique Id for Detailed Transaction
TransactionId	int			Account Transaction Identifier
ScriptId	varchar(10)		Yes	Script Identifier
ScriptUnitPrice	money			Unit price for script item data
Brokerage	money			Brokerage Applicable
ScriptQty	float			Quantity of Script item for transaction
TransactionAmount	money			Total Transaction Amount

Table 12: AccountTransactionDetail [Foreign Keys]

Name	Foreign Table	Primary Key
FK_AccountTransaction-Detail_AccountTransaction	AccountTransactionDetail	PK_AccountTransaction
FK_AccountTransaction-Detail_Script	AccountTransactionDetail	PK_Script

Table 13: AccountTransactionDetail [Indexes]

Name	Unique	Clustered	Type	Collation
PK_AccountTransactionDetail	Yes	Yes	BTREE	ASCENDING

5.2.4 Table: AssetMaster

Description*:* Portfolio holder may have different types of Assets. It may be Bank Account, Stock Account, Mutual Fund Account, Provident Fund Account, or account for Gold, Real estate etc. Some assets provide the facility to avail loan on it while some may have locking tenure.

Table 14: AssetMaster [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
AssetTypeID	varchar(10)	Yes		Unique Identifier for Asset
UserId	varchar(10)		Yes	Unique Identifier for User Ref. Login
AssetTypeDesc	varchar(50)			Description for Asset Type
Lockingteure	int		Yes	Locking Tenure restricts the liquidity
Loanstrength	float		Yes	Liquidity-Liability in term of % against Asset Value
PresentValue	money		Yes	Present Value of Asset

Table 15: AssetMaster [Indexes]

Name	Unique	Clustered	Type	Collation
PK_AssetType	Yes	Yes	BTREE	ASCENDING

5.2.5 Table: Company

Description: As name indicates the table holds information about companies. Company rating is performed by evaluating management group, historical records, Attitude towards Investors, financial strength etc.

Table 16: Company [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
CompanyId	varchar(10)	Yes		Unique Identifier for Company
CompanyName	varchar(100)			Full Name of Company
CompanyAdd1	varchar(50)		Yes	CompanyAdd Main
CompanyAdd2	varchar(50)		Yes	CompanyAdd street
CompanyAdd3	varchar(50)		Yes	CompanyAdd City
ContactDetails	varchar(50)		Yes	Phone and Mail-id
Rating	int		Yes	Overall rating for company

Table 17: Company [Foreign Keys]

Name	Foreign Table	Primary Key
FK_MFSchemeDetail_Company	MFSchemeDetail	PK_Company
FK_Script_Company	Script	PK_Company
FK_Script_Company1	Script	PK_Company

Table 18: Company [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Company	Yes	Yes	BTREE	ASCENDING

5.2.6 Table: FinanceALGI

Description: All Assets, Liabilities, Goals and Intangibles must have entry before used by portfolio holder. Class Type includes major classification which further used for classification purpose by account type like Saving Account, Treasury Bond, Company Bond, Stock, Preference Stock, Mutual Fund, ULIP, Intangibles, Provident Fund, Public Provident Fund, Real Estate, Gold, Home Loan, Loan Against Security, Mortgage, Personal Loan, Credit Card, Life Insurance, Vehicle Insurance, Medical Insurance etc. If return on asset or interest on liability is exempted by tax act, it can be known from table.

Table 19: FinanceALGI [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
ClassId	varchar(10)	Yes		Unique Identifier for Any Asset, Liability, Goal or Intangible
ClassType	varchar(50)		Yes	Name or other classifier for ALGI
TaxBenifitId	int		Yes	Income Tax Exemption

Table 20: FinanceALGI [Foreign Keys]

Name	Foreign Table	Primary Key
FK_AccountMaster_FinanceALGI	AccountMaster	PK_FinanceALGI
FK_Script_FinanceALGI	Script	PK_FinanceALGI
FK_Watchlist_FinanceALGI	Watchlist	PK_FinanceALGI

Table 21: FinanceALGI [Indexes]

Name	Unique	Clustered	Type	Collation
PK_FinanceALGI	Yes	Yes	BTREE	ASCENDING

5.2.7 Table: FinancialHealth

Description: This table holds the different classifications about financial health.

Table 22: FinancialHealth [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
FinanceHealthId	varchar(10)	Yes		Unique Identifier for Financial Health
FinanceHealthDesc	varchar(50)		Yes	Finance Health Description like Very Danger, Danger, Okay, Good, Very Good etc
MinQuickRatio	numeric(18,0)		Yes	Min Value of Quick Ratio Asset/Liability
MaxQuickRatio	numeric(18,0)		Yes	Max Value of Quick Ratio Asset/Liability

Foreign Keys: Not Applicable

Table 23: FinancialHealth [Indexes]

Name	Unique	Clustered	Type	Collation
PK_FinancialHealth	Yes	Yes	BTREE	ASCENDING

5.2.8 Table: IntangibleMaster

Description: Intangible assets are mostly available in form of insurance policies. Different insurance products are broadly categories in two classes, Life Insurances and General Insurances. Which can further classified educational planning or marriage endowment, Term coverage, Endowment, Money back, Whole life etc.

Table 24: IntangibleMaster [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
IntangibleId	varchar(10)	Yes		Unique Identifier for insurance policy
IntangibleDesc	varchar(50)		Yes	Description about insurance Policy
UserId	varchar(10)		Yes	Unique Identifier for policy holder
IsFutureReturn	binary(1)		Yes	True or False
FutureAmountApprox	money		Yes	Sum assured+ Bonus etc.
FutureTenure	datetime		Yes	Validity period of Intangible
ReturnTypeId	varchar(10)		Yes	Fix, Variable, Fixed Interval, Structured, Regular, etc.
IsPremiumWaiver	binary(1)		Yes	True or False

Table 25: IntangibleMaster [Foreign Keys]

Name	Foreign Table	Primary Key
FK_IntangibleMaster_Login	IntangibleMaster	PK_Login
FK_IntangibleMaster_ReturnType	IntangibleMaster	PK_ReturnType

Table 26: IntangibleMaster [Indexes]

Name	Unique	Clustered	Type	Collation
PK_IntangibleMaster	Yes	Yes	BTREE	ASCENDING

5.2.9 Table: LiabilityGoalMaster

Description: All liabilities and future goals need expenses, close monitoring and optimized management. This table keeps all major details of liabilities of portfolio holder.

Table 27: LiabilityGoalMaster [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
LiabilityId	varchar(10)	Yes		Unique Identifier for Liability
UserId	varchar(10)		Yes	Identifier for Liability Holder
LiabilityAmount	money		Yes	Liability Amount
LiabilityInterestRate	float		Yes	Applicable Interest Rate for Liability Per year
LiabilityTenureMonths	int		Yes	Tenure for Liability
LiabilityInstallments	money		Yes	Payment amount
IsInsured	binary(1)		Yes	Risk Covered or Not for Liability
IsGoal	binary(1)		Yes	True If not borrowed and account is to achieve Goal

Table 28: LiabilityGoalMaster [Foreign Keys]

Name	Foreign Table	Primary Key
FK_LiabilityGoalMaster_Login	LiabilityGoalMaster	PK_Login

Table 29: LiabilityGoalMaster[Indexes]

Name	Unique	Clustered	Type	Collation
PK_LiabilityGoalMaster	Yes	Yes	BTREE	ASCENDING

5.2.10 Table: Login

Description: This table stores the login information of portfolio holder. All other details information is stored in Register table. Some simple roles are assigned by system administrator to restrict access for security.

Table 30: Login [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Userid	varchar(10)	Yes		Unique identifier for User
Password	varchar(10)			Authentication Check
Role	smallint		Yes	Authorization

Table 31: Login [Foreign Keys]

Name	Foreign Table	Primary Key
FK_IntangibleMaster_Login	IntangibleMaster	PK_Login
FK_LiabilityGoalMaster_Login	LiabilityGoalMaster	PK_Login
FK_Portfolio_Login	Portfolio	PK_Login
FK_PortfolioTransaction_Login	PortfolioTransaction	PK_Login
FK_Register_Login	Register	PK_Login
FK_Watchlist_Login	Watchlist	PK_Login

Table 32: Login [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Login	Yes	Yes	BTREE	ASCENDING

5.2.11 Table: MFNature

Description: This table is holding different mutual fund's nature and used by table MFSchemeDetail.

Table 33: MFNature [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
NatureId	varchar(10)	Yes		Unique Identification for MF Nature
NatureDesc	varchar(50)		Yes	Description about MF nature

Table 34: MFNature [Foreign Keys]

Name	Foreign Table	Primary Key
FK_MFSchemeDetail_MFNature	MFSchemeDetail	PK_MFNature

Table 35: MFNature [Indexes]

Name	Unique	Clustered	Type	Collation
PK_MFNature	Yes	Yes	BTREE	ASCENDING

5.2.12 Table: MFNAV

Description: Store historical NAV values for scripts.

Table 36: MFNAV [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
ScriptID	varchar(10)	Yes		Unique Identifier for Script of MutualFund
NavDate	datetime			Date for Net Asset Value
UnitNav	money		Yes	Nat Asset Value as on date for a unit

Table 37: MFNAV [Foreign Keys]

Name	Foreign Table	Primary Key
FK_MFNAV_Script	MFNAV	PK_Script

Table 38: MFNAV [Indexes]

Name	Unique	Clustered	Type	Collation
PK_MFNAV	Yes	Yes	BTREE	ASCENDING

5.2.13 Table: MFSchemeDetail

Description: This table holds the details of mutual fund attribute.

Table 39: MFSchemeDetail [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
ScriptId	varchar(10)	Yes		Unique Identifier for MF Script
CompanyId	varchar(10)		Yes	Company Identifier
NatureId	varchar(10)			Nature Identifier for Fund: Debt, Balanced, Aggressive Etc.
Typeid	varchar(10)		Yes	Open Ended, Close Ended etc.
MinInvesment	money		Yes	Minimum Investment Required for Investment in fund
IsNRIallowed	binary(1)		Yes	Applicability for NRI
IsRepartiability	binary(1)		Yes	Repatiability Yes/No
TaxBenefitId	varchar(10)		Yes	Tax Benefit Act Applicability
SectorId	varchar(10)		Yes	Sector Identifier
Rating	int		Yes	Rating Based on Past Performance, Management Ability, Liquidity etc
InceptionDate	datetime		Yes	Date of MF Inception

Table 40: MFSchemeDetail [Foreign Keys]

Name	Foreign Table	Primary Key
FK_MFSchemeDetail_Company	MFSchemeDetail	PK_Company
FK_MFSchemeDetail_MFNature	MFSchemeDetail	PK_MFNature
FK_MFSchemeDetail_MFType	MFSchemeDetail	PK_MFType
FK_MFSchemeDetail_Script	MFSchemeDetail	PK_Script
FK_MFSchemeDetail_Sector	MFSchemeDetail	PK_Sector
FK_MFSchemeDetail_TaxBenifit	MFSchemeDetail	PK_TaxBenifit

Table 41: MFSchemeDetail [Indexes]

Name	Unique	Clustered	Type	Collation
PK_MFSchemeDetail	Yes	Yes	BTREE	ASCENDING

5.2.14 Table: MFSchemeNature

Description: This Table holds the different natures like equity, balanced, debt etc for mutual fund**.**

Table 42: MFSchemeNature [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
NatureId	int	Yes		Unique Identifier for Nature of Fund
NatureDesc	char(10)			Nature Description

Foreign Keys: Not Applicable

Table 43: MFSchemeNature [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Nature	Yes	Yes	BTREE	ASCENDING

5.2.15 Table: MFType

Description: Table holds information for Type like income, growth etc.

Table 44: MFType [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
TypeId	varchar(10)	Yes		Unique Identifier for Type
TypeDesc	varchar(50)			Open Ended, Close Ended, and Close Ended for Specified Period along with Dividend and Growth options.

Table 45: MFType [Foreign Keys]

Name	Foreign Table	Primary Key
FK_MFSchemeDetail_MFType	MFSchemeDetail	PK_MFType

Table 46: MFType [Indexes]

Name	Unique	Clustered	Type	Collation
PK_MFType	Yes	Yes	BTREE	ASCENDING

5.2.16 Table: Mtranscation

Description: This table holds all daily transaction details of the scripts for financial market. Presently we update the table on daily basis (When Stock Market is Open) as our model is based on long term prediction. Agent is able to update the table even every minute, if required. However we can store the daily details of scripts in different market say BSE and NSE, as Scriptid has considered exchange name in code design.

Table 47: Mtranscation [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Scriptid	varchar(10)	Yes		Unique Identification for Script
Tdate	datetime	Yes		Transaction Date
Cprice	numeric(7,2)		Yes	Last Price on Tdate
Topen	numeric(7,2)		Yes	Opening Price of Script
Preclose	numeric(7,2)		Yes	Price of Last Closing
Change	numeric(4,2)		Yes	% Change w r t last closing
Volume	int		Yes	Script Volume on Tdate
Pe	numeric(5,2)		Yes	PE if Applicable

Table 48: Mtranscation [Foreign Keys]

Name	Foreign Table	Primary Key
FK_Transcation_Script	Mtranscation	PK_Script

Table 49: Mtranscation [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Transcation	Yes	Yes	BTREE	ASCENDING

5.2.17 Table: News

Description: Tables stores the basic details of new announced.

Table 50: News [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Newsid	numeric(5,0)	Yes		Unique Identifier for Each News
Anndate	datetime		Yes	Announcement Date
Effdate	datetime		Yes	Effective Date
scale	numeric(4,0)		Yes	Importance of News
NewsSourceId	varchar(10)		Yes	Source Identifier
NewsanalysisID	varchar(10)		Yes	News Analysis Detail Reference

Table 51: News [Foreign Keys]

Name	Foreign Table	Primary Key
FK_News_NewsAnalysis	News	PK_NewsAnalysis
FK_News_NewsSource	News	PK_NewsSource

Table 52: News [Indexes]

Name	Unique	Clustered	Type	Collation
PK_news	Yes	Yes	BTREE	ASCENDING

5.2.18 Table: NewsAnalysis

Description: Tables stores the analytical details of new announced.

Table 53: NewsAnalysis [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
NewsAnalysisId	varchar(10)	Yes		Unique Identifier for News Analysis
NewsEffect-ApplicabilityId	varchar(10)			Applicability Like Market, Sector, Stock etc
NewsEffect-Description	char(10)		Yes	Very Positive, Positive, Neutral, Negative, Very Negative
NewsEffectFrom	datetime		Yes	Effect Starting From
NewEffectTo	datetime		Yes	Effect Up to
PreEffectValue	numeric(18,0)		Yes	Index or Stock Value before News Announced
PostEffectValue	numeric(18,0)		Yes	Index or Stock Value After News Effect Period
ScriptId	varchar(10)		Yes	Concern Script Identifier
SectorId	varchar(10)		Yes	Concern Sector Identifier

Table 54: NewsAnalysis [Foreign Keys]

Name	Foreign Table	Primary Key
FK_News_NewsAnalysis	News	PK_NewsAnalysis
FK_NewsAnalysis_NewsApplicable	NewsAnalysis	PK_NewsApplicable
FK_NewsAnalysis_Script	NewsAnalysis	PK_Script
FK_NewsAnalysis_Sector	NewsAnalysis	PK_Sector

Table 55: NewsAnalysis [Indexes]

Name	Unique	Clustered	Type	Collation
PK_NewsAnalysis	Yes	Yes	BTREE	ASCENDING

5.2.19 Table: NewsApplicable

Description: The applicable segment affected from news is kept in this table.

Table 56: NewsApplicable [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
NewsEffectApplicabilityId	varchar(10)	Yes		Unique Id for Applicability like Market, Sector, Script
NewsEffectApplicability-Description	varchar(50)		Yes	News Effect Applicability Description

Table 57: NewsApplicable [Foreign Keys]

Name	Foreign Table	Primary Key
FK_NewsAnalysis_NewsApplicable	NewsAnalysis	PK_NewsApplicable

Table 58: NewsApplicable [Indexes]

Name	Unique	Clustered	Type	Collation
PK_NewsApplicable	Yes	Yes	BTREE	ASCENDING

5.2.20 Table: NewsSource

Description: This table holds the basic details of news sources.

Table 59: NewsSource [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
NewsSourceId	varchar(10)	Yes		Unique Identifier for News Source
NewsSourceDesc	varchar(50)		Yes	Description of News Source
NewsSourceReliability-Index	numeric(18,0)		Yes	Ranges 0 to 100

Table 60: NewsSource [Foreign Keys]

Name	Foreign Table	Primary Key
FK_News_NewsSource	News	PK_NewsSource

Table 61: NewsSource [Indexes]

Name	Unique	Clustered	Type	Collation
PK_NewsSource	Yes	Yes	BTREE	ASCENDING

5.2.21 Table: Portfolio

Description: This table holds the basic details for portfolio, which is not essentially entered in Accounts.

Table 62: Portfolio [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Userid	varchar(10)	Yes		User Identifier
UpdateDate	datetime	Yes		Date of Update Portfolio
FinancialHealthId	datetime		Yes	Financial Health Identifier Ref FinancialHealth
ApproxMonthlyIncome	numeric(6,0)		Yes	Average Monthly Income
ApproxMonthlyExpence	numeric(7,2)		Yes	Average Monthly Expense
PresentPortfolioTypeId	varchar(10)		Yes	Portfolio Type: Safe, Aggressive, Risky etc
RecommandedPortfolio TypeID	varchar(10)		Yes	Safe, Aggressive etc

Table 63: Portfolio [Foreign Keys]

Name	Foreign Table	Primary Key
FK_Portfolio_Login	Portfolio	PK_Login

Table 64: Portfolio [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Portfolio	Yes	Yes	BTREE	ASCENDING

5.2.22 Table: PortfolioTransaction

Description: Keeps the historical details of portfolio for further reference as well as analysis.

Table 65: PortfolioTransaction [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
UserID	varchar(10)	Yes		User Identifier
PortfolioDate	datetime	Yes		Date of Portfolio Value
Networth	money		Yes	Difference of Asset and Liability; Financial Strength
Liquidity	money		Yes	Total Liquidity
AssetTotal	money		Yes	Asset Valuation
LiabilityTotal	money		Yes	Liability Valuation
GoalTotal	money		Yes	Goal to be set one form of non compulsory liability
IntengibleTotal	money		Yes	Intangible Valuation
RiskCoveredTotal	money		Yes	Total Risk Covered

Table 66: PortfolioTransaction [Foreign Keys]

Name	Foreign Table	Primary Key
FK_PortfolioTransaction_Login	PortfolioTransaction	PK_Login

Table 67: PortfolioTransaction [Indexes]

Name	Unique	Clustered	Type	Collation
PK_PortfolioTransaction	Yes	Yes	BTREE	ASCENDING

5.2.23 Table: Register

Description: This table holds the registration information of portfolio holder, and used to communicate recommendations and alerts.

Table 68: Register [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Userid	varchar(10)	Yes		User Identifier
Password	varchar(10)		Yes	Users Password to access account interfaces
First_name	varchar(50)		Yes	First Name of User
Second_name	varchar(50)		Yes	Second Name of User
Birth_Date	datetime		Yes	Date of Birth of User
Sexcode	char(1)		Yes	Sex:M/F
Address_1	varchar(100)		Yes	Address Details
Address_2	varchar(100)		Yes	Address Details
Address_3	varchar(50)		Yes	Address Details
City	varchar(50)		Yes	City of User
District	varchar(50)		Yes	District of Address
pincode	numeric(6,0)		Yes	Pincode of Address
State	varchar(50)		Yes	State
Country	varchar(30)		Yes	Country
Ophone	numeric(30,0)		Yes	Office Contact No
Rphone	numeric(30,0)		Yes	Res. contact number
Mobile	numeric(15,0)		Yes	Mobile Contact Number
Fax	numeric(15,0)		Yes	Fax number
Email	varchar(50)		Yes	Email-ID of User
Url	varchar(50)		Yes	URL if users have

Table 69: Register [Foreign Keys]

Name	Foreign Table	Primary Key
FK_Register_Login	Register	PK_Login

Table 70: Register [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Register	Yes	Yes	BTREE	ASCENDING

5.2.24 Table: Results

Description: All financial results of listed stock scripts are stored in this table. The table is used for fundamental analysis either by user or by Analyzer agent.

Table 71: Results [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Rdate	datetime	Yes		Result date
Scriptid	varchar(10)	Yes		Script Identifier
Netsales	numeric(12,2)		Yes	Net Sales / Interest Earned / Operating Income
Otherincome	numeric(12,2)		Yes	Other Income
TotalIncome	numeric(12,2)		Yes	Total Income
Expenditure	numeric(12,2)		Yes	Expenditure
OperatingProfit	numeric(18,0)		Yes	Operating Profit
Interest	numeric(5,2)		Yes	Interest
PBDT	numeric(18,0)		Yes	Profit Before Depreciation and Tax
Depreciation	numeric(6,2)		Yes	
PBT	numeric(18,0)		Yes	Profit before Tax
Tax	numeric(6,2)		Yes	
Extraitem	numeric(6,2)		Yes	Extraordinary Items
Reserve	numeric(12,2)		Yes	Reserve
BEPSAF	numeric(18,0)		Yes	Basic And Diluted EPS after Extraordinary item
DEPSAF	numeric(18,0)		Yes	Diluted EPS after Extraordinary item
PublicEquity	numeric(18,0)		Yes	Nos. of Shares - Public
PublicSharePercent	numeric(18,0)		Yes	Percent of Shares-Public
OperatingProfitMargin	numeric(18,0)		Yes	Operating Profit Margin
NetProfitMargin	numeric(18,0)		Yes	Net Profit Margin

CashEPS	numeric(18,0)		Yes	
PromotorsShare	numeric(5,2)		Yes	Promotors Share
InstitutinalShare	numeric(18,0)		Yes	Institutional Share
Dividend	numeric(5,2)		Yes	Dividend
Ddate	datetime		Yes	Dividend Date
Resulttype	varchar(50)		Yes	Quarterly or Annual
Equity	numeric(5,2)		Yes	Total Equity
Betav	numeric(2,2)		Yes	Beta Value
Cfacev	numeric(2,0)		Yes	Face Value of Stock
Owngroup	varchar(30)		Yes	Owner Group

Table 72: Results [Foreign Keys]

Name	Foreign Table	Primary Key
FK_quarter_Script	Results	PK_Script

Table 73: Results [Indexes]

Name	Unique	Clustered	Type	Collation
PK_quarter	Yes	Yes	BTREE	ASCENDING

5.2.25 Table: ReturnType

Description: This table holds the information of intangible return type, and used by IntangibleMaster.

Table 74: ReturnType [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
ReturnTypeId	varchar(10)	Yes		Unique Identifier for Return Type
DescriptionReturnType	varchar(50)		Yes	Return Type Description: Fixed, Variable Etc

Table 75: ReturnType [Foreign Keys]

Name	Foreign Table	Primary Key
FK_IntangibleMaster_ReturnType	IntangibleMaster	PK_ReturnType

Table 76: ReturnType [Indexes]

Name	Unique	Clustered	Type	Collation
PK_ReturnType	Yes	Yes	BTREE	ASCENDING

5.2.26 Table: Script

Description: This Table stores the basic information about script.

Table 77: Table: Script [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Scriptid	varchar(10)	Yes		Unique Script Identifier
ScriptClassid	varchar(10)		Yes	Like Stock, Mutual Fund
Companyid	varchar(10)		Yes	Company Identifier
Sname	varchar(100)		Yes	Script Name
Sgroup	char(3)		Yes	Script Group
Wh52	numeric(7,2)		Yes	52 Week High Value
Wl52	numeric(7,2)		Yes	52 Week Low Value
Minpe3	numeric(5,2)		Yes	3 Yr Min PE Value
Maxpe3	numeric(5,2)		Yes	3 Year Max PE Value

Table 78: Script [Foreign Keys]

Name	Foreign Table	Primary Key
FK_AccountTransactionDetail-_Script	AccountTransactionDetail	PK_Script
FK_MFNAV_Script	MFNAV	PK_Script
FK_MFSchemeDetail_Script	MFSchemeDetail	PK_Script
FK_Transcation_Script	Mtranscation	PK_Script
FK_NewsAnalysis_Script	NewsAnalysis	PK_Script
FK_quarter_Script	Results	PK_Script
FK_UlipMaster_Script	UlipMaster	PK_Script
FK_UlipTransaction_Script	UlipTransaction	PK_Script
FK_Watchlist_Script	Watchlist	PK_Script
FK_Script_Company	Script	PK_Company
FK_Script_Company1	Script	PK_Company
FK_Script_FinanceALGI	Script	PK_FinanceALGI

Table 79: Script [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Script	Yes	Yes	BTREE	ASCENDING

5.2.27 Table: Sector

Description: This table holds the historical and analytical information about a particular sector.

Table 80: Sector [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Sectorid	varchar(10)	Yes		Unique Identifier for Sector
Sectorname	varchar(70)		Yes	Sector Name
Sectorgrowth	numeric(6,2)		Yes	Growth Rate in % for Sector
Sectorpe	numeric(5,2)		Yes	Average PE Value for Sector

Table 81: Sector [Foreign Keys]

Name	Foreign Table	Primary Key
FK_MFSchemeDetail_Sector	MFSchemeDetail	PK_Sector
FK_NewsAnalysis_Sector	NewsAnalysis	PK_Sector
FK_Watchlist_Sector	Watchlist	PK_Sector

Table 82: Sector [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Sector	Yes	Yes	BTREE	ASCENDING

5.2.28 Table: Index

Description: This table holds the transaction details of different financial markets.

Table 83: Index [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
Sdate	datetime	Yes		Date of Index Value
Index	varchar(20)		Yes	Index Name Like BSE, NSE
Sopen	float		Yes	Day Opening value of Index
Shigh	float		Yes	Day High of Index
Slow	float		Yes	Day Low Value for Index
Sclose	float		Yes	Closing Value of Index
SVolume	float		Yes	Volume of Index Transaction
SAdvance	int		Yes	No of Advance Script
SDecline	int		Yes	Number of Decline Script

Foreign Keys: Not Applicable

Table 84: Index [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Index	Yes	Yes	BTREE	ASCENDING

5.2.29 Table: TaxBenefit

Description: This table holds the different Tax Act Benefits, which should be consider at the decision making for asset allocation or liability management.

Table 85: TaxBenefit [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
TaxBenefitId	varchar(10)	Yes		Unique Identifier for Tax Benefit Act
TaxBenefitDesc	varchar(15)		Yes	Description about Tax Benefit Act

Table 86: TaxBenefit [Foreign Keys]

Name	Foreign Table	Primary Key
FK_MFSchemeDetail_TaxBenefit	MFSchemeDetail	PK_TaxBenefit

Table 87: TaxBenefit [Indexes]

Name	Unique	Clustered	Type	Collation
PK_TaxBenefit	Yes	Yes	BTREE	ASCENDING

5.2.30 Table: UlipMaster

Description: This table holds the basic details of ULIP scripts.

Table 88: UlipMaster [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
ScriptId	varchar(10)	Yes		Script Identifier
NoOfInstallment	int		Yes	Total Number of Installments in ULIP
MinInstallment	money		Yes	Minimum installment amount
SwitchModes	int		Yes	Number of Switch modes
SafestMode	text		Yes	Alias in ULIP for the field mode
SafeMode	text		Yes	Alias in ULIP for the field mode
BalancedMode	text		Yes	Alias in ULIP for the field mode
EquityMode	text		Yes	Alias in ULIP for the field mode

Table 89: UlipMaster [Foreign Keys]

Name	Foreign Table	Primary Key
FK_UlipMaster_Script	UlipMaster	PK_Script

Table 90: UlipMaster [Indexes]

Name	Unique	Clustered	Type	Collation
PK_UlipMaster	Yes	Yes	BTREE	ASCENDING

5.2.31 Table: UlipTransaction

Description: This table holds the transactional details of ULIP scripts.

Table 91: UlipTransaction [Columns]

Column Name	Data Type	Is in Key?	Is Nullable?	Description
ScriptID	varchar(10)	Yes		Script Identifier
Udate	datetime	Yes		Record Date
Mode1	float		Yes	Safest Mode
Mode2	float		Yes	Safe Mode
Mode3	float		Yes	Balanced Mode
Mode4	float		Yes	Equity Mode

Table 92: UlipTransaction [Foreign Keys]

Name	Foreign Table	Primary Key
FK_UlipTransaction_Script	UlipTransaction	PK_Script

Table 93: UlipTransaction [Indexes]

Name	Unique	Clustered	Type	Collation
PK_UlipTransaction	Yes	Yes	BTREE	ASCENDING

5.2.32 Table: Watchlist

Description: The Watchlist is basic requirements to keep track movement particular sector, monitoring the price variation. Watchlist generator module recommends the best ranked scripts from the all scripts belonging to sector, which is to be recommending highest-ranking scripts in the sector, and store in table with System as a Userid and accessible to all portfolio holders.

Table 94: Watchlist [Columns]

Column Name	Data Type	Is in Key?	Description
Watchlistid	varchar(10)	Yes	Unique Identifier for Watch list Created
Userid	varchar(10)		User Identifier
WatchlistDesc	varchar(50)		Watch list Description
Scriptid	varchar(10)		Script Identifier
Sectorid	varchar(10)		Sector Identifier
ScriptTypeId	varchar(10)		Script Type Identifier

Table 95: Watchlist [Foreign Keys]

Name	Foreign Table	Primary Key
FK_Watchlist_FinanceALGI	Watchlist	PK_FinanceALGI
FK_Watchlist_Login	Watchlist	PK_Login
FK_Watchlist_Script	Watchlist	PK_Script
FK_Watchlist_Sector	Watchlist	PK_Sector

Table 96: Watchlist [Indexes]

Name	Unique	Clustered	Type	Collation
PK_Watchlist	Yes	Yes	BTREE	ASCENDING

5.3 Sample Data: The actual data size is very large. We are screening only the data generated by environment at regular interval, and useful to generate knowledge, rest of the data contains data related to user profile, account information and master data needed for model.

Table 97: Mtranscation [Data]

Scriptid	Tdate	Cprice	Topen	Preclose	Change	Volume
500002.BO	7/6/2005	1477	1420	1414.7	4.4	33054
500003.BO	7/6/2005	93.8	93	92.7	1.19	34890
500004.BO	7/6/2005	198.7	198	195.55	1.61	14852
500008.BO	7/6/2005	136.75	135.1	135.75	0.74	12288
500010.BO	7/6/2005	926	900	901.65	2.7	111743
500019.BO	7/6/2005	52.4	52.5	52	0.77	83711
500020.BO	7/6/2005	348.9	342	342.55	1.85	241698
500023.BO	7/6/2005	294	295.95	292.25	0.6	17417
500027.BO	7/6/2005	85.25	85.5	85.95	-0.81	4578
500032.BO	7/6/2005	155	150.5	150.75	2.82	302765
500034.BO	7/6/2005	290.05	293.5	289.25	0.28	1865
500038.BO	7/6/2005	68	67.4	66.15	2.8	1333932
500040.BO	7/6/2005	287.5	280	283.3	1.48	211773
500041.BO	7/6/2005	610.05	610	595	2.53	1564
500042.BO	7/6/2005	203.5	203.5	202.65	0.42	3641
500043.BO	7/6/2005	87.8	87.6	87.15	0.75	67186
500048.BO	7/6/2005	654.9	654	649.5	0.83	106327
500049.BO	7/6/2005	740	775	730.95	1.24	10973
500055.BO	7/6/2005	176	174.9	172.1	2.27	75755
500060.BO	7/6/2005	29.2	29	29	0.69	14426
500064.BO	7/6/2005	82	85.7	83.35	-1.62	1990
500070.BO	7/6/2005	30.7	30.7	30.6	0.33	28547
500074.BO	7/6/2005	46	42.55	43.8	5.02	41760
500075.BO	7/6/2005	15.17	15	14.65	3.55	1047923
500083.BO	7/6/2005	9.45	9.1	9.35	1.07	5119
500084.BO	7/6/2005	208.5	207.95	205.8	1.31	41226
500085.BO	7/6/2005	32	31.85	31.55	1.43	160551
500086.BO	7/6/2005	171.5	167.1	172.9	-0.81	21546
500087.BO	7/6/2005	321	322	318.95	0.64	64356
500089.BO	7/6/2005	169.75	166	167.3	1.46	3846
500091.BO	7/6/2005	16.05	17	16.26	-1.29	24501
500092.BO	7/6/2005	1032.1	1049	1032.1	0	70
500093.BO	7/6/2005	472	473	466.65	1.15	6224
500095.BO	7/6/2005	494.95	499.9	489.5	1.11	4231
500096.BO	7/6/2005	133.7	135	133.75	-0.04	27872
500097.BO	7/6/2005	377	382	386	-2.33	896
500099.BO	7/6/2005	8.59	8.7	8.24	4.25	10261
500101.BO	7/6/2005	130.4	129.9	130.1	0.23	53717

Scriptid	Tdate	Cprice	Topen	Preclose	Change	Volume
500102.BO	7/6/2005	112	110.6	111.4	0.54	42872
500103.BO	7/6/2005	877.1	841.5	863.85	1.53	28951
500104.BO	7/6/2005	309.5	310	310.35	-0.27	86796
500105.BO	7/6/2005	176.9	177	175.45	0.83	401966
500106.BO	7/6/2005	14.12	14.1	14.01	0.79	766933
500108.BO	7/6/2005	129.3	125.5	124.2	4.11	889555
500109.BO	7/6/2005	45.85	45.95	45.6	0.55	93297
500110.BO	7/6/2005	189	189	187.1	1.02	9940
500111.BO	7/6/2005	396.05	382	379.25	4.43	5216441
500112.BO	7/6/2005	707.5	705	703.6	0.55	299497
500113.BO	7/6/2005	49.85	49.4	48.95	1.84	1521036
500114.BO	7/6/2005	408	407.9	403.45	1.13	118217
500116.BO	7/6/2005	108.65	107	107.8	0.79	400226
500117.BO	7/6/2005	40.5	40.65	40.35	0.37	16931
500119.BO	7/6/2005	132.55	130.9	129.8	2.12	266888
500124.BO	7/6/2005	786.5	785	781.6	0.63	14521
500125.BO	7/6/2005	131.6	131.9	130.45	0.88	75572
500128.BO	7/6/2005	406.5	409.7	407.75	-0.31	1655
500132.BO	7/6/2005	24	25.5	25.35	-5.33	22400
500134.BO	7/6/2005	43.35	42.35	42.25	2.6	3759218
500135.BO	7/6/2005	315.6	313	313.1	0.8	2120
500144.BO	7/6/2005	237	237	233.35	1.56	5563
500145.BO	7/6/2005	49.6	50.6	50	-0.8	26782
500148.BO	7/6/2005	60.3	60	59.75	0.92	70474
500150.BO	7/6/2005	329	332.9	330	-0.3	789
500151.BO	7/6/2005	95.9	94.1	93.9	2.13	211111
500155.BO	7/6/2005	53.6	52.55	52.45	2.19	50590
500160.BO	7/6/2005	98	97.4	96.6	1.45	249385
500163.BO	7/6/2005	780	776.8	778.2	0.23	682
500164.BO	7/6/2005	231.55	230.5	230.15	0.61	6995
500165.BO	7/6/2005	589	558	575	2.43	517
500170.BO	7/6/2005	73	73	73	0	3890
500171.BO	7/6/2005	62.5	61.6	60.65	3.05	899763
500173.BO	7/6/2005	968	949.7	940.4	2.93	1678
500174.BO	7/6/2005	9.26	9.26	8.82	4.99	64991
500179.BO	7/6/2005	780	785	784.3	-0.55	514
500180.BO	7/6/2005	639.6	630	633	1.04	228834
500182.BO	7/6/2005	577.05	577	577.65	-0.1	75559
500183.BO	7/6/2005	21.55	20.5	20.3	6.16	5283587
500185.BO	7/6/2005	552.35	525	546.35	1.1	43622
500186.BO	7/6/2005	162	162.5	161.3	0.43	205698
500187.BO	7/6/2005	148	150	147.75	0.17	1547
500002.BO	7/7/2005	1472.7	1500	1489.65	-1.14	19852
500003.BO	7/7/2005	92.4	96.25	95.55	-3.3	32981
500004.BO	7/7/2005	190.75	198	196.2	-2.78	5229
500008.BO	7/7/2005	132.55	137.75	135.45	-2.14	28872

500010.BO	7/7/2005	903.85	930	930.7	-2.88	88993
500019.BO	7/7/2005	53.25	54.6	54.55	-2.38	466765
500020.BO	7/7/2005	347.35	350	346.05	0.38	237761
500023.BO	7/7/2005	295	290.05	292.1	0.99	5460
500027.BO	7/7/2005	85.7	85.2	85.75	-0.06	13214
500032.BO	7/7/2005	153.85	156.4	154.95	-0.71	450042
500034.BO	7/7/2005	296.8	298	294.25	0.87	4887

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Scriptid	Tdate	Cprice	Topen	Preclose	Change	Volume
500102.BO	11/20/2008	23.5	22.6	22.9	2.6	88653
500103.BO	11/20/2008	1231	1261	1266.55	-2.8	604999
500104.BO	11/20/2008	228.45	232	230.65	-0.9	95539
500106.BO	11/20/2008	17.35	18	17.65	-1.7	3458551
500108.BO	11/20/2008	72.15	71.05	71.4	1	245157
500109.BO	11/20/2008	35	38	37.75	-7.2	230442
500112.BO	11/20/2008	1079.5	1110.7	1108.3	-2.6	1182615
500113.BO	11/20/2008	58.95	62.6	61.4	-3.9	5973321
500114.BO	11/20/2008	849.25	825	830.25	2.2	50453
500116.BO	11/20/2008	62.05	65.25	65.4	-5.1	321276
500117.BO	11/20/2008	7.36	8	7.68	-4.1	52901
500119.BO	11/20/2008	21.6	21.55	21.8	-0.9	20322
500124.BO	11/20/2008	417.1	402.5	400.5	4.1	60711
500125.BO	11/20/2008	148.15	152.9	150.2	-1.3	1051
500128.BO	11/20/2008	16.6	17.2	17.05	-2.6	144316
500132.BO	11/20/2008	7	7	7.1	-1.4	100
500133.BO	11/20/2008	285.15	303	300	-4.9	910
500134.BO	11/20/2008	67.5	66.5	68.5	-1.4	1322873
500135.BO	11/20/2008	12.31	12.6	12.55	-1.9	19132
500144.BO	11/20/2008	23.25	22.65	22.7	2.4	17735
500148.BO	11/20/2008	62	60	60.6	2.3	641
500150.BO	11/20/2008	274	270	274	0	62
500151.BO	11/20/2008	43.6	47	47.3	-7.8	30493
500160.BO	11/20/2008	195.2	196	192.7	1.3	29857
500164.BO	11/20/2008	62.55	66	64.3	-2.7	52404
500165.BO	11/20/2008	385	388	387.05	-0.5	373
500170.BO	11/20/2008	8.52	8.03	8.74	-2.5	852
500171.BO	11/20/2008	27.15	29.25	29.15	-6.8	231740
500173.BO	11/20/2008	75.15	78	77.25	-2.7	4851
500174.BO	11/20/2008	3.19	3.28	3.13	1.9	8191
500179.BO	11/20/2008	69.85	74	69.65	0.2	10513
500180.BO	11/20/2008	887	912	917.05	-3.2	495618
500182.BO	11/20/2008	748.55	719.8	721.9	3.6	52410
500183.BO	11/20/2008	7.01	7.25	7.04	-0.4	470861
500185.BO	11/20/2008	39.55	44.5	43.2	-8.4	847370
500002.BO	11/21/2008	433.6	420	420.05	3.2	90315
500003.BO	11/21/2008	60.9	61.5	60.8	0.1	1485

Scriptid	Tdate	Cprice	Topen	Preclose	Change	Volume
500008.BO	11/21/2008	41.25	43.5	42.45	-2.8	4753
500010.BO	11/21/2008	1399.3	1268.6	1289.8	8.4	882271
500019.BO	11/21/2008	33.75	32.1	33.7	0.1	29504
500020.BO	11/21/2008	154.8	155	155.5	-0.4	293892
500027.BO	11/21/2008	37.35	36.5	36.05	3.6	7141
500032.BO	11/21/2008	41.55	43	42.95	-3.2	898878
500041.BO	11/21/2008	650	650	650.05	0	1743
500042.BO	11/21/2008	217.5	212.45	210.85	3.1	6131
500043.BO	11/21/2008	82	78.1	77.95	5.2	35240
500048.BO	11/21/2008	339.3	339	338	0.3	2604
500049.BO	11/21/2008	590.45	607	594.75	-0.7	2580
500055.BO	11/21/2008	536.5	521.05	571	-6	62297
500060.BO	11/21/2008	6.49	5.8	6.4	1.4	3444
500074.BO	11/21/2008	15.6	15.45	15.45	0.9	17356
500075.BO	11/21/2008	14.15	14	14.05	0.7	1104162
500083.BO	11/21/2008	2.15	2.11	2.25	-4.4	10268
500084.BO	11/21/2008	199.9	200	199.9	0	17296
500085.BO	11/21/2008	31.9	32.5	31.75	0.4	5407313
500086.BO	11/21/2008	43.1	41.6	42.3	1.8	74742
500087.BO	11/21/2008	184.7	174	177	4.3	446702
500089.BO	11/21/2008	105.8	100	99.05	6.8	962
500092.BO	11/21/2008	2393.15	2425	2438.6	-1.8	595
500093.BO	11/21/2008	118.65	115	114.35	3.7	563175
500095.BO	11/21/2008	403.2	408	411	-1.9	2386
500096.BO	11/21/2008	74.5	74.5	75.05	-0.7	780600
500097.BO	11/21/2008	79.1	81	80.25	-1.4	2872
500101.BO	11/21/2008	14.03	13.5	13.49	4	289021
500102.BO	11/21/2008	20.7	21.5	21.3	-2.8	73482
500103.BO	11/21/2008	1281.25	1195	1194.2	7.2	790322
500104.BO	11/21/2008	228.45	226	222.8	2.5	215899
500106.BO	11/21/2008	17.2	16.85	16.85	2	3212163
500108.BO	11/21/2008	69.2	69.9	69.35	-0.2	201119
500109.BO	11/21/2008	34.7	34	34.3	1.1	172580
500112.BO	11/21/2008	1183.15	1103.5	1092.55	8.2	1417591
500113.BO	11/21/2008	62.9	56.05	58.65	7.2	3051434
500114.BO	11/21/2008	878.35	815	825.5	6.4	56647
500116.BO	11/21/2008	62.35	63.75	62.7	-0.5	709976
500117.BO	11/21/2008	7.02	6.75	6.92	1.4	66583
500119.BO	11/21/2008	20.1	20.25	21	-4.2	39885
500124.BO	11/21/2008	415.05	413.9	415.5	-0.1	39170
500125.BO	11/21/2008	139.5	148	144.5	-3.4	3063
500128.BO	11/21/2008	15.45	15.3	15.35	0.6	98992
500132.BO	11/21/2008	6.7	6.35	6.66	0.6	1100
500133.BO	11/21/2008	267.85	272.65	272.6	-1.7	1696
500134.BO	11/21/2008	67.85	68	67.25	0.8	952334
500135.BO	11/21/2008	11.48	12	11.73	-2.1	32844

Table 98: ULIP Transaction [Data]

ScriptID	Udate	Mode1	Mode2	Mode3	Mode4
000001.UL	4/10/2006	10.03	9.9972	10.28	10.73
000001.UL	4/12/2006	10.03	9.9775	10.17	10.43
000001.UL	4/13/2006	10.04	9.9782	10.11	10.29
000001.UL	4/17/2006	10.04	9.9839	10.2	10.55
000001.UL	4/18/2006	10.04	9.9897	10.26	10.76
000001.UL	4/20/2006	10.05	10.0042	10.31	10.93
000001.UL	4/21/2006	10.05	10.0067	10.3	10.89
000001.UL	4/24/2006	10.06	10.0111	10.28	10.85
000001.UL	4/25/2006	10.06	10.0133	10.2	10.61
000001.UL	4/26/2006	10.06	10.0129	10.29	10.85
000001.UL	4/27/2006	10.06	10.014	10.24	10.74
000001.UL	4/28/2006	10.06	10.0174	10.25	10.75
000001.UL	4/29/2006	10.06	10.0195	10.31	10.91
000001.UL	5/2/2006	10.07	10.0223	10.37	11.08
000001.UL	5/3/2006	10.07	10.0229	10.4	11.15
000001.UL	5/4/2006	10.08	10.0228	10.41	11.13
000001.UL	5/8/2006	10.08	10.0295	10.44	11.21
000001.UL	5/9/2006	10.08	10.0334	10.47	11.28
000001.UL	5/10/2006	10.09	10.035	10.5	11.35
000001.UL	5/11/2006	10.09	10.0347	10.44	11.19
000001.UL	5/12/2006	10.09	10.0355	10.4	11.09
000001.UL	5/15/2006	10.1	10.0375	10.23	10.61
000001.UL	5/16/2006	10.1	10.0403	10.24	10.65
000001.UL	5/17/2006	10.1	10.0418	10.37	10.98
000001.UL	5/18/2006	10.11	10.0397	10.09	10.21
000001.UL	5/19/2006	10.11	10.0428	9.92	9.77
000001.UL	5/22/2006	10.11	10.0479	9.77	9.36
000001.UL	5/23/2006	10.11	10.0493	9.89	9.67
000001.UL	5/24/2006	10.11	10.0506	9.81	9.46
000001.UL	5/25/2006	10.12	10.0523	9.85	9.57
000001.UL	5/26/2006	10.12	10.054	9.91	9.75
000001.UL	5/29/2006	10.12	10.058	9.94	9.82
000001.UL	5/30/2006	10.13	10.0588	9.9	9.71
000001.UL	5/31/2006	10.13	10.0602	9.78	9.4
000001.UL	6/1/2006	10.09	10.0607	9.65	9.08
000001.UL	6/2/2006	10.09	10.0604	9.75	9.41
000001.UL	6/5/2006	10.1	10.065	9.67	9.21
000001.UL	6/6/2006	10.1	10.0639	9.57	8.97
000001.UL	6/7/2006	10.1	10.0651	9.49	8.74
000001.UL	6/8/2006	10.1	10.0665	9.32	8.32
000001.UL	6/9/2006	10.11	10.0638	9.47	8.72
000001.UL	6/12/2006	10.11	10.0685	9.36	8.43
000001.UL	6/13/2006	10.11	10.0704	9.21	8.03

ScriptID	Udate	Mode1	Mode2	Mode3	Mode4
000001.UL	6/14/2006	10.11	10.0734	9.17	7.9
000001.UL	6/15/2006	10.12	10.0742	9.38	8.45
000001.UL	6/16/2006	10.12	10.0745	9.5	8.78
000001.UL	6/19/2006	10.12	10.0753	9.55	8.91
000001.UL	6/20/2006	10.13	10.0769	9.48	8.73
000001.UL	6/21/2006	10.13	10.0756	9.54	8.89
000001.UL	6/22/2006	10.13	10.0769	9.63	9.12
000001.UL	6/23/2006	10.13	10.0703	9.66	9.2
000001.UL	6/26/2006	10.14	10.0749	9.54	8.91
000001.UL	6/27/2006	10.14	10.0759	9.57	9
000001.UL	6/28/2006	10.14	10.0738	9.57	9
000001.UL	6/29/2006	10.14	10.0755	9.58	9.01
000001.UL	6/30/2006	10.15	10.0767	9.73	9.4
000001.UL	7/3/2006	10.15	10.0826	9.76	9.46
000001.UL	7/4/2006	10.15	10.0826	9.75	9.45
000001.UL	7/5/2006	10.16	10.0844	9.82	9.63
000001.UL	7/6/2006	10.17	10.1375	9.86	9.55
000001.UL	7/7/2006	10.17	10.1383	9.78	9.33
000001.UL	7/10/2006	10.18	10.1416	9.84	9.47
000001.UL	7/11/2006	10.18	10.1432	9.81	9.39
000001.UL	7/12/2006	10.18	10.1448	9.89	9.59
000001.UL	7/13/2006	10.18	10.1465	9.86	9.52
000001.UL	7/14/2006	10.19	10.1484	9.81	9.39
000001.UL	7/17/2006	10.19	10.1535	9.69	9.07
000001.UL	7/18/2006	10.19	10.1554	9.66	8.99
000001.UL	7/19/2006	10.19	10.1576	9.58	8.77
000001.UL	7/20/2006	10.2	10.1601	9.7	9.06
000001.UL	7/21/2006	10.2	10.1634	9.62	8.85
000001.UL	7/24/2006	10.21	10.169	9.65	8.92
000001.UL	7/25/2006	10.21	10.1705	9.72	9.08
000001.UL	7/26/2006	10.21	10.1701	9.79	9.26
000001.UL	7/27/2006	10.21	10.1705	9.83	9.37
000001.UL	7/28/2006	10.21	10.1738	9.83	9.33
000001.UL	7/31/2006	10.22	10.1791	9.86	9.4
000001.UL	8/1/2006	10.22	10.1803	9.87	9.43
000001.UL	8/2/2006	10.23	10.184	9.93	9.57
000001.UL	8/3/2006	10.23	10.186	9.94	9.59
000001.UL	8/4/2006	10.23	10.1884	9.91	9.53
000001.UL	8/7/2006	10.23	10.1946	9.9	9.47
000001.UL	8/8/2006	10.23	10.198	9.96	9.62
000001.UL	8/9/2006	10.23	10.2043	10.01	9.75
000001.UL	8/10/2006	10.24	10.2068	10.02	9.75
000001.UL	8/11/2006	10.24	10.2081	10.04	9.81
000001.UL	8/14/2006	10.24	10.2136	10.09	9.94
000001.UL	8/16/2006	10.25	10.2177	10.14	10.07

000001.UL	8/17/2006	10.25	10.221	10.15	10.07
000001.UL	8/18/2006	10.25	10.2218	10.14	10.05
000001.UL	8/21/2006	10.26	10.2273	10.17	10.12

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ScriptID	Udate	Mode1	Mode2	Mode3	Mode4
000001.UL	8/18/2008	12.08	11.613	12.16	12.84
000001.UL	8/20/2008	12.08	11.6119	12.14	12.8
000001.UL	8/21/2008	12.09	11.6073	12.04	12.53
000001.UL	8/22/2008	12.09	11.6093	12.08	12.64
000001.UL	8/25/2008	12.1	11.6171	12.11	12.69
000001.UL	8/26/2008	12.1	11.6199	12.13	12.73
000001.UL	8/27/2008	12.1	11.6227	12.1	12.66
000001.UL	8/28/2008	12.11	11.6255	12.07	12.55
000001.UL	8/29/2008	12.11	11.6296	12.2	12.92
000001.UL	9/1/2008	12.12	11.6404	12.21	12.92
000001.UL	9/2/2008	12.12	11.6459	12.32	13.22
000001.UL	9/4/2008	12.13	11.6552	12.28	13.12
000001.UL	9/5/2008	12.13	11.6584	12.2	12.85
000001.UL	9/8/2008	12.14	11.667	12.28	13.11
000001.UL	9/9/2008	12.15	11.6699	12.26	13.03
000001.UL	9/10/2008	12.15	11.6754	12.21	12.89
000001.UL	9/11/2008	12.15	11.6757	12.14	12.69
000001.UL	9/12/2008	12.16	11.6804	12.1	12.57
000001.UL	9/15/2008	12.17	11.6941	11.98	12.21
000001.UL	9/16/2008	12.17	11.699	11.99	12.26
000001.UL	9/17/2008	12.17	11.6992	11.95	12.11
000001.UL	9/18/2008	12.18	11.6921	11.95	12.14
000001.UL	9/19/2008	12.18	11.6831	12.1	12.59
000001.UL	9/22/2008	12.19	11.6891	12.1	12.56
000001.UL	9/23/2008	12.19	11.693	12.01	12.28
000001.UL	9/24/2008	12.2	11.6921	12.06	12.43
000001.UL	9/25/2008	12.2	11.6945	12.04	12.36
000001.UL	9/26/2008	12.2	11.6922	11.94	12.07
000001.UL	9/29/2008	12.21	11.6983	11.83	11.76
000001.UL	9/30/2008	12.21	11.7012	11.9	11.96
000001.UL	10/1/2008	12.22	11.705	11.99	12.13
000001.UL	10/3/2008	12.22	11.7207	11.89	11.81
000001.UL	10/6/2008	12.23	11.7289	11.71	11.3
000001.UL	10/7/2008	12.24	11.7161	11.66	11.19
000001.UL	10/8/2008	12.24	11.6764	11.51	10.88
000001.UL	10/10/2008	12.25	11.688	11.3	10.27
000001.UL	10/13/2008	12.26	11.6969	11.56	11.01
000001.UL	10/14/2008	12.26	11.6912	11.58	11.09
000001.UL	10/15/2008	12.26	11.6908	11.41	10.59

Table 99: Index [Data]

Sdate	Index	Sopen	Shigh	Slow	Sclose	SVolume	SAdvance	SDecline
7/6/2005	BSE	7227.22	7296.18	7227.22	7287.6	13400	0.735207	0.264793
7/7/2005	BSE	7281.07	7306.54	7123.11	7145.13	16800	0.235207	0.764793
7/8/2005	BSE	7171.52	7240.39	7158.14	7212.08	14600	0.748521	0.251479
7/11/2005	BSE	7227.51	7320.25	7227.51	7306.74	13400	0.70858	0.29142
7/12/2005	BSE	7297.95	7352.46	7217.6	7303.95	17000	0.400888	0.599112
7/13/2005	BSE	7303.19	7338.01	7236.78	7247.91	11600	0.539941	0.460059
7/14/2005	BSE	7262.86	7263.03	7163.85	7187.7	13600	0.423077	0.576923
7/15/2005	BSE	7192.45	7283.04	7178.09	7271.54	10400	0.653846	0.346154
7/18/2005	BSE	7325.65	7359.81	7308.87	7347.1	17400	0.717456	0.282544
7/19/2005	BSE	7348.6	7385.69	7317.85	7346.63	11000	0.294379	0.705621
7/21/2005	BSE	7345.98	7380.69	7275.59	7304.32	12600	0.326923	0.673077
7/22/2005	BSE	7306.64	7429.95	7273.19	7423.25	12200	0.662722	0.337278
7/25/2005	BSE	7427.65	7526.88	7427.65	7505.6	17200	0.464497	0.535503
7/26/2005	BSE	7524.1	7564.79	7473.24	7552.77	20200	0.292899	0.707101
7/27/2005	BSE	7559.76	7620.37	7504.96	7605.03	13200	0.420118	0.579882
7/29/2005	BSE	7556.17	7708.59	7545.79	7635.42	21800	0.266272	0.733728
8/1/2005	BSE	7632.01	7681.11	7596.74	7669.45	13800	0.426036	0.573964
8/2/2005	BSE	7683.13	7762.8	7683.13	7743.38	19400	0.736686	0.263314
8/3/2005	BSE	7774.29	7843.77	7740.83	7756.47	28600	0.356509	0.643491
8/4/2005	BSE	7810.05	7826.36	7756.97	7797.08	23400	0.566568	0.433432
8/5/2005	BSE	7806.11	7817.61	7738.64	7755.55	17400	0.571006	0.428994
8/8/2005	BSE	7760.67	7781.04	7594.94	7606.17	16800	0.298817	0.701183
8/9/2005	BSE	7617.46	7686.85	7559.8	7607.05	23200	0.37426	0.62574
8/10/2005	BSE	7774.27	7828.01	7737.76	7768.24	14000	0.633136	0.366864
8/11/2005	BSE	7771.78	7870.62	7735.37	7859.53	27000	0.650888	0.349112
8/12/2005	BSE	7902.84	7921.39	7791.91	7811.33	16800	0.323964	0.676036
8/22/2005	BSE	7814.93	7845.96	7711.18	7750.6	16000	0.428994	0.571006
8/23/2005	BSE	7764.86	7770.83	7601.34	7615.99	11000	0.159763	0.840237
8/24/2005	BSE	7615.68	7639.68	7537.5	7612	15000	0.207101	0.792899
8/30/2005	BSE	7681.67	7758.36	7679.44	7745	9800	0.671598	0.328402
8/31/2005	BSE	7746.8	7807.67	7726.98	7805.43	9600	0.606509	0.393491
9/1/2005	BSE	7818.9	7902.19	7818.9	7876.15	11200	0.730769	0.269231
9/2/2005	BSE	7888.11	7928.07	7836.34	7899.77	12600	0.400888	0.599112
9/5/2005	BSE	7901.35	7983.33	7901.35	7913.75	10200	0.689349	0.310651
9/12/2005	BSE	8072.99	8142.81	8072.99	8138.42	8200	0.649408	0.350592
9/13/2005	BSE	8137.39	8202.04	8121.08	8193.96	9400	0.534024	0.465976
9/14/2005	BSE	8207.53	8260.01	8144.32	8189.48	17400	0.323964	0.676036
9/15/2005	BSE	8208.21	8294.24	8203.77	8283.76	11800	0.727811	0.272189
9/16/2005	BSE	8296.88	8388.8	8268.6	8380.96	12800	0.553254	0.446746
9/19/2005	BSE	8399.51	8461.1	8382.96	8444.84	10600	0.536982	0.463018
9/20/2005	BSE	8412.71	8515.28	8379.41	8500.28	15600	0.266272	0.733728
9/21/2005	BSE	8499.33	8521.75	8263.62	8487.14	26800	0.090237	0.909763
9/22/2005	BSE	8480.62	8519.6	8186.13	8221.64	27200	0.016272	0.983728

Sdate	Index	Sopen	Shigh	Slow	Sclose	SVolume	SAdvance	SDecline
9/23/2005	BSE	8255.05	8299.08	8126.86	8222.59	20000	0.523669	0.476331
9/26/2005	BSE	8280.06	8487.17	8280.06	8478.91	18600	0.872781	0.127219
9/27/2005	BSE	8497.25	8585.76	8444.98	8525.52	20000	0.531065	0.468935
9/28/2005	BSE	8535.81	8613.83	8476.47	8606.03	18000	0.474852	0.525148
9/29/2005	BSE	8588.47	8722.17	8588.47	8650.17	19800	0.218935	0.781065
9/30/2005	BSE	8672.66	8681.58	8528.05	8634.48	23400	0.264793	0.735207
10/3/2005	BSE	8662.99	8725.75	8662.99	8697.65	16600	0.741124	0.258876
10/4/2005	BSE	8706.7	8808.83	8706.7	8799.96	27400	0.714497	0.285503
10/5/2005	BSE	8815.67	8821.84	8695.69	8724.47	23600	0.300296	0.699704
10/6/2005	BSE	8693.2	8693.2	8508.43	8528.7	29400	0.16716	0.83284
10/10/2005	BSE	8516.44	8564.85	8466.57	8483.86	16200	0.238166	0.761834
10/11/2005	BSE	8547.95	8563.85	8381.96	8540.56	21200	0.278107	0.721893
10/13/2005	BSE	8520.48	8547.8	8347.17	8376.9	24200	0.25	0.75
10/14/2005	BSE	8389.45	8393.7	8180.1	8201.73	25200	0.075444	0.924556
10/17/2005	BSE	8230.47	8254.8	8133.39	8202.62	21800	0.244083	0.755917
10/18/2005	BSE	8232.26	8317.38	8067.91	8122.25	19200	0.37574	0.62426
10/19/2005	BSE	8066.06	8084.79	7922.89	7971.06	26400	0.056213	0.943787
10/20/2005	BSE	8075.82	8134.83	7839.13	7935.12	27200	0.155325	0.844675
10/21/2005	BSE	7930.5	8080.77	7901.21	8068.95	25600	0.62574	0.37426
10/24/2005	BSE	8096.49	8126.27	7900.43	7920.8	21400	0.498521	0.501479
10/25/2005	BSE	7974.17	8074.08	7922.32	7991.74	22200	0.532544	0.467456
10/26/2005	BSE	7996.92	8047.86	7951.49	7974.69	15800	0.426036	0.573964
10/27/2005	BSE	7989.35	7993.9	7766.99	7798.49	26800	0.426036	0.573964
10/28/2005	BSE	7795.03	7795.03	7656.15	7685.64	21800	0.18787	0.81213
10/31/2005	BSE	7717.07	7905.7	7717.07	7892.32	15600	0.692308	0.307692
11/1/2005	BSE	7717.07	7905.7	7717.07	7892.32	6200	0.017751	0.982249
11/2/2005	BSE	7953.28	8086.84	7891.23	8072.75	16600	0.776627	0.223373
11/7/2005	BSE	8083.59	8216.42	8053.71	8206.83	27200	0.798817	0.201183
11/8/2005	BSE	8218.82	8353.1	8214.76	8317.8	24000	0.715976	0.284024
11/9/2005	BSE	8332.01	8405.19	8269.09	8308.78	19400	0.37426	0.62574
11/10/2005	BSE	8314.39	8342.53	8265.89	8308.93	1200	0.510355	0.489645
11/11/2005	BSE	8332.94	8483.68	8332.94	8471.04	20200	0.748521	0.251479
11/14/2005	BSE	8503.7	8569.91	8416.89	8494.29	16200	0.480769	0.519231
11/16/2005	BSE	8513.17	8606.79	8503	8595.92	15000	0.596154	0.403846
11/17/2005	BSE	8592.64	8662.57	8575.55	8649.52	17000	0.434911	0.565089
11/18/2005	BSE	8669.84	8739.57	8661.6	8686.65	22400	0.476331	0.523669
11/21/2005	BSE	8633.63	8673.51	8591.61	8610.74	21400	0.29142	0.70858
11/22/2005	BSE	8602.82	8664.3	8518.18	8534.97	19600	0.263314	0.736686
11/23/2005	BSE	8542.61	8649.37	8537.48	8638.34	19600	0.542899	0.457101
11/24/2005	BSE	8655.14	8765.71	8655.14	8744.04	19800	0.60503	0.39497
11/25/2005	BSE	8760.7	8863.93	8760.7	8853.21	19000	0.593195	0.406805
11/28/2005	BSE	8962.53	9004.72	8938.44	8994.94	18800	0.656805	0.343195
11/29/2005	BSE	9000.65	9000.65	8875.82	8931.16	19400	0.278107	0.721893
11/30/2005	BSE	8962.92	9032.03	8768.8	8788.81	18200	0.301775	0.698225
12/1/2005	BSE	8813.82	8958.49	8770.59	8944.78	18200	0.58284	0.41716

12/2/2005	BSE	9010.58	9057.76	8946.37	8961.61	18400	0.443787	0.556213

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Sdate	Index	Sopen	Shigh	Slow	Sclose	SVolume	SAdvance	SDecline
6/13/2008	BSE	15327.1	15337.1	15135.81	15189.62	20200	0.470414	0.529586
6/16/2008	BSE	15400.57	15553.37	15340.34	15395.82	15200	0.647929	0.352071
6/17/2008	BSE	15388.36	15732.75	15358.75	15696.9	18200	0.639053	0.360947
6/18/2008	BSE	15744.21	15789.62	15390.22	15422.31	22000	0.377219	0.622781
6/19/2008	BSE	15250.47	15259.36	15051.66	15087.99	18600	0.198225	0.801775
6/20/2008	BSE	15194.73	15194.73	14520.88	14571.29	26000	0.069527	0.930473
6/23/2008	BSE	14423.05	14509.69	14163.45	14293.32	24600	0.073964	0.926036
6/24/2008	BSE	14290.16	14432.9	13991.31	14106.58	24800	0.205621	0.794379
6/25/2008	BSE	13776.21	14247.16	13736.01	14220.07	23000	0.470414	0.529586
6/26/2008	BSE	14300.72	14449.81	14196.68	14421.82	21800	0.529586	0.470414
6/27/2008	BSE	14127.76	14127.76	13760.78	13802.22	32200	0.10503	0.89497
6/30/2008	BSE	13791.02	13872.06	13405.54	13461.6	22400	0.112426	0.887574
7/1/2008	BSE	13480.02	13613.01	12904.09	12961.68	27600	0.069527	0.930473
7/2/2008	BSE	12948.05	13711.01	12822.75	13664.62	32000	0.662722	0.337278
7/3/2008	BSE	13458.3	13458.3	12934.92	13094.11	29200	0.181953	0.818047
7/4/2008	BSE	13097.01	13508.38	13031.43	13454	31400	0.673077	0.326923
7/7/2008	BSE	13561.92	13793.39	13476.29	13525.99	21200	0.715976	0.284024
7/8/2008	BSE	13226.04	13451.67	13049.96	13349.65	25400	0.377219	0.622781
7/9/2008	BSE	13581.41	13998.48	13581.41	13964.26	27600	0.816568	0.183432
7/10/2008	BSE	13851.59	14046.59	13763.94	13926.24	27400	0.467456	0.532544
7/11/2008	BSE	14063.45	14063.45	13351.34	13469.85	29000	0.226331	0.773669
7/14/2008	BSE	13333.03	13557.21	13270.4	13330.51	23600	0.297337	0.702663
7/15/2008	BSE	13067.08	13067.08	12607.62	12676.19	30000	0.297337	0.702663
7/16/2008	BSE	12759.76	12935.25	12514.99	12575.8	31200	0.377219	0.622781
7/17/2008	BSE	12909.57	13150.35	12843.79	13111.85	33600	0.62574	0.37426
7/18/2008	BSE	13238.32	13684.27	13093.34	13635.4	36600	0.606509	0.393491
7/21/2008	BSE	13782.13	13878.88	13581.19	13850.04	32400	0.403846	0.596154
7/22/2008	BSE	13839.32	14206.13	13798.18	14104.2	35600	0.701183	0.298817
7/23/2008	BSE	14568.22	14979.9	14568.22	14942.28	39000	0.863905	0.136095
7/24/2008	BSE	15120.54	15129.99	14608.05	14777.01	31200	0.35355	0.64645
7/25/2008	BSE	14451.95	14483.52	14210.63	14274.94	27800	0.372781	0.627219
7/28/2008	BSE	14267.03	14420.6	14219.38	14349.11	21800	0.633136	0.366864
7/29/2008	BSE	14085.53	14152.29	13727.14	13791.54	23600	0.239645	0.760355
7/30/2008	BSE	14049.23	14320.21	14002.19	14287.21	26000	0.647929	0.352071
7/31/2008	BSE	14359.48	14369.42	14161.76	14355.75	27800	0.414201	0.585799
8/1/2008	BSE	14064.26	14682.33	14032.87	14656.69	40200	0.565089	0.434911
8/4/2008	BSE	14594.64	14725.94	14503.51	14577.87	24800	0.681953	0.318047
8/5/2008	BSE	14562.68	14986.63	14529.21	14961.07	35600	0.661243	0.338757
8/6/2008	BSE	15263.65	15422.82	15035.6	15073.54	32600	0.412722	0.587278
8/7/2008	BSE	15031.86	15280.06	14992.97	15117.25	25800	0.468935	0.531065
8/8/2008	BSE	15036.57	15228.82	14888.12	15167.82	21000	0.421598	0.578402

Sdate	Index	Sopen	Shigh	Slow	Sclose	SVolume	SAdvance	SDecline
8/11/2008	BSE	15430.31	15520.71	15367.97	15503.92	26200	0.633136	0.366864
8/12/2008	BSE	15577.2	15579.78	15124.91	15212.13	27000	0.278107	0.721893
8/13/2008	BSE	15030.21	15272.56	15013.06	15093.12	19200	0.359467	0.640533
8/14/2008	BSE	15017.68	15033.28	14686.66	14724.18	22000	0.176036	0.823964
8/18/2008	BSE	14681.14	14824.92	14600.65	14645.66	19600	0.251479	0.748521
8/19/2008	BSE	14517.76	14604.11	14368.72	14543.73	17600	0.340237	0.659763
8/20/2008	BSE	14610.57	14746.2	14584.03	14678.23	18400	0.60503	0.39497
8/21/2008	BSE	14646.98	14646.98	14201.18	14243.73	19400	0.12426	0.87574
8/22/2008	BSE	14153.39	14428.52	14136.86	14401.49	20400	0.392012	0.607988
8/25/2008	BSE	14643.37	14672.69	14416.2	14450.35	17000	0.451183	0.548817
8/26/2008	BSE	14338.27	14495.27	14286.38	14482.22	18800	0.380178	0.619822
8/27/2008	BSE	14563.1	14563.1	14261.69	14296.79	15600	0.300296	0.699704
8/28/2008	BSE	14289.97	14347.19	14002.43	14048.34	18800	0.227811	0.772189
8/29/2008	BSE	14279.02	14586.16	14279.02	14564.53	32400	0.724852	0.275148
9/1/2008	BSE	14412.99	14547.41	14281.1	14498.51	14800	0.399408	0.600592
9/2/2008	BSE	14609.44	15106.15	14543.21	15049.86	25800	0.661243	0.338757
9/4/2008	BSE	14895.85	14994.15	14766.01	14899.1	19800	0.405325	0.594675
9/5/2008	BSE	14569.01	14601.39	14438.59	14483.83	23200	0.252959	0.747041
9/8/2008	BSE	15038.06	15107.01	14917.06	14944.97	23400	0.615385	0.384615
9/9/2008	BSE	14814.33	14998.32	14714.92	14900.76	19800	0.309172	0.690828
9/10/2008	BSE	14717.53	14866.32	14609.83	14662.61	22800	0.235207	0.764793
9/11/2008	BSE	14557.33	14557.33	14265.38	14324.29	22800	0.183432	0.816568
9/12/2008	BSE	14433.2	14433.2	13933.87	14000.81	26800	0.170118	0.829882
9/15/2008	BSE	13592.05	13592.05	13150.81	13531.27	24000	0.047337	0.952663
9/16/2008	BSE	13051.73	13556.03	13051.73	13518.8	33600	0.266272	0.733728
9/17/2008	BSE	13620.74	13620.74	13127.96	13262.9	30400	0.245562	0.754438
9/18/2008	BSE	12712.82	13346.79	12558.14	13315.6	48000	0.223373	0.776627
9/19/2008	BSE	13763.83	14097.44	13674.96	14042.32	47400	0.772189	0.227811
9/22/2008	BSE	14215.33	14215.33	13917.48	13994.96	35800	0.211538	0.788462
9/23/2008	BSE	13721.42	13978.26	13543.47	13570.31	29600	0.205621	0.794379
9/24/2008	BSE	13636.71	13840.81	13592.79	13692.52	40200	0.483728	0.516272
9/25/2008	BSE	13716.88	13716.88	13430.68	13547.18	36600	0.254438	0.745562
9/26/2008	BSE	13486.2	13486.2	13054.42	13102.18	29000	0.085799	0.914201
9/29/2008	BSE	13109.96	13109.96	12402.84	12595.75	37000	0.076923	0.923077
9/30/2008	BSE	12178.18	12995.2	12153.55	12860.43	38400	0.534024	0.465976
10/1/2008	BSE	13006.72	13203.86	12697.3	13055.67	32400	0.553254	0.446746
10/3/2008	BSE	12851.47	13001.19	12472.61	12526.32	37200	0.14497	0.85503
10/6/2008	BSE	12284.49	12284.49	11732.97	11801.7	33000	0.029586	0.970414
10/7/2008	BSE	12068.11	12181.08	11501.85	11695.24	40400	0.241124	0.758876
10/8/2008	BSE	11245.51	11405.73	10740.76	11328.36	66200	0.096154	0.903846
10/10/2008	BSE	10632.27	10904.13	10239.76	10527.85	62400	0.068047	0.931953
10/13/2008	BSE	10872.49	11361.32	10842.81	11332.23	43800	0.695266	0.304734
10/14/2008	BSE	11781.43	11870.22	11410.49	11483.4	36000	0.618343	0.381657
10/15/2008	BSE	11245.27	11257.15	10761.44	10809.12	34800	0.102071	0.897929
10/16/2008	BSE	10221.53	10787.2	10017.8	10581.49	51600	0.272189	0.727811

Table 100: Results [Data]

Scriptid	REnddate	No of Months	Net sales	Other income	Total Income	Expenditure	Operating Profit	Interest	PBDT	Depreciation	PBT	Tax	PAT	Extra item	Net Profit	Equity Capital	Reserve	BD EPS AE	Non Promoter Stack	Non Promoter Percent	Result type
500463.BO	3/31/2003	12	3182.4	13.4	3196	-2824.04	371	-20	350	-51.2	299	-114	185		185	142	934.7	13	7E+06	49	A
500490.BO	3/31/2003	12	43363	1449.9	44813	-35204.1	9608	-11	9597	-1712	7886	-2502	5384	-37.9	5346	1011	31394	52	7E+07	70	A
532351.BO	3/31/2003	12	802.02	22.49	824.5	-779.57	44	-41	3	-45.8	-42	21.91	-20	-20.7	-20	110		0	1E+07	43	A
532399.BO	3/31/2003	12	741.91	38.67	780.6	-466.3	314	-10	304	-42.1	262	-95.8	166		166	107		7	4E+06	20	A
500003.BO	3/31/2004	12	808	34.4	842.4	-653.5	188	-45	143	-31.4	112	-27	85		85	162	482	5	6E+06	37	A
500008.BO	3/31/2004	12	1635.2	41.58	1677	-1540.44	136	-1	134	-123	11	2.38	13		13	113		1	5E+06	48	A
500019.BO	3/31/2004	12	5028.6	1770.1	6799	-4945.72	1853	-3130			1853	-276	690	1076	1766	1075		6	6E+07	55	A
500020.BO	3/31/2004	12	9055	608.4	9663	-8470.3	1193	-123	1069	-344	725	-191	535		535	385	3475	13	2E+07	56	A
500023.BO	3/31/2004	12	2039.1	4.1	2043	-1427.4	615	-304	311	-210	101	-48.4	53	-2.7	50	228					A
500027.BO	3/31/2004	12	5939.8	96.1	6036	-5477.89	558	-215	342	-273	69	-46.9	22	12.4	35	296		1	2E+07	64	A
500034.BO	3/31/2004	12	1056.5	279.9	1336	-518.3	561	-256		-18.8	542	-157	385		385	164	2174	23	9E+06	53	A
500041.BO	3/31/2004	12	4694.8	81.02	4776	-3932.41	843	-113	729	-271	459	-128	331		331	95	1619	34	5E+06	53	A
500048.BO	3/31/2004	12	17706	324.7	18031	-17308	722	-14	708	-184	525	-195	330		330	367	5730	8	1E+07	38	A
500101.BO	3/31/2004	12	14353	125.9	14479	-10829.7	3649	-1132	2516	-1503	1013	-45.5	967		967	1953	9165		1E+08	61	A
500103.BO	3/31/2004	12	79910	2789.4	82699	-70320.8	12378	-570	11807	-2021	9787	-3432	6355		6355	2447		25	8E+07	32	A
500128.BO	3/31/2004	12	6721	317	7038	-5674.7	1363	-50	1313	-228	1085	-348	736		736	161		45	6E+06	37	A
500145.BO	3/31/2004	12	1103.7	81.24	1185	-187.45	484	-513		-248	236	-20.4	215		215	227	1303	10	2E+07	71	A
500215.BO	3/31/2004	12	12604	59	12663	-12497	166	-54	112	-28	84	4	88	-62	26	244	512	1	8E+06	30	A
500343.BO	3/31/2004	12	1106.2	17.5	1124	-967.2	156	-32	124	-82.6	41	-8.4	33	-16.4	16	82	856.5	2	4E+06	47	A
500463.BO	3/31/2004	12	3951.6	7.69	3959	-3303.65	655	-11	644	-118	526	-200	326		326	142	1189	22	7E+06	49	A
500470.BO	3/31/2004	12	107024	1405.1	1E+05	-72069.8	36359	-1221	35137	-6251	28886	-9197	19689	-2227	17462	3691		47	3E+08	73	A
500490.BO	3/31/2004	12	49168	3534.5	52703	-40639.8	12062	-9	12053	-1799	10254	-2289	7965	-582	7383	1011	35924	73	7E+07	70	A
500547.BO	3/31/2004	12	482543	4669	5E+05	-454195	33017	-1050	31967	-5612	26355	-9409	16946		16946	3000	55497	56	1E+08	33	A

Scriptid	REnddate	No of Months	Net sales	Other income	Total Income	Expenditure	Operating Profit	Interest	PBDT	Depreciation	PBT	Tax	PAT	Extra item	Net Profit	Equity Capital	Reserve	BD EPS AE	Non Promoter Stack	Non Promoter Percent	Result type
500674.BO	3/31/2004	3	1637	34	1671	-1235	436		436	-42	394	-142	252	68	320	230		13	9E+06	39	Q
500770.BO	3/31/2004	12	25442	771.1	26213	-20843.6	5369	-509	4859	-1442	3418	-1056	2362	-158	2205	2151	18202	10	2E+08	74	A
500820.BO	3/31/2004	12	17425	216.77	17641	-14729.24	2912	-52	2859	-480	2379	-836	1543	-70.1	1477	959	4356	15	5E+07	57	A
500825.BO	3/31/2004	12	14396	546	14942	-12695	2247	-60	2187	-224	1963	-656	1307	-119	1188	251	4059	42	1E+07	51	A
500830.BO	3/31/2004	12	9391.9	299.2	9691	-7927.8	1763	-5	1757	-243	1514	-435	1080		1080	1360	1083	7	7E+07	49	A
500840.BO	3/31/2004	12	4450.3	594.6	5045	-3893.6	1151	-347	803	-389	414	-133	281		281	523	6101	3	3E+07	57	A
500877.BO	3/31/2004	12	19108	60.3	19168	-17492	1675	-186	1489	-437	1052	-348	704		704	383	5307	21			A
500940.BO	3/31/2004	12	8455.6	471.7	8927	-6958.27	1969	-134	1834	-429	1404	-503	901		901	1240	3406	7	1E+08	81	A
501425.BO	3/31/2004	12	1270.8	158.6	1429	-1234.7	194	-104	90	-36.6	54	-1.3	52		52	139	539.5	3	5E+06	36	A
502330.BO	3/31/2004	12	3985.7	66.2	4052	-3487.4	564	-98	466	-200	266	-32.7	233		233	118	1864	19	4E+06	32	A
503940.BO	3/31/2004	12	871.3	64.5	935.8	-676.7	259	-78	180	-94.5	86	-31.8	54	-8.1	46	85	1056	5	5E+06	60	A
505688.BO	3/31/2004	12	936.2	102.4	1039	-853	185	-111	73	-88.5	-14		-14		-14	60	-1.9	-2	4E+06	73	A
506655.BO	3/31/2004	12	3187	46.3	3233	-2906.7	326	-67	259	-124	135	-40.2	95		95	69	753.5	13	3E+06	41	A
508814.BO	3/31/2004	12	3133	85.7	3219	-2450	768	-77	691	-303	388	-73	315		315	169	963.6	19	9E+06	51	A
508869.BO	3/31/2004	12	4946	52	4998	-4009	989	-192	797	-211	586	-215	371		371	395	2228	9	3E+07	66	A
509480.BO	3/31/2004	12	6758.2	51.9	6810	-6028.1	782	-28	754	-139	614	-174	440	-0.5	440	265	1594		9E+06	33	A
511427.BO	3/31/2004	12	13.16	0.01	13.17	-19.48	-8	-2	-8	-2.08	-10	4.45	-6		-6	394	4.2	0			A
512296.BO	3/31/2004	12	965.02	46.83	1012	-869.39	142	-6	136	-33.2	103	-8.5	94	-0.4	94	63	521.7	14	1E+06	18	A
512599.BO	3/31/2004	12	70784	769.8	71553	-69840.69	1712	-443	1269	-17.9	1251	-20.5	1231	9.9	1240	220	5917	55	1E+07	44	A
515035.BO	3/31/2004	12	1267.6	10	1278	-944.51	333	-133	199	-116	83	-46.4	37	-22.9	14	365	154.4	0	1E+07	59	A
517206.BO	3/31/2004	12	2308.8	17.91	2327	-2019.86	306	-56	249	-142	108	6.29	91		91	83	404.3	11	3E+06	41	A
517506.BO	3/31/2004	12	1385.4	63.5	1449	-1333	115	-92	23	-18.3	5	-3.4	2		2	113	276.4	0	3E+06	27	A
519281.BO	3/31/2004	12	1360.1	28.16	1388	-975.34	412	-156	256	-70.3	186	-56.4	130		130	147	598.1		9E+06	63	A
521014.BO	3/31/2004	12	2369.9	26.02	2396	-2151.35	244	-71	172	-80.6	92	-12.1	79		79	87	518.1	8	4E+06	42	A
521034.BO	3/31/2004	12	1621.4	27.6	1649	-1401.8	247	-69	177	-70.1	107	0	107	-24.1	83	147	277.4	7	9E+06	62	A

5.4 Limitation of Data:

1. Stock Quotes are not live: Stock Quote data when captured by web service, it creates little delay, i.e. it is not consider live quote as available in trading terminals, As little delay may differ stock price from actual price So we can not use this data for real time requirements but we can test the models and build simulators with the data available with out any problem.

2. Missing Result Values: In some of the corporate results, fundamental values like NetSales, Equity Capital, Reserves, Non Promoter Stack etc are not available. To process the data for further use we have to estimate these values from past set of results, and the estimation may vary from actual values.

3. Data Formats are different: Especially in corporate results there are number of formats in which result values are available. Anyway this limitation has been overcome by software program and we have stored all results in uniform format for our purpose.

4. Use of different accounting standards: All companies are not necessarily follows the same accounting standards to calculate result parameters like depreciation, interest etc, so one to one comparison among the companies are always not possible.

5. Delay in News Announcement: In most of the cases official news about the company announces late or confirmed late, and the stock price change has already adjusted at the time when news reaches to the public.

6. Frequency of NAV declaration: All mutual fund are not releasing NAV on daily basis, so it is difficult to compare such a fund one to one with other fund.

7. FII data: It is difficult to predict, also the volume is significant in Indian market scenario, Actual data released after two-three day from the day of trading.

8. Regulatory Policy Change: The policy change data (like EXIM) decisions for specific business sector, also affects the stock prices for the sector are difficult to account.

9. Global Market impacts: There is huge correlation among the regional as well as global market, One can estimate well to gain for the day in theory but as market is efficient enough to adjust changes with in vary sort time of opening. Practically it is very difficult to use the data for trading profitability.

10. Speculation: Speculation by trading firms/brokerage houses misguides the analysts.

Except this there is data related to qualitative parameters like managerial expertise, competitive advantages, business model strength, corporate governance etc., which makes impact on future value of stock but to analyze these parameter is art rather than science, hence needs different method for calculation.

5.5 Beliefs and Analysis of its Impact on Stock Prices:

Different technical and fundamental beliefs Influences stock and affect its performance.

Fundamental Beliefs: We have assumed that fundamentals affected by quarterly results, so fundamental beliefs influence stock performance for maximum 90 days. We have taken data for 3 Years duration (Dec-2005 to Dec-2008) to verify the impacts of fundamental beliefs and BSE 30 is taken as Benchmark index.

1. H0: Companies having good growth in quarter revenue growths (more than 200%) gives good return on investment.

Table 101: Companies achieved top growth in quarter results

ScriptID	Quarter From	Quarter To	SName	Qrev Growth	Price Start Quarter	Price Nxt30	Price Nxt60	Price Nxt90
500295.BO	Jan-06	Mar-06	SESA GOA LTD	210.43%	1012.3	1057.2	1192.6	1284.8
532256.BO	Apr-06	Jun-06	JINDAL ST	485.14%	409.2	396.3	363.9	296.05
532123.BO	Apr-06	Jun-06	BSEL INFRAST	210.02%	40.95	53.35	72.4	45.1
531936.BO	Apr-06	Jun-06	BLUE CHI IND	209.62%	1.18	1.44	1.28	1.04
532374.BO	Oct-06	Dec-06	STR OPTICAL	290.71%	170.6	193.05	225.65	232.9
506910.BO	Jan-07	Mar-07	JAYSYN DYEST	1988.89%	7	8.92	7.59	7.61
526785.BO	Jan-07	Mar-07	CREST ANIM	437.27%	134.7	146.5	109.15	96.6
500134.BO	Jan-07	Mar-07	ESSAR OIL LTD.	400.22%	54.55	61.2	55.5	51.75
532324.BO	Apr-07	Jun-07	CINEVISTS LT	1042.83%	20.35	24.55	50.95	53.5
532256.BO	Apr-07	Jun-07	JINDAL ST	954.05%	305	345.2	491.4	682.75
506910.BO	Apr-07	Jun-07	JAYSYN DYEST	357.98%	7.61	6.38	6	6.48
511716.BO	Jul-07	Sep-07	ESCORTS FINA	1648.53%	6.38	6.68	6.76	8.14
506395.BO	Oct-07	Dec-07	COROMANDL FR	261.91%	112.25	105.85	116.5	124.65
526785.BO	Jan-08	Mar-08	CREST ANIM	593.30%	145.55	82.6	79	58.75
500295.BO	Jan-08	Mar-08	SESA GOA LTD	254.07%	3872.3	3030.2	3464.2	3130.35
500186.BO	Apr-08	Jun-08	HIND.OIL EXP	981.25%	109.3	144.95	135.65	129.75
500049.BO	Apr-08	Jun-08	BHARAT ELECT	246.37%	1101.4	1336.55	1165.05	1015.15
500132.BO	Apr-08	Jun-08	EMPEE SUG CH	206.41%	9.31	10.07	9.51	7.77

Table 102: Impact Analysis for Quarter Revenue on Stock Growth

Companies	Revenue Growth	30 Days Return	60 Days Return	90 Days Return
Average Index ROI		4.23 %	0.94 %	-1.069%
Average ROI from Belief	>200 %	7.16 %	16.19 %	13.08 %
Correlation Coefficient	1.00	0.244	0.190	0.353

2. H1: Companies having good growth in Quarter profit will give good return on investment.

Table 103: Companies of excellent quarter profit growth (more than 15%) are taken for test the hypothesis.

ScriptID	Quarter From	Quarter To	SName	QNet Profit Growth %	Price at Quarter Start	Price Nxt30	Price Nxt60	Price Nxt90
517206.BO	Jan-06	Mar-06	LUMAX INDUST	17	125.1	134.85	122.9	129.5
515030.BO	Apr-06	Jun-06	ASAHI INDIA	26.875	97.85	101.4	92.25	85.8
506655.BO	Apr-06	Jun-06	SUDARSHAN CH	19	173.95	188.25	174	130.35
517562.BO	Oct-06	Dec-06	TRIGYN TECHN	96.6667	16.4	17.7	15.95	23.35
532256.BO	Oct-06	Dec-06	JINDAL ST	63	330	334	321.7	338.6
524404.BO	Oct-06	Dec-06	TASC PHARMAE	57	103.9	103.5	116.2	107.9
500495.BO	Oct-06	Dec-06	ESCORTS LTD.	19.4	125.95	128.9	117.5	111.4
500878.BO	Oct-06	Dec-06	CEAT LTD	18	120.7	117.15	126.9	123.95
506590.BO	Oct-06	Dec-06	PHIL CAR BLK	16	74.6	94.9	123.5	116.7
514286.BO	Jan-07	Mar-07	ASHIMA LTD	165	8.69	10.7	9.72	8.43
500101.BO	Jan-07	Mar-07	ARVIND MILLS LTD.	18.0364	51.7	59.15	49.8	43.5
500540.BO	Jan-07	Mar-07	PREMIER LTD	17.3043	33.15	46.15	44.15	43.05
505029.BO	Apr-07	Jun-07	ATLAS CYC HR	350	117.4	131.25	142.6	159.55
521076.BO	Apr-07	Jun-07	AMIT SPIN ID	22	6.49	6.9	6.66	6.49
507260.BO	Jul-07	Sep-07	OUDH SUGAR	69.75	57.45	52.55	52.15	59.7
530813.BO	Oct-07	Dec-07	KRBL LTD	141	87.45	85.5	100.5	161.45
500355.BO	Oct-07	Dec-07	RALLI INDIA	71.7143	408.4	460.7	434.65	540.3
521014.BO	Jan-08	Mar-08	EUROTE IND E	29	55.4	32	26.7	21.5
509684.BO	Jul-08	Sep-08	INDIA FOILS	39	8.38	7.85	8.22	7.85
517140.BO	Jul-08	Sep-08	MOSER BAER	20.3333	184.95	182.9	189.65	207.55

Table 104: Impact Analysis for Quarter Net profit-Stock Growth

Companies	Quarter profit Growth	30 Days Return	60 Days Return	90 Days Return
Average Index ROI		5.12%	4.91%	5.17%
Average ROI from Belief	>15 %	5.11%	4.47%	8.75%
Correlation Coefficient	1.00	0.108	0.177	0.383

1. H2: Companies having good earning capacity (Profitability= Operating Profit/Equity) will give good return.

Table 105: Companies of excellent profitability (more than 15)

ScriptID	Quarter From	Quarter To	SName	Profitability	Price at Quarter Start	Price Nxt30	Price Nxt60	Price Nxt90
500376.BO	Apr-06	Jun-06	SATYAM COMP	24.25	849.2	749.35	691.15	711.4
500209.BO	Apr-06	Jun-06	INFOSYS TECHNOLOG	22.7029	2980.85	3133.9	2908.05	3077.55
500295.BO	Apr-06	Jun-06	SESA GOA LTD	20.9491	1284.8	1247.55	1218.1	1115.35
500032.BO	Oct-06	Dec-06	BAJAJHINDLTD	24.8511	324.55	313.45	248.75	219.45
523204.BO	Apr-07	Jun-07	ABAN LOYD CH	41.1644	2018.2	2620	2607.45	3012.25
505029.BO	Apr-07	Jun-07	ATLAS CYC HR	27.5313	117.4	131.25	142.6	159.55
527001.BO	Apr-07	Jun-07	ASHA MINECHE	22.5128	210.9	220.85	283.2	371.2
500490.BO	Apr-07	Jun-07	BAJAJ AUTO	19.5114	2425.45	2445	2224.35	2128.85
532517.BO	Jan-08	Mar-08	PATNI COMPUT	18.8129	332.8	259.8	241.15	222.7
500002.BO	Jan-08	Mar-08	ABB LTD	18.8085	1510.95	1120.4	1156.2	1174
500295.BO	Apr-08	Jun-08	SESA GOA LTD	58.0025	2923.6	4217.4	4286.45	3378.8
513023.BO	Apr-08	Jun-08	NAVBHAR FERO	26.5677	221.45	255.25	280.15	245.45
500253.BO	Apr-08	Jun-08	LIC H. FINAN	23.6506	293.15	359.25	340.05	265.15
500055.BO	Apr-08	Jun-08	BHU STEE STR	20.8962	669.2	801.9	909.15	807.85
532296.BO	Apr-08	Jun-08	GLENMARK PHA	20.2298	473.5	668.4	657	638.7
500209.BO	Apr-08	Jun-08	INFOSYS TECHNOLOG	19.7413	1421.35	1753.75	1957.55	1734.75
500228.BO	Apr-08	Jun-08	JSW STEEL	19.3139	825.7	875.55	1171.1	901.1
532544.BO	Apr-08	Jun-08	INDIABULLS	18.5316	412.45	535.1	367.15	257.55

Table 106: Impact Analysis for Profitability-Stock Growth

Companies	Profitability	30 Days Return	60 Days Return	90 Days Return
Average Index ROI	N.A.	5.70 %	2.50%	-6.42%
Average ROI from Belief	>15	11.05%	14.56%	11.64%
Correlation Coefficient	1.00	0.499	0.397	0.300

2. H3: Companies having good growth in YOY revenue will give good return

Table 107: Companies achieved excellent yearly revenue growths (>60%)

ScriptID	Quarter From	Quarter To	SName	YRev Growth	Price at Quarter Start	Price Nxt30	Price Nxt60	Price Nxt90
531936.BO	Apr-06	Jun-06	BLUE CHI IND	197.75%	1.18	1.44	1.28	1.04
532454.BO	Apr-06	Jun-06	BHARTI TELE	100.00%	412.85	405.85	365.95	370
532351.BO	Apr-06	Jun-06	AKSH OPTIFIB	90.83%	63.25	74.8	64.75	65.1
532273.BO	Apr-06	Jun-06	CENTURION BK	62.47%	26.55	24.15	26.05	20.4
532454.BO	Apr-07	Jun-07	BHARTI TELE	83.93%	763.2	813	847.8	835.95
503940.BO	Apr-07	Jun-07	ASIAN ELECT	74.49%	460.4	562	592.15	839.25
532374.BO	Apr-07	Jun-07	STR OPTICAL	73.44%	182.05	188.8	207.95	240.55
532544.BO	Apr-07	Jun-07	INDIABULLS	73.22%	416.5	484.1	529.6	587.9
532287.BO	Apr-07	Jun-07	ENTEGRA LTD	70.26%	16.45	15.75	15.7	24.3
522205.BO	Apr-07	Jun-07	PRAJ INDUSTRIES L	64.46%	378.7	501.5	487.15	474.5
532123.BO	Apr-07	Jun-07	BSEL INFRAST	63.50%	65.55	76.05	69.65	69.85
526299.BO	Apr-07	Jun-07	MPHASIS BFL	63.31%	282.25	314	307.1	328.35
532298.BO	Apr-07	Jun-07	ZENITH INFOT	60.86%	274.4	290	356.45	497.8
532287.BO	May-07	Jul-07	ENTEGRA LTD	70.26%	15.75	15.7	24.3	27.45
532544.BO	Apr-08	Jun-08	INDIABULLS	111.13%	412.45	535.1	367.15	257.55
517562.BO	Apr-08	Jun-08	TRIGYN TECHN	64.66%	18.25	23	23.75	18.2
506910.BO	Apr-08	Jun-08	JAYSYN DYEST	62.83%	8	11.01	12	9.98
511243.BO	May-08	Jul-08	CHOL INV FN	76.11%	181.1	143	120.1	104.5
526299.BO	May-08	Jul-08	MPHASIS BFL	67.33%	230.2	237.8	214.9	209.65
511243.BO	Jun-08	Aug-08	CHOL INV FN	76.11%	143	116.5	99.75	103.95
532281.BO	Jul-08	Sep-08	HCL TECHNO	62.25%	502.1	520.2	579.65	550.15

Table 108: Impact Analysis for YOY Revenue Growth on Stock Growth

Companies	Revenue Growth	30 Days Return	60 Days Return	90 Days Return
Average Index ROI		4.36 %	2.21 %	0.22%
Average ROI from Belief	>60%	9.51 %	10.29 %	13.91 %
Correlation Coefficient	1.00	0.178	-0.20	-0.31

3. H4: Companies having good growth in YOY profit will give good return assumption

Table 109: Companies Scored excellent yearly profit growth (more than 125%)

ScriptID	Quarter From	Quarter To	SName	Y-Net Profit	Price at Quarter Start	Price Nxt30	Price Nxt60	Price Nxt90
505688.BO	Jan-06	Mar-06	BHARAT GEAR	196.55%	81.25	97.7	80.7	91.8
517562.BO	Apr-06	Jun-06	TRIGYN TECHN	3350.00%	9.57	12.3	17.38	13.6
532273.BO	Apr-06	Jun-06	CENTURION BK	3276.92%	26.55	24.15	26.05	20.4
521076.BO	Apr-06	Jun-06	AMIT SPIN ID	985.71%	9.04	9.41	9.68	10.42
511427.BO	Apr-06	Jun-06	ATN INTER	501.50%	2.9	3	3.02	3.02
521056.BO	Apr-06	Jun-06	CHESLIND TEX	200.00%	17.2	17.6	17	15.5
532307.BO	Apr-06	Jun-06	MELST INFTEC	139.52%	11.9	11.26	11.15	8.8
500027.BO	Apr-06	Jun-06	ATUL LTD.	138.51%	145.85	154.6	138.65	114.75
508136.BO	Jan-07	Mar-07	B & A SUGER	233.33%	42.45	42.55	37.3	32
500878.BO	Apr-07	Jun-07	CEAT LTD	211.93%	107.3	142.5	181.4	156.25
532324.BO	Apr-07	Jun-07	CINEVISTS LT	203.45%	20.35	24.55	50.95	53.5
517562.BO	Apr-07	Jun-07	TRIGYN TECHN	203.31%	25.6	29.9	30.7	27.75
531439.BO	Apr-07	Jun-07	GOLDSTON TEC	135.08%	65.7	65.6	79.25	90.9
500215.BO	Apr-07	Jun-07	AGRO TECH F	133.33%	76.35	86.6	125.6	121.65
521056.BO	Apr-08	Jun-08	CHESLIND TEX	447.59%	12.45	14.1	12	10.05
506590.BO	Apr-08	Jun-08	PHIL CAR BLK	172.81%	157.55	202.55	173.4	160
506109.BO	Apr-08	Jun-08	GENE INT COR	168.52%	35	65.65	107.6	94.75
500878.BO	Apr-08	Jun-08	CEAT LTD	137.00%	106.4	135.6	96.4	77.75
500271.BO	Apr-08	Jun-08	MAX INDIA L.	126.74%	147.2	158.25	177.25	154.8
506109.BO	Jul-08	Sep-08	GENE INT COR	168.52%	90.05	97.5	130.2	130.2

Table 110: Impact Analysis for YOY Profit Growth on Stock Growth

Companies	Y-Profit Growth	30 Days Return	60 Days Return	90 Days Return
Average Index ROI		6.88 %	2.28 %	-1.92 %
Average ROI from Belief	>125 %	15.33%	32.99%	22.99%
Correlation Coefficient	1.00	-0.10	0.016	-0.09

4. H5: Promoters have more stacks in companies will give good return

Table 111: Companies of major promoter holdings (more than 75%)

ScriptID	SName	Promoters Holding %
524230.BO	RASHTRIYA CHEMICA	93
532178.BO	ENGINEERS IN	91
532234.BO	NAT ALUM CO	88
526612.BO	BLUE DART EX	82
511716.BO	ESCORTS FINA	81
532525.BO	BANK MAHA	77
505885.BO	ALFA LAVAL	77
532525.BO	BANK MAHA	77
505885.BO	ALFA LAVAL	77
590024.BO	FERT CHEM	99
500134.BO	ESSAR OIL LTD.	89

Table 112: Impact Analysis for Promoter holding on Stock Growth

Companies	Promoter Stack	Avg. 30 Days Return	Avg. 60 Days Return	Avg. 90 Days Return
Average Index ROI	N.A.	6.88 %	2.28 %	-1.92 %
Average ROI from Belief	>85 %	6.03 %	6.4 %	8.37 %
Correlation Coefficient	1.00	0.075	0.654	0.480

7. H6: Companies has low price-reserve ratio will give good return

Table 113: Companies of lowest P/BV (Price to Book Value) ratio.

ScriptID	Month From	Month To	SName	Price at Month Start	Reserve	P-BV Ratio	Price Nxt30	Price Nxt60	Price Nxt90
500271.BO	Jan-06	Mar-06	MAX INDIA L.	600.1	1052.28	0.570285	729.8	769.3	886.25
500215.BO	Feb-06	Apr-06	AGRO TECH F	115.15	513	0.224464	129.3	142.15	153.45
532324.BO	Mar-06	May-06	CINEVISTS LT	29.5	57.6269	0.511914	24.9	25.1	20.65
500878.BO	Apr-06	Jun-06	CEAT LTD	65.75	872.7	0.075341	73.9	89.75	81
532392.BO	Aug-06	Oct-06	CREATIVE EYE	5.02	90.2	0.055654	8.03	7.22	7.07
531823.BO	Aug-06	Oct-06	ARVIN REMEDI	1.28	4.1167	0.310929	1.64	1.43	1.43
500650.BO	Aug-06	Oct-06	EXCEL INDUST	37.9	63.8357	0.593712	40.05	43	51.15
532507.BO	Dec-06	Feb-07	BAG FILMS	8.57	11.481	0.746451	8.92	18.19	27.95
509684.BO	Mar-07	May-07	INDIA FOILS	7.74	13.7185	0.564202	7.4	7.79	7.36
515035.BO	Mar-07	May-07	BELL CERAMIC	13.76	22.2973	0.617115	11.37	12.5	12.8
500186.BO	Apr-07	Jun-07	HIND.OIL EXP	68.8	130.0021	0.529222	94.8	115.6	113.5
500075.BO	Apr-07	Jun-07	NAGA FERT CH	13.55	14.5987	0.928165	16.97	22.1	22.95
506910.BO	Jun-07	Aug-07	JAYSYN DYEST	6	30.525	0.19656	6.48	6.95	9.64
514286.BO	Jul-07	Sep-07	ASHIMA LTD	7.69	9.584	0.802379	8.5	8.1	9
521014.BO	Apr-08	Jun-08	EUROTE IND E	21.1	48.3833	0.436101	25	26	20.55
500102.BO	Apr-08	Jun-08	BALLARPUR IN	27.1	39.2005	0.691318	30.2	34.8	33.55
532521.BO	Jul-08	Sep-08	FOUR SOFT	21.6	261.5433	0.082587	29.75	27.65	21
531936.BO	Jul-08	Sep-08	BLUE CHI IND	1.04	10.8825	0.095566	0.83	1.3	1.05
506355.BO	Jul-08	Sep-08	CHEMPLAST SA	6.62	28.9	0.229066	7.02	7.1	6.2
500060.BO	Jul-08	Sep-08	BIRLA ER OPT	12.72	43.5822	0.291862	15.52	14.65	12.57
532307.BO	Jul-08	Sep-08	MELST INFTEC	8	18.52	0.431965	8.64	8.7	11.9
532525.BO	Jul-08	Sep-08	BANK MAHA	20.25	21.9722	0.921619	21.2	27.05	31.15
526785.BO	Aug-08	Oct-08	CREST ANIM	46.9	100.3522	0.467354	47.85	32.45	22.45

Table 114: Impact Analysis for low P/BV ratio on Stock Growth

Companies	P/BV ratio	30 Days Return	60 Days Return	90 Days Return
Average Index ROI	N.A.	6.66 %	8.56 %	0.70 %
Average ROI from Belief	< 1	12.08 %	23.20 %	30.38 %
Correlation Coefficient	1.00	-0.231	0.252	0.316

So it is observed that fundamental have importance and most of the time stocks having good fundamental beats the benchmark return.

Technical Beliefs: Most of technical beliefs are based on moving average of price and volume analysis. It has observed that if price crosses its 30 past days moving average price with high volume, it may be positive trigger for stock.

The following table summarizes the impact of beliefs on stock return.

Table 115: Beliefs and its Impact Statistics Summary

	Belief	**30Days ROI**	**60Days ROI**	**90Days ROI**
H_0	Quarters revenue growth >200 %	7.16 %	16.19 %	13.08 %
H_1	Quarters Net Profit Growth>15 %	5.11%	4.47%	8.75%
H_2	OperatingProfit/Equity >15	11.05%	14.56%	11.64%
H_3	YOY Revenue Growth > 60%	9.51 %	10.29 %	13.91 %
H_4	YoY Profit Growth>125%	15.33%	32.99%	22.99%
H_5	Promoter Stack>85%	6.03 %	6.4 %	8.37 %
H_6	P/BV Ratio < 1	12.08 %	23.20 %	30.38 %

The analysis proves that most of the time fundamental beliefs reflected in the stock price growth and most of the time ROI based on belief beaten the benchmark index. The further observation shows that the dynamic factors like Price Vs Book Value ration has made highest impact on short term gain; it disproves efficient market theory and inspired to work further with non-linear modeling tools like neural networks in order to analyze and predicts market to get benefit on different investments categories.

5.6 Research Methodology Applied to Implement Knowledge Discovery Simulators:

Basically in our model two methodologies applied; one for capital market investment decision while second is for trend forecasting for ULIP and Asset Allocation of Mutual Fund.

5.6.1 Capital Market Simulator for higher return stock prediction:

The methodology used in order to discover the very selected stock having potential to return good return consists the following steps:

- Identify and filtering the prime beliefs affecting price growth
- Identify the stock trading signal, predict earning and perform time-window evaluation.
- Eliminate the stock unmatched with high growth patterns available during time-window evaluation.
- Forecast ROI for Stocks qualified in time-window evaluation, and Retain until technical beliefs indicate reversal of trend
- Analysis the actual earning of stock qualified in time-window evaluation.
- Periodically update the high growth patterns.

Step 1: Identify and filtering the prime beliefs affecting price grow:

We have analyzed all possible technical beliefs and fundamental beliefs using the Principal Component Analysis Method (PCA) for historical exceptional growth stock to achieve objectives of reducing the predicate component and ensure independent components.

Step 2: Identify the stock trading signal, predict earning and perform time-window evaluation:

It is interesting to know that most of stocks follows a transition pattern, and that can be triggered by rule based on technical beliefs. Identified stocks are evaluated for performance using feed forward back propagation neural network neural network.

Rules based on technical beliefs are acting as a trigger to analyze stock pattern for different activity like to analyze and add probable future high growth stocks in portfolio or remove the existing stock from portfolio.

Artificial Neural Networks pattern recognition capability makes it useful to forecast for future growth. We have used back propagation with momentum term to do prediction for stock return.

Once the stock is identified by the rules based on technical and fundamental beliefs, followed by neural network as a probable high return stock, we perform time-window evaluation and retain the stock in portfolio until the pattern is unmatched by time-window analysis or evaluation time finished.

The back propagation method discussed in the following section.

Learning Through Back Propagation:

Let M1 and M2 be these matrices of weights. Then what does M1[i][j] represent? It is the weight on the connection from the i^{th} input neuron to the j^{th} neuron in the hidden layer. Similarly, M2[i][j] denotes the weight on the connection from the i^{th} neuron in the hidden layer and the j^{th} output neuron.

Next, we will use x, y, z for the outputs of neurons in the input layer, hidden layer, and output layer, respectively, with a subscript attached to denote which neuron in a given layer we are referring to. Let P denote the desired output pattern, with p_i as the components. Let m be the number of input neurons, so that according to our notation, ($x1$, $x2$, …, xm) will denote the input pattern. If P has, say, r components, the output layer needs r neurons. Let the number of hidden layer neurons be n. Let β_h be the learning rate parameter for the hidden layer, and $\beta_{o'}$, that for the output layer. Let θ with the appropriate subscript represent the threshold value or bias for a hidden layer neuron, and τ with an appropriate subscript refer to the threshold value of an output neuron.

Let the errors in output at the output layer be denoted by e_js and those at the hidden layer by t_i's. If we use a Δ prefix of any parameter, then we are looking at the change in or adjustment to that parameter. Also, the threshold function we would use is the **sigmoid** function, $f(x) = 1 / (1 + \exp(-x))$.

Equations

Output of j^{th} hidden layer neuron:

$$y_j = f((\Sigma_i\ x_i M_1[\ i\ ][\ j\ ]\ ) + \theta j\ ) \qquad (1)$$

Output of j^{th} output layer neuron:

$$z_j = f((\Sigma_i\ y_i M_2[\ i\ ][\ j\ ]\ ) + \tau_j\ ) \qquad (2)$$

I^{th} component of vector of output differences:

desired value - computed value = $P_i - z_i$

I^{th} component of output error at the output layer:

$$e_i = (\ P_i - z_i) \qquad (3)$$

I^{th} component of output error at the hidden layer:

$$t_i = y_i\ (1 - y_i\ )\ (\Sigma j\ M_2[\ i\ ][\ j\ ]\ e_j) \qquad (4)$$

Adjustment for weight between i^{th} neuron in hidden layer and j^{th} output neuron:

$$\Delta M_2[\ i\ ][\ j\ ] = \beta_o\ y_i e_j \qquad (5)$$

Adjustment for weight between i^{th} input neuron and j^{th} neuron in hidden layer:

$$M_1[\ i\ ][\ j\ ] = \beta_h x_i t_j \qquad (6)$$

Adjustment to the threshold value or bias for the j^{th} output neuron:

$\Delta\ \theta_j = \beta_o\ e_j$

Adjustment to the threshold value or bias for the j^{th} hidden layer neuron:

$\delta\theta_j = \beta_h e_j$

For use of momentum parameter α, instead of equations 5 and 6, use:

$\Delta M_2[i][j] (t) = \beta_o y_i e_j + \alpha \Delta M_2[i][j] (t - 1)$ (7)

and

$\Delta M_1[i][j] (t) = \beta_h x_i t_j + \alpha \Delta M_1[i][j] (t - 1)$ (8)

Using the concept shown above the weight for different nodes are computed, when training is performed. One full presentation of all the vectors in the training set is termed an epoch. When the weights approach values such that the total network error, over a full epoch, falls below a pre-established threshold, the network is said to have converged.

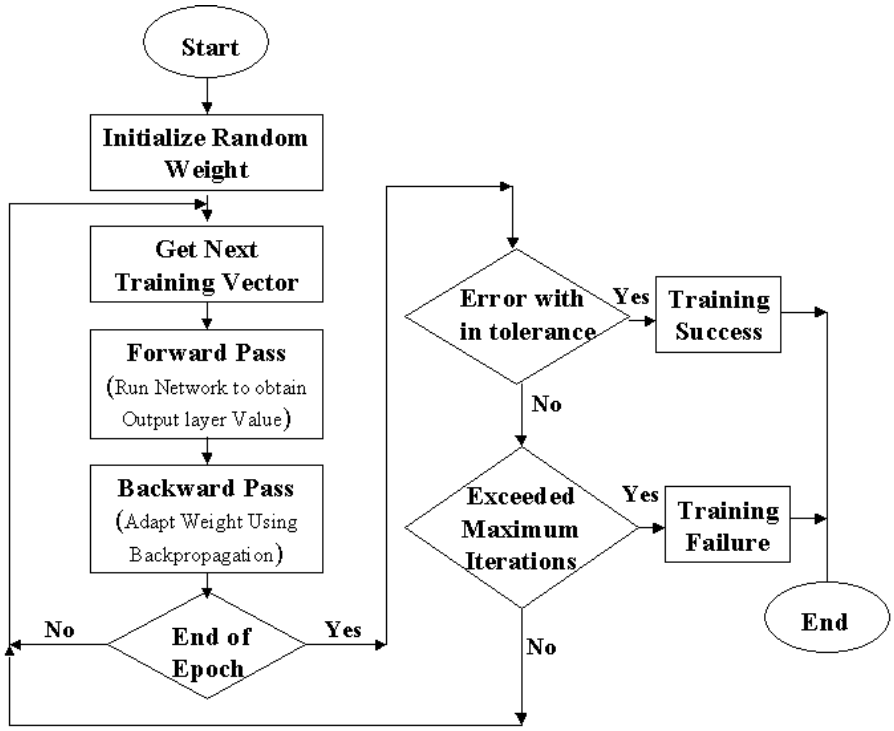

Figure 5.1: Flowchart for Backpropagation Training for Neural Network

If pattern not matched during the evaluation for three days in this period, it is recommended to exit at that point of time, and stock is no longer valid to give quarter trading return, the number of stocks qualified this test are very few and most probable to give exceptional return in future. All the stocks growth predicted by the Artificial Neural Network are classified in to the different categories by the use of fuzzy classifier. We have taken only the stock for which predicted growth rate is very high.

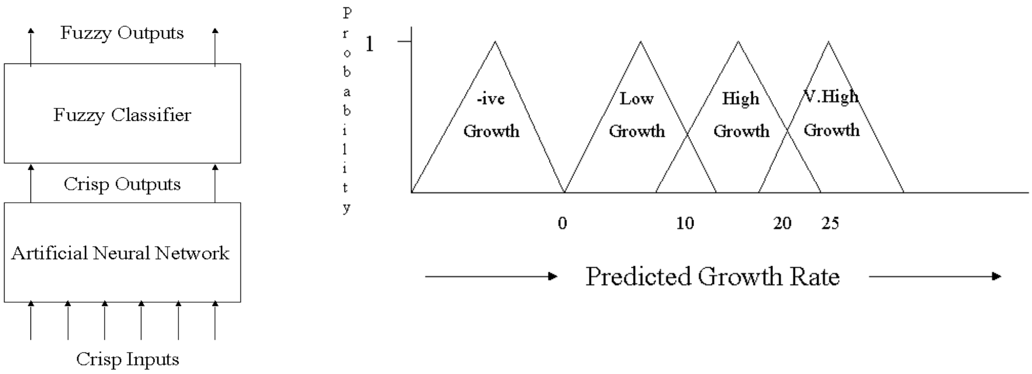

Figure 5.2: Growth Prediction from Artificial Neural Network & Fuzzy Classifier

Here is the table shown the result of simulation, which belongs to high growth stock by model.

Table 116: Companies triggered for high growth time-window test

ScriptId	Company	Prediction Date	Result Date	Price on Prediction Date	Last Yr Average Price
513023.BO	NAVBHAR FERO	27/02/06	31/12/05	48.5	53.42
532287.BO	ENTEGRA LTD	05/04/06	31/03/06	10.68	11.96
512296.BO	BHAGYANA ME	07/04/06	31/03/06	33.6	34.27
517206.BO	LUMAX INDUST	12/06/06	30/06/06	125.7	127.28
500106.BO	IFCI LTD	20/10/06	30/09/06	11.47	10.58
531439.BO	GOLDSTON TEC	21/11/06	30/09/06	23.7	22.29
500148.BO	FLEX INDUST	01/12/06	30/09/06	82.65	74.65
532507.BO	BAG FILMS	08/01/07	31/12/06	11.14	10.02
503169.BO	RUBY MILLS L	01/04/07	17/04/07	467.65	288.61
532324.BO	CINEVISTS LT	03/05/07	31/03/07	29.45	23.21
500019.BO	BANK OF RAJ.	07/05/07	31/03/07	46.8	40.16
532106.BO	REI AGRO LIM	08/08/07	30/06/07	222.3	141.67
524404.BO	MARKSANS PH	10/09/07	31/03/07	61.2	NULL
524226.BO	GUJ AMB EXPO	01/10/07	30/09/07	37.25	22.95
532290.BO	BLB LIMITED	23/10/07	30/09/07	21	13.19
500134.BO	ESSAR OIL LTD.	12/11/07	30/09/07	87.6	48.04
500083.BO	CENTURY EXT	12/11/07	30/09/07	5.34	3.12
506720.BO	ZANDU PHAR W	27/05/08	31/03/08	8043.5	3733

The past 10 days performances of probable very stocks are shown in the table generated by neural network model. As we have filtered probable high growth stock based on turnover triggered for stock rank. The pattern of 10 days turnover rank confirms the nonlinear growth pattern in volume.

Table 117: Past 10 Days Turnover Rank Movement of triggered companies for predicted high growth.

ScriptId	Past 10 Days Turnover Rank Movement									
513023.BO	188	250	362	327	268	402	442	471	481	487
532287.BO	478	615	627	625	612	623	617	630	624	628
512296.BO	184	433	447	565	563	547	557	472	528	528
517206.BO	244	308	285	490	485	591	507	586	545	479
500106.BO	32	149	153	117	261	241	244	234	268	214
531439.BO	241	468	506	564	610	592	601	569	543	561
500148.BO	163	253	557	565	332	560	508	554	524	535
532507.BO	182	490	508	409	445	456	536	540	517	455
503169.BO	295	338	371	501	464	436	478	499	387	437
532324.BO	268	584	584	593	608	476	464	483	446	565
500019.BO	47	140	176	167	229	258	271	170	190	216
532106.BO	95	72	112	129	154	154	146	128	328	323
524404.BO	59	446	467	423	319	196	381	423	374	336
524226.BO	239	355	413	373	451	418	515	459	495	559
532290.BO	525	598	575	563	563	568	557	582	643	642
500134.BO	9	20	40	19	91	94	156	126	93	169
500083.BO	349	541	565	604	595	597	599	598	589	596
506720.BO	100	229	318	528	528	562	399	535	498	479

Past 10 days price performance is considered to check the sustainability of stock in future pattern.

Statistically we can confirm that next 10 days price is higher than the price on which stock is recommended to purchase. In technical analysis term the same thing can be confirmed by moving average.

Table 118: Next 10 Days Price Of Triggered Companies.

ScriptId	Next 10 Days Price									
513023.BO	63.35	62.45	53.1	51.1	54.4	50.1	44.75	45.1	45	46.45
532287.BO	14.58	14.46	14.17	12.26	11.68	11.13	10.05	10.56	11.04	11.21
512296.BO	58.05	55.75	58.7	37.45	37.6	37.45	37.65	35.35	35.95	35
517206.BO	142.65	142.85	147.8	131.65	131.9	126.4	129.6	127.15	121.3	112.9
500106.BO	13.93	12.84	12.14	12.21	12.22	12.97	13.17	13.92	13.18	12.23
531439.BO	21.95	22.2	22.2	22.15	22.45	22.4	22.7	22.7	23.15	23.1
500148.BO	115.35	104.9	95.4	96.15	106.8	105.65	103.1	105.95	109.05	99.15
532507.BO	19.58	21.61	21.04	19.13	18.71	15.68	13.07	12.64	11.9	11.44
503169.BO	524.35	500.05	490	501.65	528	555.75	527.95	541.3	515.55	491
532324.BO	57.85	60.7	60.75	57.9	52.65	50.9	51.2	46.55	42.35	35.3
500019.BO	51.3	50.55	52.2	52.9	52.6	52.4	54	46.45	45.9	45.4
532106.BO	272.2	265.6	271.35	265.6	272.25	240.1	237.15	246.5	246.85	228.35
524404.BO	93.55	89.1	86.95	84.5	81.65	81.65	77.8	74.15	70.65	67.3
524226.BO	36.5	37	36.5	37	36.4	36.35	34	35	35	35.8
532290.BO	28.7	29.25	27.9	26.6	24.2	22	20	21.15	20.95	20.8
500134.BO	221.75	191.2	194.45	172.85	176.8	204.35	192.35	157.65	120.8	88.5
500083.BO	7.28	7.66	8.06	8.48	8.92	9.36	8.51	7.74	7.04	6.4
506720.BO	10324.7	10500	9817	9949.9	10344	10131	9455.7	9714.9	8127.2	7012

Step 3: Eliminate the stock unmatched with high growth patterns available during time-window evaluation:

Many scripts are triggered but during time-window evaluation they differ from the pattern stored and need to be remove.

Table 119: Past 10 Days Price of triggered companies

ScriptId	Past 10 Days Price									
513023.BO	48.5	45.7	44.2	43.8	44.1	42.6	42.65	43.6	43.6	44.2
532287.BO	10.68	9.8	9.34	8.9	8.48	8.2	7.85	7.98	8.22	8.01
512296.BO	33.6	30.15	30.35	28	27.85	28	27.6	27.45	27.55	27.5
517206.BO	125.7	118	110.05	115.5	119.45	118.7	117.95	124.75	127.25	133.95
500106.BO	11.47	10.04	10.13	10.07	9.73	9.62	9.72	9.52	9.63	9.75
531439.BO	23.7	21.4	20.8	20.5	20.4	20.4	20.6	20.5	20.3	20.3
500148.BO	82.65	68.9	60.5	60.4	60.3	59	59.4	61.95	61.2	59.2
532507.BO	11.14	9.38	9.35	9.26	9.15	8.92	8.61	8.62	8.66	8.56
503169.BO	467.65	445.4	424.2	404	406.5	411.1	391.55	383.45	384	395.6
532324.BO	29.45	24.55	24.95	25.45	25.8	26.15	25.65	25.2	23.2	23.05
500019.BO	46.8	42.9	42.1	42	40	39.95	40.1	40.55	39.9	38.9
532106.BO	222.30	210.5	202.65	198.2	196.2	201.8	203.25	198.9	205	203.7
524404.BO	61.2	49.35	49.2	49.45	48.35	49.5	47.25	46.95	47.2	46.75
524226.BO	37.25	34.55	33.05	32.5	31.85	31.75	31.1	31.45	31.25	30.75
532290.BO	21	20.15	20.4	20.7	20.7	19.75	19.6	19.9	19.05	19.1
500134.BO	87.6	66.3	61.3	64.7	57.05	56.25	53.55	56.65	56.4	53.85
500083.BO	5.34	3.85	4	3.96	3.95	3.98	4	4.06	4.07	4.15
506720.BO	8043.5	6851	6814.5	6851	6855.3	6858.4	6850	6860	6861.2	6850

Table 120: Example of Script failing in time-window evaluation

ScriptId	Company	Prediction Date	Result Date	Price on Prediction Date	Last Yr Average Price
523610.BO	ITI LTD	02/03/06	31/12/06	71.35	68.91

ScriptId	Past 10 Days Price									
523610.BO	71.35	69.3	70.55	71.05	70	68.75	70.3	70.1	69.65	70.05

ScriptId	Next 10 Days Price									
523610.BO	**68.1**	**68.5**	**69.95**	**70.5**	72.15	72.45	72.65	71.5	69.7	70.4

We have taken script triggered by technical belief, but eliminated just before the end of time-window evaluation.

Step 4: Forecast ROI for Stocks qualified in time-window evaluation, and Retain until technical beliefs indicate reversal of trend:

Predict 30days 60days and 90 days future price of the stocks qualified in test with the help of neural network, however If technical belief indicates strong reversal in trend we will remove the script from portfolio.

Table 121: Forecasted 30, 60, and 90 Days Prices by trained neural network for high growth pattern stocks.

ScriptId	Date	Price	Predicted Price after 30 days	Predicted Price After 60 days	Predicted Price After 90 days
513023.BO	27/02/06	48.5	70.45403	89.44181	128.6032
532287.BO	05/04/06	10.68	12.18476	16.88779	31.00718
512296.BO	07/04/06	33.6	59.80234	78.85107	77.40607
517206.BO	12/06/06	125.7	168.8366	218.1991	350.1246
500106.BO	20/10/06	11.47	20.55579	22.88635	33.34314
531439.BO	21/11/06	23.7	46.68879	33.24208	70.17653
500148.BO	01/12/06	82.65	138.3942	159.195	273.8381
532507.BO	08/01/07	11.14	24.56744	32.12203	37.72333
503169.BO	01/04/07	467.65	551.4488	592.7836	1102.275
532324.BO	03/05/07	29.45	51.55946	74.6625	77.95208
500019.BO	07/05/07	46.8	71.34695	73.17719	110.6785
532106.BO	08/08/07	222.3	385.1968	620.4445	893.0607
524404.BO	10/09/07	61.2	51.23827	52.94765	96.7497
524226.BO	01/10/07	37.25	100.6009	150.9378	206.672
532290.BO	23/10/07	21	28.6078	29.06246	65.07181
500134.BO	12/11/07	87.6	305.4029	349.1902	460.6124
500083.BO	12/11/07	5.34	10.69509	9.514001	19.58923

Step 5: Analysis the actual earning of stock qualified in time-window evaluation:

Table 122: Actual Earning of Qualified Stocks

ScriptId	Date	Price	Actual Price after 30 days	Actual Price After 60 days	Actual Price After 90 days
513023.BO	27/02/06	48.5	72.5	112.35	115.85
532287.BO	05/04/06	10.68	14.58	30.3	20.9
512296.BO	07/04/06	33.6	58.05	56.9	63.6
517206.BO	12/06/06	125.7	161.25	185.7	229.95
500106.BO	20/10/06	11.47	12.39	10.9	26.77
531439.BO	21/11/06	23.7	63.8	84.15	89.75
500148.BO	01/12/06	82.65	137.45	227.8	202
532507.BO	08/01/07	11.14	20.55	23.85	28.8
503169.BO	01/04/07	467.65	490	614.7	1006.45
532324.BO	03/05/07	29.45	51.1	56.15	58.25
500019.BO	07/05/07	46.8	61.1	70.55	104.6
532106.BO	08/08/07	222.3	372.35	547.45	800
524404.BO	10/09/07	61.2	40.05	71.75	90.45
524226.BO	01/10/07	37.25	113.65	140.1	171.5
532290.BO	23/10/07	21	31.75	54.15	64.5
500134.BO	12/11/07	87.6	309.5	301.75	209.25
500083.BO	12/11/07	5.34	10.99	13.25	8.32

Step 6: Periodically update the high growth patterns:

In order to add new pattern, time to time all stocks performance is analyzed and the new high growth patterns are added.

5.6.2 Trend Prediction Simulator is also based on feed forward neural network model; the difference in both the model exists in its application. To forecast the future trend of market of market is predicted by giving different parameters like crude price, inflation index, GDP rate, open, high, close value of index, Index value at regular interval to calculate volatility, Market breath (Ratio of Number of stock advances Vs Number of stock declines), and moving average parameters. The output node parameter is binary number can have two value one for positive trend and another is for negative trend. Large set of all input parameters along with the trend behaved by index or ULIP fund NAV is required to first train neural network. The sample we have taken initially is sufficient to learn and handling the issues of network like memorization or over fitting.

5.7 Result Analyses and Discussion:

<u>5.7.1 Stock Market Recommendations For High Growth Stocks</u>:

The simulated model has tested for three years of more than 600 stocks data. The total sample is taken 6200 for high return on investment, and 80% from them is used and training set, while rest 20% is used as a testing set. 150 qualified stocks in time window evaluation. We have predicted 30 days, 60 days, and 90 days gain in percentage.

Input nodes are 17, included 10 days price change (%), promoter holding (%), Ratio of Reserves Vs Net profit, Ratio of Operating Profit Vs Equity, Quarter revenue growth (%), YOY revenue growth (%), Quarter net profit growth (%), YOY net profit growth (%). Nodes in hidden layer are taken 8. Adaptive gradient is taken as learning rule, Output layer function is taken sigmoid, and evaluation function is correlation, Torrance is chosen 0.001.

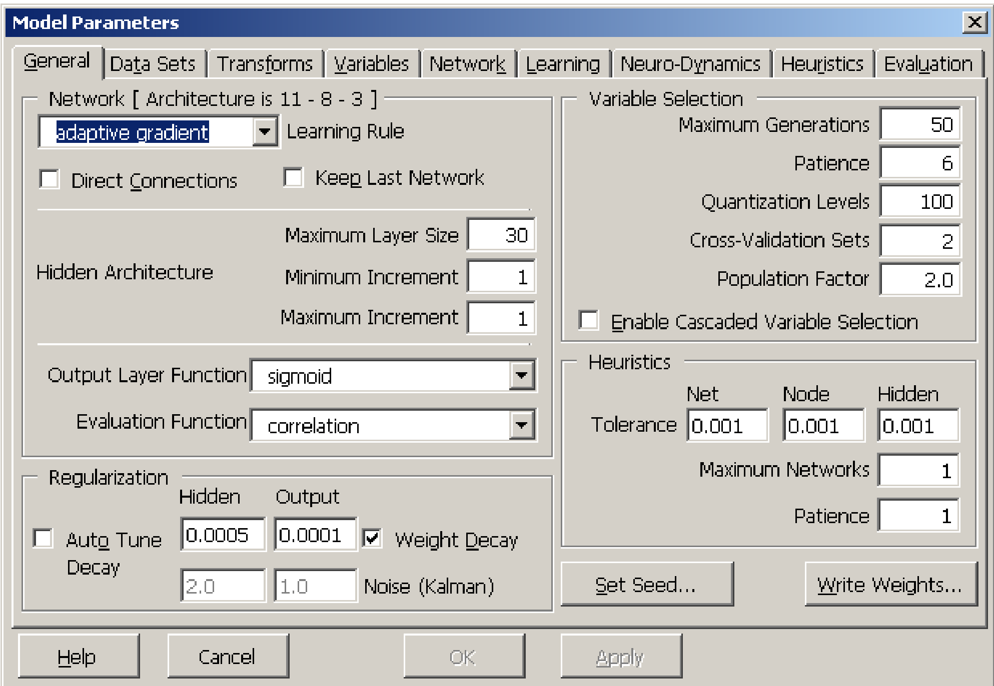

Figure 5.3: Model Parameters During Training-I

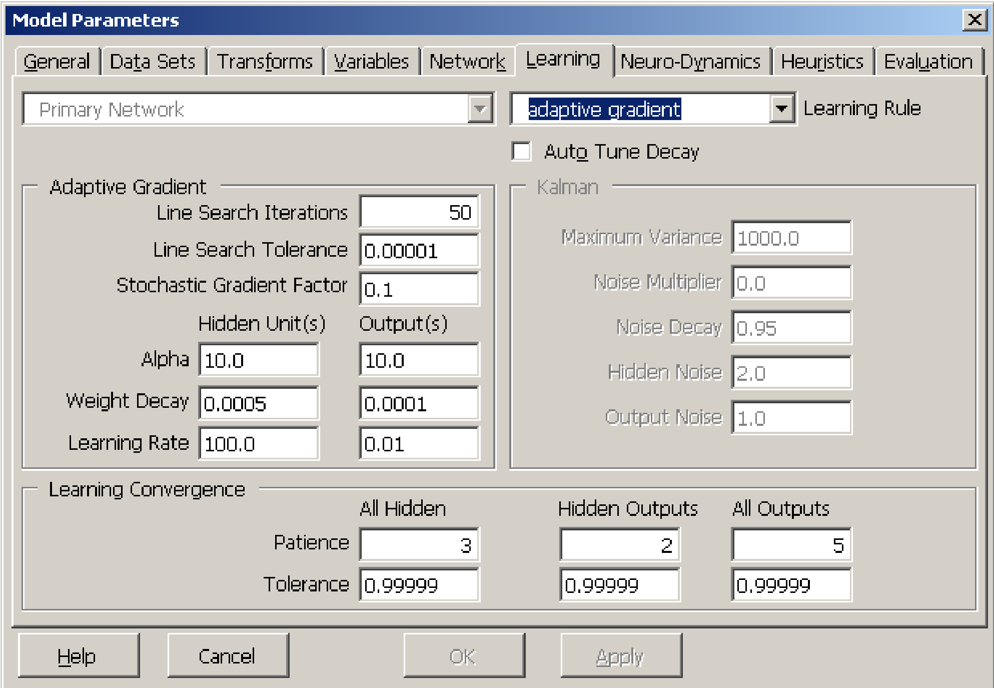

Figure 5.4: Model Parameters During Training-II

The result of 150 predicted high growth stocks has evaluated by T-Test using SPSS software, the generated the statistics as shown below: (Result of T-Test)

Table 123: Paired Samples Statistics Result of T-Test I

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	ACT30	.5344	150	.5449	4.449E-02
	ESTIM30	.5021	150	.4838	3.950E-02
Pair 2	ACT60	.9353	150	.7035	5.744E-02
	ESTIM60	.8581	150	.6516	5.320E-02
Pair 3	ACT90	1.7196	150	.8198	6.693E-02
	ESTIM90	1.5435	150	.8505	6.944E-02

Table 124: Paired Samples Correlations Result of T-Test II

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	ACT30 & ESTIM30	150	.841	.000
Pair 2	ACT60 & ESTIM60	150	.858	.000
Pair 3	ACT90 & ESTIM90	150	.837	.000

Table 125: Paired Samples Test: Result of T-Test III

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	80% Confidence Interval of the Difference Lower	Upper			
Pair 1	ACT30 - ESTIM30	3.225E-02	.2963	2.420E-02	1.103E-03	6.340E-02	1.333	149	.185
Pair 2	ACT60 - ESTIM60	7.722E-02	.3647	2.978E-02	3.889E-02	.1156	2.593	149	.010
Pair 3	ACT90 - ESTIM90	.1761	.4779	3.902E-02	.1259	.2263	4.513	149	.000

The statistics proves that result is significant for 90 days. The performance of model recommended scripts at a glance.

Table 126: Average Performance of Stocks Qualified in Simulation

Companies	Growth	30 Days Return	60 Days Return	90 Days Return
Index		3.08 %	5.08 %	11.96%
Model Recommendations	Average	21 %	47 %	74 %

One interesting findings with the same repetition of work, except we have included one more parameter Price of Stock for the estimation of 30 days, 60 days, and 90 days gain in percentage. The generated the statistics as shown below:

Table 127: Paired Samples Statistics Result of T-Test I with Price Model

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	ACT30	.5344	150	.5449	4.449E-02
	ESTP30	.5096	150	.4841	3.953E-02
Pair 2	ACT60	.9353	150	.7035	5.744E-02
	ESTP60	.8908	150	.6419	5.241E-02
Pair 3	ACT90	1.7196	150	.8198	6.693E-02
	ESTP90	1.6401	150	.7715	6.299E-02

Table 128: Paired Samples Correlations Result of T-Test II with Price Model

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	ACT30 & ESTP30	150	.846	.000
Pair 2	ACT60 & ESTP60	150	.876	.000
Pair 3	ACT90 & ESTP90	150	.863	.000

Table 129: Paired Samples Test: Result of T-Test III with Price Model

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper			
Pair 1	ACT30 - ESTP30	2.473E-02	.2911	2.377E-02	-2.22E-02	7.170E-02	1.040	149	.300
Pair 2	ACT60 - ESTP60	4.450E-02	.3402	2.778E-02	-1.04E-02	9.939E-02	1.602	149	.111
Pair 3	ACT90 - ESTP90	7.957E-02	.4190	3.421E-02	1.196E-02	.1472	2.326	149	.021

5.7.1.1 Findings from Result Analysis for Predicted High Growth Stocks:

- The improved values of correlation and Std. Deviation indicate that stock price has also impacts on the ROI, as stock price has sentimental effect on market participants.
- We can observe from the result that the model is most significant for long duration as the fluctuations of short term price can be absorb with long time.
- Another observation tell us that when we consider price as a one parameter for predictions, the pair wise co-relation as well as standard deviation improve, but overall significance of test reduces.
- The most important confirmation from finding is that Efficient Market Hypothesis is not verified; hence intelligent model can produce higher profit.

5.7.2 IIAM-ULIP Results:

The result of our model is also very exciting, as model not only beaten index return but also given very high return compared to index as well as buy and hold modes of ULIP.

Table 130: Report on Value Appreciation as per IIAM-ULIP Recommendations

Report on Value Appreciations as per IIAM Recommendations

Product: ICICI Prudential Life Link Super — **Tenure: 10-Apr-2006 to 16-Oct-2007**

Date(DD/MM/YY)	Life Preserver III	Life Protector III	Life Balancer III	Life Maximiser III	IIAM Recommendations	Value in INR	Unit-Maximiser	Unit-Preserver
10/Apr/06	10.0301	9.9972	10.28	10.73	Maximiser	100000	9319.664492	0
12/May/06	10.0921	10.0355	10.4	11.09	Preserver	103355.0792	0	10241.18659
16/Jun/06	10.1189	10.0745	9.5	8.78	Maximiser	103629.543	11802.90923	0
10/Jul/06	10.1811	10.1416	9.84	9.47	Preserver	111773.5504	0	10978.53379
25/Jul/06	10.207	10.1705	9.72	9.08	Maximiser	112057.8944	12341.1778	0
11/Dec/06	10.477	10.4681	10.84	11.44	Preserver	141183.074	0	13475.52487
15/Dec/06	10.4846	10.4543	10.89	11.59	Maximiser	141285.488	12190.29232	0
19/Dec/06	10.494	10.4641	10.8	11.32	Preserver	137994.1091	0	13149.81028
26/Dec/06	10.5071	10.468	10.89	11.61	Maximiser	138166.3716	11900.63493	0
12/Feb/07	10.6092	10.5026	11.02	11.93	Preserver	141974.5748	0	13382.21306
19/Feb/07	10.6239	10.4897	11.07	12.1	Maximiser	142171.2933	11749.69366	0
21/Feb/07	10.628	10.4953	11.02	11.93	Preserver	140146.1483	0	13189.10852
12/Mar/07	10.6678	10.5152	10.6	10.82	Maximiser	140698.7719	13003.58335	0
15/Mar/07	10.6747	10.5121	10.53	10.64	Preserver	138358.1269	0	12961.31291
21/Mar/07	10.6895	10.5243	10.66	10.95	Maximiser	138549.9543	12652.96387	0
07/Jun/07	10.8884	10.7256	11.25	12.02	Preserver	152088.6257	0	13967.9499
15/Jun/07	10.909	10.738	11.27	12.06	Maximiser	152376.3654	12634.85617	0
06/Aug/07	11.0693	10.9824	11.8	13	Preserver	164253.1302	0	14838.61945
27/Aug/07	11.1241	10.9851	11.78	12.96	Maximiser	165066.2866	12736.59619	0
16/Oct/07	11.255	11.1327	12.97	16.18	Maximiser	206078.1263	12736.59619	0

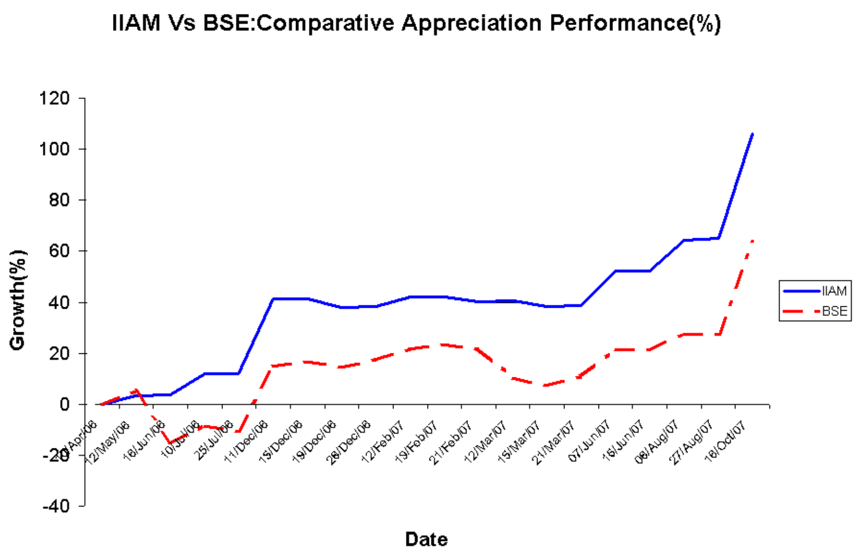

Figure 5.5: Comparative Appreciation Performance IIAM-ULIP Vs BSE

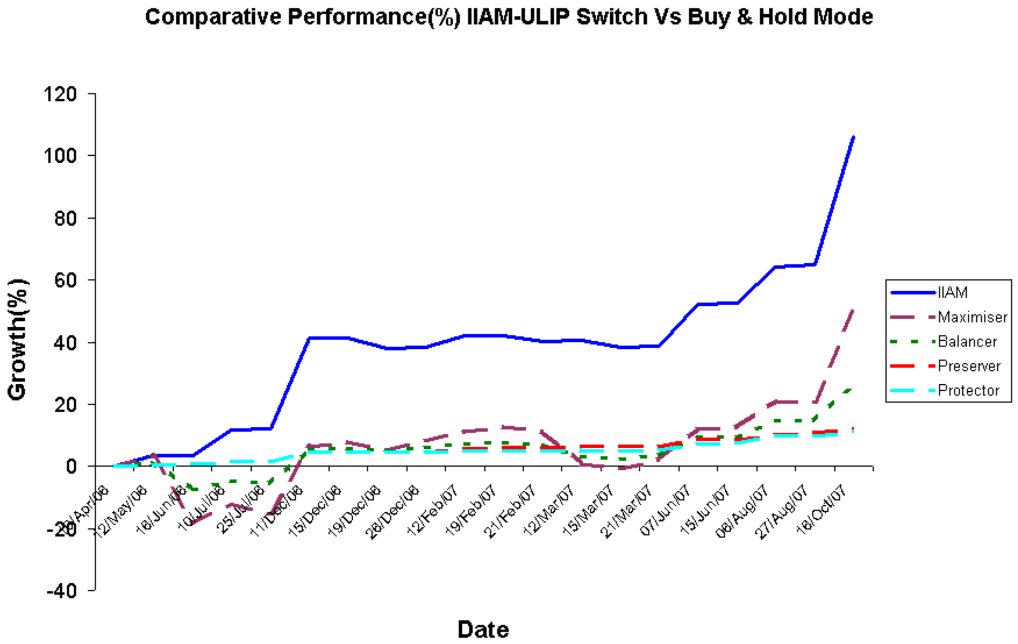

Figure 5.6: Comparative Appreciation Performance IIAM-ULIP Vs Buy & Hold Modes

As compare to default buy and hold mode or Market Index appreciation the performance of model is superior.

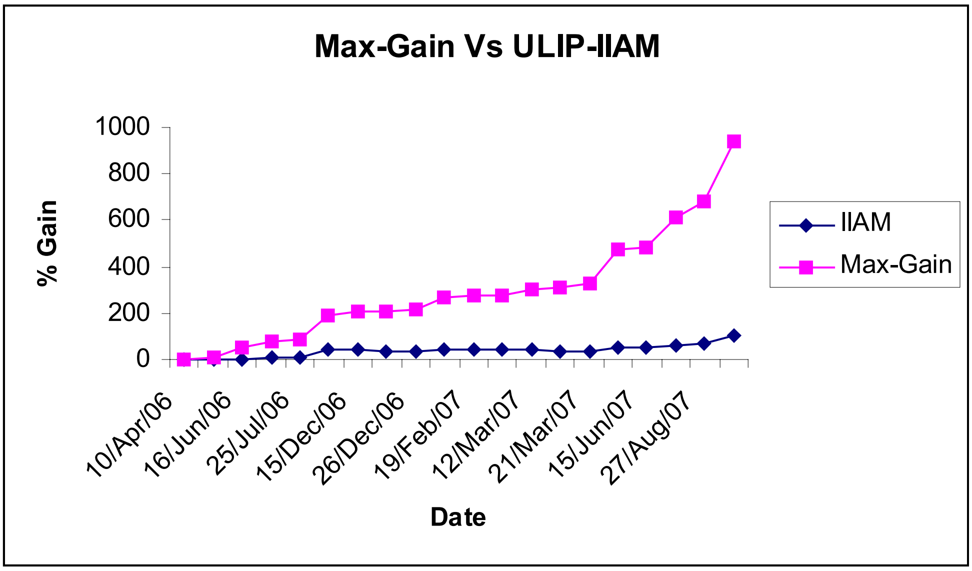

Figure 5.7: Comparative Appreciation Performance Max-Gain Switch Vs IIAM-ULIP

When we compare it with ideal maximum gain of model, it shows huge scope for improvement is possible.

5.7.3 IIAM-Mutual Fund Asset Allocation Model Results:

Using Model Asset allocation we have checked the performance for long-term real data and it has proven usefulness. This period contains almost all type of cycles of capital market e.g. Bullish Trend, Bearish Trend, Volatility etc. The prepared model has proven its usefulness by maximize the profit as it picks maximum financial market opportunity in bullish trend and tolerate risk of financial market by ensuring fixed return based on Debt, money market in bearish trend. Model has performed technical analysis which make decision successfully most of the time hence disproves the efficient market hypothesis. The superiority of model can be verified from the benchmark return for experimental duration.

Table 131: IIAM-Mutual Fund Performances at Regular Interval

Fund Performance Comparison at 6 Month Interval							
Sr. No	Period	Index-Start	Index-End	Index Gain	NAV-Start	NAV-End	Gain(%)
1	July-Dec 2006	10695.26	13786.91	28.91	10.00	12.54	26.95
2	Jan-June 2007	13786.91	14650.51	6.26	12.54	14.40	12.31
3	July-Dec 2007	14650.51	20286.99	38.47	14.40	20.47	40.76
4	Jan-June 2008	20286.99	13461.6	-33.64	20.47	16.70	-19.80
5	July-Oct 2008	13461.6	8509	-36.79	16.70	16.89	-0.62
	Total	**10695.26**	**8509**	**-20.44**	**10.00**	**16.89**	**68.93**

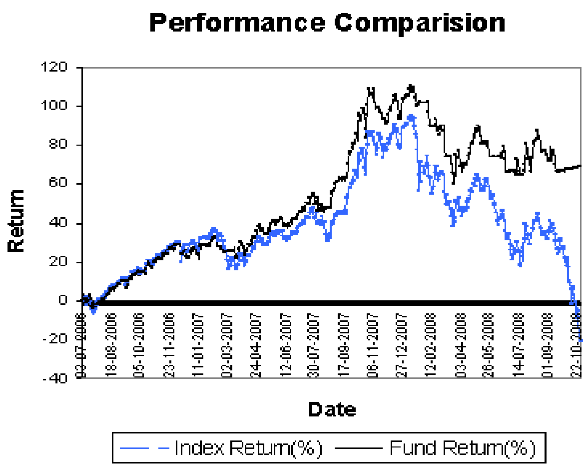

Figure 5.8: Comparative Performance IIAM-Mutual Fund Vs BSE

5.8 Scope of Research:

The work performed is confined to utilization of multi agent system in area of business intelligence is limited to the few aspect of personal finance management only. The research findings are tested with the dataset limited to Indian context. The complete work carried out can be divided in to two major financial model classification, First one is forecasting model based on Non-deterministic simulation, where model generate recommendations using business intelligence for three asset categories ULIP, Mutual Funds and Common Stocks, and Second is optimization financial model, where rest of work contributed for accounting and managing details of personal portfolio. The result of common stock value prediction is limited maximum up to 90 days from the date of prediction subject to growth sustainability. The key consideration for model is expert system incorporated with feed forward backpropagation neural network. But the qualitative parameters have not played any role in model. In ULIP and Mutual Fund Asset Allocation model the key decision parameter is prediction of overall market trend in future and its influence on portfolio. The ROI by model recommendations are compared with benchmark index or the independent beliefs affecting stocks return, Any evolutionary technique like Genetic programming or other neural network model like Generalize Neural Network or Granular Neural Network are not tested or compared with the results obtained by the model. The purpose of model is to generate maximize ROI in different class of asset categories using artificial intelligence.

5.9 Some Issues and Suggestion:

Issues:

- Public Participation: It has observed that the knowledge of finance management is not well disseminated in common people and because of it there is only 5-10% contribution of Indian public in equity market or its derivatives.
- Participants Attitude: Most of the people are speculator rather than investor, as a result most of common public are losing their money.
- Profit Floods To Abroad: As we have excellent Gross Domestic Product (GDP) growth as compare to other countries, most of the benefit of finance market growth floods to abroad as foreign investors directed the market for long time.
- Data Related Issues: Interpretation Data are difficult because of inconsistency in term of formats. Just by looking result values it is very difficult to find debt owned by company.
- Lack of Financial Literacy: The purpose of life insurance in common public is to save tax, not to provide proper protection to dependents. Most of ULIP investors are unaware about premium allocation charges, policy admin charges, and even power of switching. The investor advisors are not honest to their Job.

Suggestion:

In short it is suggested, efforts are required to create finance awareness in public. Every one should have basic understanding and knowledge of finance products and its management. Financial literacy should be included in basic education objective to promote financial planning and put restriction on speculation activities. Every one must have their portfolio diversified in nature but focused towards growth of Networth with enough protection/provision for their dependents.

5.10 Significance of Research:

The work performed during the research motivated me to help people in their finance planning and management towards growth in prospers. The work is unique in nature as in modeling part incorporate personal finance, econometric, agent oriented modeling and business intelligence in a single platform, also efforts are placed to develop and test various modules of model to perform finance management. This research work has provided an insight into finance management especially portfolio management. The work explained in the thesis must be helpful for the researchers; especially literature survey is effort to provide roadmap to develop a simulation model in the area of finance. Also understanding of time series data modeling can be useful in development of other applications. The research work carried out disproves the efficient market hypothesis.

5.11 Limitation of Study and Future Scope:

Full care has been taken to ensure that the research is designed and conducted to optimize the ability to achieve the research objectives.

This is really a thrilling area, in which lot of potential for future work is possible. There is huge scope of experiment and extension in the existing work. However there are some constraints that do not invalidate the research, but should be acknowledged.

The work is focused in one country only, and limited to few class of assets. It would be useful to extend the number of countries covered, and test the model at global level.

Given the vast data covered for the purpose of primary research coupled with time constraints. Use of latest presentation techniques of business intelligence can enhance the user interface.

It may also be worthwhile to add more parameter variables in addition to the ones used in this work.

Further the research can be undertaken to evaluate time-based performance of the model using different system architecture like parallel computers and distributed systems for fine tune distributed co-operative multi agent business intelligence model.

More dynamic rules can be derived from analyzing historical data and applied for initial filtering.

Manual intervention of News analysis can be eliminate by developing intelligence through textual analysis/text mining in news and analyzing historical data pattern.

Intelligent systems to automate qualitative parameters for company can be develop.

The data patterns available there are evidence of seasonality, volatility and correlation among the data. Further improvement in model can be carried out by hybridizing the econometric models like VAR (Vector Autoregressive), GARCH (Generalized Autoregressive Conditionally Heteroscedastic) GJR (Glosten, Jagannathan, and Runkle).

Experiments and analysis can be performed with existing set of data to evaluate sector base performance, Equity capital base performance or segregating the patterns on such criteria, and analyze the growth performance.

Annexure
Related Published work

A Comparative Analysis of Programming Methodologies towards Agent Oriented Programming

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Abstract

Programming Methodologies evaluation is fulfillment of requirement of software with time, technology, both user and programmer friendly, reusability and supports higher granularity in software development process. The evaluation and invention of the programming methodologies and modeling techniques for handling application and it's environment issues like heterogeneity, heave interaction, complexity, Distribution ability, openness, dynamics and unpredictability. In the journey of evolution we passes through Machine and assembly language Programming, Procedural Programming, Structured Programming, Object-Based Programming, Component Oriented Programming and Agent Oriented Programming, Where in the development the level of abstraction is increased, development complexities are decreases, also Reusability of already existing autonomous component increases.

Agents as a new software engineering paradigm, including specification and verification of agent systems, interaction based programming, and agent mobility. The emergence of Agent Oriented Programming is one of the most exciting and important events to occur in computer science. Agent orientation software paradigm has characteristics such as autonomy, sociality, reactivity and pro-

activity, and communicative and cooperative abilities are expected to offer greater functionality and higher quality, as comparison to earlier paradigms. It is widely believed that this technology will play a central role in the development of complex distributed systems, networked information systems, and computer interfaces during the twenty-first century. Still it is not supported directly by most of higher level languages and there are a number of fascinating and largely unexplored open research directions in development of efficient agent platforms.

Introduction:

The requirement of any software starts form Analysis and follows design, development, testing, and deployment.

Introduction to Programming Methodologies:

1950's Monolithic Programming: Machine and assembly language

1960's Procedural programming

1970's Structured programming

1980's Object-Based programming, Declarative programming

1990's Frameworks, design patterns, scenarios, and protocols (Component Oriented Programming)

2000's Agent Oriented Programming.

The initial phase of programming is based on Top-Down programming, It was just the way to write the instruction based on machine architecture to do programming. It was very difficult to write large, complex program, trace the errors and reuse the code using **Monolithic Programming**.

Then the concept of reusability introduces by the Procedural Programming where programmer can reuse the build in support routine or own routine created, It was limited to the reusability of code only. The Emphasis of a program is on how to accomplish a task.

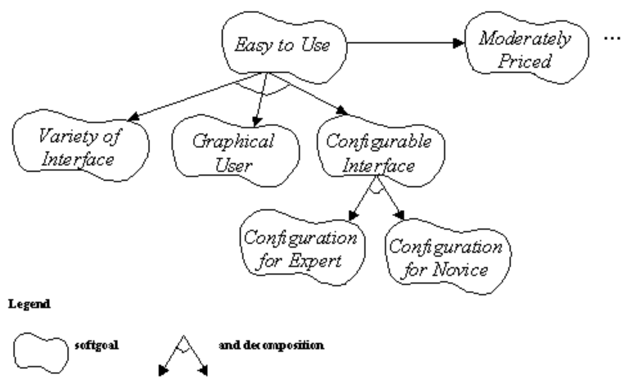
In **Structured Programming** user has given the control over the flow of program execution along with code reusability.

Object-Oriented Programming Emphasis of a program is on the objects included in the interface and the events that occur on those objects and User has a lot of control. Object-oriented approaches began with the invention of object-oriented programming languages. Most of the key concepts of object-oriented programming include objects and classes, subclasses (inheritance), virtual procedures. As the benefits of object-oriented programming began to gain recognition object design approaches are developed and adopted. OOAD approaches have been available/in use for over 15 years.

During that time, software systems have continued to increase in complexity, heterogeneous, distributed, autonomous control, stakeholders involved throughout, web based, systems that need to change and it observed that object-oriented approaches don't take care of all the problems efficiently. Component and Agent-oriented approaches are being proposed to solve some problems.

Component Oriented Programming enhances the object orientation and introduces the concept of a *single unit of deployment*

Goal-oriented approaches begin the software development process by capturing the stakeholders' goals and subsequently refine them into requirements



Goal-Oriented Approaches

Agent Oriented Programming Paradigm has characteristics such as autonomy, sociality, reactivity and pro-activity, and communicative and cooperative abilities are expected to offer greater functionality and higher quality

Agent Definition: *Agent can be defined to be autonomous, problem solving computational entities capable of effective operation in dynamic and open environments.*
Agents are autonomous in the sense that they perform their tasks regardless of whether they are required or not. Intelligent agents are computational systems that inhabit in a complex dynamic environment and they can act autonomously and have the capacity to reason by themselves in this environment. This environment can be the network, and the intelligent agent can be seen as a software entity that assist people and gathers information or perform some other services without the immediate presence of a human being. An intelligent agent could be characterized by the following attributes: **Autonomy, Reactivity, Pro-Activity And Social Ability**.
Software agents are persistent computations that include percepts, reasoning, action, and communication [Russell & Norvig, 1995]
Micro-level aspects of multi-agent systems, including agent architectures, agent representation formalisms and notations, agent development methodologies, practical reasoning, decision theory and agency, software agents and expert assistants, human-agent interaction, agent learning and adaptivity, and believable/synthetic agents.
Macro-level aspects of multi-agent systems, including cooperation, coordination, conflict detection and resolution, negotiation, organizational structuring and design for multi-agent systems, computational market systems, self-organization, emergent

functionality and swarm intelligence, multi-agent learning, languages for cooperation and coordination, agent communication languages, and issues of overall performance of multi-agent systems.

An Agent Attributes:

Autonomy: This attribute is one of the most important characteristics that allow us to distinguish the intelligent agents from other type of software. When we say that an agent must have autonomy, we are talking about the capacity of reacting by themselves in an environment using their experience. This means; the capacity of observation and operation without the direct intervention of human beings or other agent.

Reactivity: Is the capacity that the agents have to perceive their environment and act depending of the changes that occur in it, in a correct and fast way. Internet can also be one environment where intelligent agents can interact.

Pro-activity: As we had seen before, the agents can react to an environment, but they also have the ability of obtain a goal by taking the initiative. They have a goal-directed behavior without external influences (they are self-sufficient).

Social ability: Sometimes more than one agent is needed to make a task or solve some problems. The social ability is the capacity that one agent have to interact with other agents (or humans), by using some "agent language", for the possibility to cooperate or negotiate.

Additional Agent attribute for Distributed Multi Agent Systems:

Embedded: The agent respects the real time of their environment and act depending on this one.

Distributed: Many different kind of agents can work together in the same system and each one of them can be added or removed without interrupting it. In the environment agent interact, and maybe co-operate with other agents. Agents may have conflicting aims, such a system is known as a multi-agent system.

Agent architecture is the fundamental engines such an autonomous components that support effective behavior in real-world, dynamic and open environments.
In implementing multi-agent system where agents respond in a rational way to their goals and events that occur in their environment. These agents have a specific set of conditions and associated goals, which indicate the events they should respond to. This architecture stresses the problem of heterogeneous information and knowledge sources.

Agents vs. Objects: Agents are regarded as a possible successor of objects since they can improve the abstractions of ***active*** entities objects are successfully used as abstractions for ***passive*** entities in the real world
Objects are controlled from the outside; agents that have autonomous behavior, which can't be directly controllable from the outside, agents can say ``no'' to a request.
In a Multi–agent system agents interact in order to meet their goals in community. Interaction includes: Cooperation, Competition, and Negotiation.
Two types of modeling used in agent systems:
MAS modeling: Multi-Agent System modeling
ABS modeling: Agent Base System modeling
Agent system applications are mostly in problems dealing with distributed and concurrent systems like Electronic commerce and electronic markets, Real time monitoring and management of telecommunication networks, Information handling in information environments like the Internet, Improving the flow of transport traffic, Optimization of industrial manufacturing and production processes etc.

AGENT PROGRMMING VS OTHER PROGRAMMING PARADIGMS:

Agent Oriented Programming Vs Object Oriented Programming:

Both object- and the agent- oriented emphasize the importance of interactions between entities.

Objects are generally passive in nature while agents are active and they need to be sent a message before they come alive.

Objects encapsulate state and behavior while agents encapsulate behavior activation (action choice) too.

Agent oriented software are higher level of granularity and abstraction as compared to object oriented, so they are more suitable for complex applications.

Basic Unit	**Object**	**Agent**
Parameters defining state of basic unit	Unconstrained	Beliefs Commitments Choices
Process of computation	Message Passing And Response Methods	Message Passing And Response Methods
Types of messages	Unconstrained Inform Request Offer	Promise Decline
Constraints on methods	None	Honesty Consistency

Agent Oriented Programming Vs Component Oriented Programming:

Agents also share with components the concept of a *single unit of deployment.*

Agents are more autonomous than the components also Components do not have corresponding notion of reactive, proactive, or social behavior as in agent.

Finally it seems that agent oriented software paradigm are more developer friendly and able to handle higher complexity as compare to any other programming paradigm.

Comparative Analysis of Methodologies

Concept	**Procedural Languages**	**Object Oriented Languages**	**Agent Oriented Languages.**
Abstraction	Type	Class	Society
Building block	Data	Object	Agent
Computational	Procedure	Method	Perceive
Model	Call	Message	Reason/Act
Design Paradigm	Tree Of Procedures	Interaction Patterns	Cooperative Interaction
Architecture	Functional Decompose	Inheritance Polymorph	Managers Assistants Peers
Modes of Behavior	Coding	Designing And Using	Enabling And Enacting
Terminology	Implement	Engineer	Activate

Methodology	Programming Language	Analysis	Design
Monolithic	Machine Languages Assembly Language	Textual, Algorithms	Flowcharts, Algorithms
Structure	COBOL, C, Pascal etc.	Data Flow Diagram, HIPO Charts	Data Structure Diagram and Structural Charts
Object Oriented	C++, Java etc.	UML: Use Case and Collaboration diagrams	UML: Class Diagram and it's relation, State Machine
Component Oriented	(D)COM, CORBA	UML: Use Case and Collaboration diagrams	UML: Class Diagram and it's relation, State Machine
Agent Oriented	Agent Platforms	Under Construction	Under Construction

Present Status of Agent Oriented Programming:

Agent platform

Agent platform is a software environment that provides recourses and functionality for software agents to operate. Some of these recourses and functionality are:

• Sophisticated communication infrastructures (e.g. in JADE, FIPA-OS),

• Support for agent mobility (e.g. in ADK, Voyager).

• Reasoning engine (e.g. in Jack, ABLE)

Agent Methodologies: Idea and Comparison
Agent-Oriented Software Engineering (AOSE) methodologies

1. **Tropos**
2. **Gaia**
3. **MaSE**
4. **A framework to Extending UML**
5. **Object-oriented framework for agent**

Here, we compare these methodologies based on framework establishment

Comparison framework establishment is used to evaluate criteria concerning building blocks of both from formal software engineering process and agent-oriented characteristics Framework adopted from four major divisions like

1. Concepts and Properties
2. Notations and Modeling Technique
3. Software Engineering Process
4. Pragmatics

1. Concepts and properties

Agent-oriented

The design of the methodology originated from the consideration of agent-oriented ways

Agent abstraction

The methodology has theory to describe agents using high level abstractions.

Collaboration

An agent has ways to cooperate with other agents to achieve goals.

Communication

There are protocols or mechanisms defined for agent interactions.

Concurrency

An agent may need to perform multi tasks at the same time.

Adaptation

An agent is flexible enough to adjust its activities according to dynamic environmental changes.

Mental mechanism

An agent has mechanisms to realize its intentions by achieving goals.

Autonomy

An agent could make decisions by its own based on inner states without external supervision.

Autonomy	An agent could make decision by its own based on inner state without supervision.
Mental Mechanism	An agent has mechanism t realize its intensions by achieving goals.
Adaptation	An agent is flexible enough to adjust its activities according to dynamic environmental changes.
Concurrency	An agent may need to perform multiple tasks at the same time.
Communication	There are protocol or mechanism defined for agent interaction.
Collaboration	An agent has ways to cooperate other agents to achieve goals.
Agent Abstraction	A methodology has theory to describe agents using high-level abstractions.
Agent Oriented	A design of methodology oriented from the consideration of agent oriented ways.

2. Notations and Modeling Technique

Traceability

With in the methodology, it is able to track dependencies between models.

Refinement

Modeling technique can refine factors into simpler entities in order to take advantage of them.

Executable

Models used in a methodology are capable of simulation or generating prototypes in some aspects of the specification.

Modularity

Using components or modules in the methodology so as to model a system in an incremental manner.

Complexity Management

There are abstraction levels from high to low in order to tackle a complex problem into modeling.

Expressiveness

Notations are used in the methodology to help design process.

	Tropos	**Gaia**	**MaSE**	**Extending UML (ExtUML)**	**OO-Framewrk (OOF)**
Expressiveness	Yes	Yes	Yes	Yes	Yes
Complexity Management	Decomposition of Goals and Tasks	Role	Goal, Role Refine	Goal Refine	Property Aspects
Modularity	Yes	Yes	Yes	Yes	Yes
Executable	No	No	No	Yes	No
Refinement	Yes	No	Yes	Yes	No
Traceability	Yes	Yes	Yes	Yes	Yes

3. Software Engineering Process

Deployment

The methodology concerns practical deployment of agents.

Implementation Toolkits

The methodology provides suggestions on how to implement agents in the system.

Architecture Design

The methodology provides a mechanism to facilitate design by using patterns or modules.

Life-cycle coverage

The methodology covers steps from analysis, design, to implementation and testing through out the system development process.

Specification

The methodology provides ways of how to form a system specification from scratch.

	Tropos	**Gaia**	**MaSE**	**Extending UML (ExtUML)**	**OO-Framewrk (OOF)**
System Specification	Stack holders analysis	Role analysis	Use-cases goal and role analysis	Use-cases and role analysis	Aspects analysis
Life Cycle Coverage	Yes	Yes	Yes	Yes	No
Architecture Design	Yes	No	Yes	Yes	Yes
Implementation Toolkits	Yes	No	No	Yes	Yes
Deployment	No	Yes	Yes	No	No

4. Pragmatics

Scalability
The methodology is able to handle reasonable number of agents in an application.

Domain applicability
The methodology is suitable to a specific application domain.

Modeling suitability
The methodology based on a specific architecture.

Required expertise
There is required background or assumption to apply the methodology.

Tools available
There are resources and tools ready in using the methodology.

	Tropos	**Gaia**	**MaSE**	**Extending UML (ExtUML)**	**OO-Framewrk (OOF)**
Tools Available	No	No	Yes	Yes	Yes
Required Expertise	No	No	No	No	Yes
Modeling Suitability	BDI	No	No	BDI	Agenthood
Domain Applicability	Yes	Yes	Yes	Yes	Yes
Scalability	Yes	Yes	Yes	Yes	Yes

A good methodology should have:

A good mental mechanism to support Agents' autonomy, adaptation, and collaboration.

Communication protocols are crucial to Agents in the system in order to conduct their tasks.
Goal-oriented methodology should be preserved in Agent at all times, which includes goal management.
Practical conceptual theories are needed to provide execution of the methodology to ease the complexity of the design.
Notations for clear expressions and efficient modeling is a key to a successful methodology, which can facilitate easy-to-use applications of the methodology.
Executable and reliable full life-cycle software engineering process has to be addressed.
Tools and modeling has to be available pragmatically. Module and refinement capabilities are needed to analyze and integrate elements in the system.

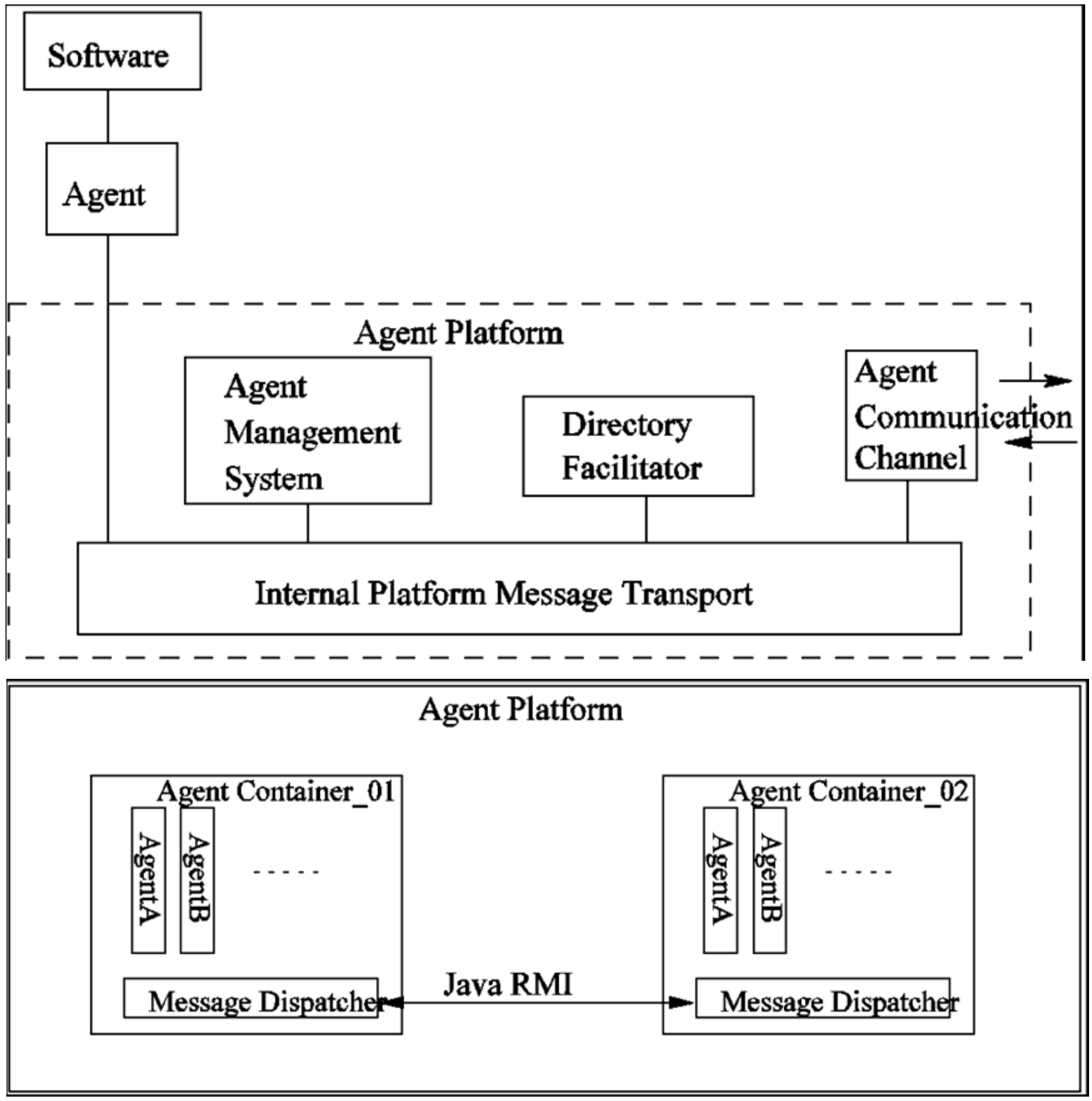
Agent-Based Platform (Middle Ware)

Zeus – Developed by British Telecom Lab.
Agent Component library, building software, visualization tools
Role modeling as well as social context supported.

JADE – Developed by Telecom Italia Lab.
Agent Management System, Directory Facilitator, Agent Communication
Channel, Internal Message Transport

JACK – Developed by Agent Oriented Software Group.
Statement additions to describe agent mechanism and declare attributes and relationships, complier support, kernel classes support for generated codes.
Team Oriented Programming, BDI architecture

Example of JADE platform



Distributed Computational Systems based on Cooperative Multi Agents: We can also extend agent programming to multiple agents if they are all independent. They together will outperform any single agent due to the fact that they have more resources and a better chance of receiving rewards. However the more practical study is to compare the performance of n independent agents with the one of n cooperative agents and to identify their tradeoffs. Because

- Agents can communicate instantaneous information such as sensation actions or rewards.

- Agents can communicate episodes that are sequences of sensation, action, reward, triples experienced by agents.
- Agents can communicate learned decision policies.

Performance of the clustering method is encouraging in most of load balancing and processing requirements; some effort should be devoted to scaling it up to real-world applications.

Limitation in Present AOP

There is no doubt in rapid development in agent oriented programming developed, but still adaptation in applications is still limited. We still required methods for support and guidance for development of agent oriented systems. We need the methodology, and modeling technique that represents objects as well as agents with their characteristics. We also need implementation tools that are suitable for building a system where objects' and agents' distinctive characteristics are preserved at the programming paradigm levels of abstraction. Towards Distributed AOP is still require and a wide research space. Still the lot of detail about the identification of conditions under which the generated options are useful requires further study.

The performance of agent-oriented implementations will be encouraging; some effort should be devoted to scaling it up to real-world applications.

This research raises several important limitations and issues of agent-oriented implementations. Like

- Required number of agents when size of a state space increase exponentially. Generalization techniques to reduce a state space and improve performance for complex tasks
- Information exchanging among agents incurs communication costs

- Cooperative methods need to be explored
- Mapping of required parallel algorithms on the system.

Conclusion

Superiority of Agent oriented Programming as compared to other paradigms is obvious because:

Agent- oriented emphasizes the importance of interactions between entities like the objects. Agents need to be sent a message before they come alive it encapsulate behavior activation (action choice) along with object state and behavior. Agent oriented software are higher level of granularity and abstraction and they more suitable for complex applications. Agents also share the concept of a *single unit of deployment.* Agents are more autonomous and have corresponding notion of reactive, proactive, or social behavior.

It is very important the amount of information and the frequency communication among the agents. We hope this study will motivate greater appreciation in emerging field agent-based computational modeling.

Finally agent oriented software paradigm are more developer friendly and able to handle higher complexity as compare to any other existing programming paradigm.

There is no doubt in rapid development in agent oriented programming developed, but still adaptation in applications is still limited. We still required methods for support and guidance for development of agent-oriented systems. Towards Distributed AOP is still require and a wide research space.

Acknowledgment

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Reinforcement Learning and Distributed Computational Systems

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Abstract

Reinforcement Learning (RL) by itself represents a stimulus-response learning mechanism comparable to the basic idea of behaviorism in cognitive psychology. In behaviorism animals are considered to simply react to a given stimulus or situation and are only influenced by the experienced quality of the result of an action in a certain situation. Similarly in reinforcement learning, an artificial learning system will execute a behavior more often that leads to a high numeric reward than a behavior that leads to a low or even negative reward. Unfortunately, many RL techniques are not able to solve moderately large problems in reasonable time. The difficulty in solving such tasks is usually a result of the combination of the size of the state space with the lack of immediate reinforcement signal. Such more complex problems can be solved by the decomposition of learning problems so size of state space reduces hence learning is accelerates. The described approach aims at appropriately adjusting these estimates by a parallel and distributed reinforcement learning scheme that only requires low-level communication and coordination among the individual nodes. This low-level characteristic makes this approach different from most other available multi-agent learning approaches. It

can be use hierarchical control architectures and associated learning algorithms.

Introduction

Any theory of intelligence must account for the wide spectrum of learning mechanisms displayed by insects, animals and humans. Although some aspects of an autonomous agent can be evolved or directly engineered, other elements of behavior require learning because they involve knowledge that can only be gained by the agent itself, or that may change in unpredictable ways over its lifetime. Although behavior-based robotics has had some success as a basis for the development of intelligent, autonomous robots, the way in which learning fits into the behavior-based framework is not yet well understood.

Reinforcement learning is well suited to the kinds of problems faced by the current generation of behavior-based robots. It provides goal-directed learning without requiring an external teacher, handles environments that are not deterministic and rewards that require multiple steps to obtain, and has a well-developed theoretical framework.

Learning Methods:

In general, learning methods have been divided into three main paradigms: **unsupervised learning, supervised learning, and reinforcement learning.** Unsupervised learning methods do not depend on an external *teacher* to guide the learning process. Instead, the teacher is built into the learning method. Unlike the unsupervised learning paradigm, both the supervised and reinforcement learning paradigms require an external teacher to provide training signals that guide the learning process. Now, the difference between these two paradigms arises from the type of training signals that guide the learning process.

In the supervised learning paradigm, the teacher provides the learning system with the desired outputs for each given input. Learning involves "memorizing" these desired outputs by minimizing the discrepancy between the actual and the desired outputs of the system. In contrast, the role of the teacher in reinforcement learning is more *evaluative* than *instructional*. Sometimes called a *critic* because of this role, the teacher provides the learning system with a scalar evaluation of the system's performance of a given task according to some performance measure. The objective of the learning system is to improve its performance, as evaluated by the critic, by generating appropriate actions. The critic in this case does not need to know what each optimal response is in order to provide useful advice. Reinforcement learning thus involves two operations: discovering the right outputs for a given input and memorizing those outputs. The ability to discover solutions to problems makes reinforcement learning important in situations where the lack of sufficient structure in the task definition makes it difficult to define a priori the desired outputs for each input, as required for supervised learning. In such cases, reinforcement learning systems can be used to learn the unknown desired outputs by providing the system with a suitable evaluation of its performance.

In most of the real intelligence applications we needs dynamic scheduling, reinforcement learning is more appropriate to use since no a priori information is available on the state of the system. Rather, it is necessary for the scheduler to learn while it operates. As there are no "correct" results to learn from, various measures of the system state need to be used to check the performance at each output. This will be described later in more detail.

Reinforcement Learning:

Reinforcement learning (RL), as opposed to supervised learning, has a more attractive feature in that it replaces the teacher by a performance measure from the environment to grade the "goodness" of the current actions (Fig. 1).

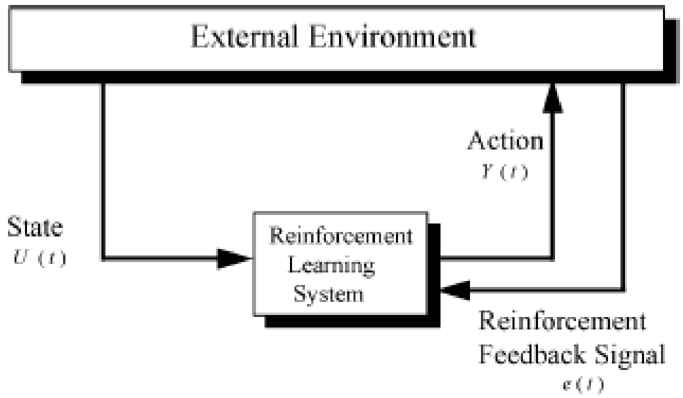

Fig. 1. Reinforcement learning scheme

Measurement of the performance of a scheduler is feasible by studying the efficiency of the computing system (e.g., execution time, throughput, utilization rate). Hence, on-line performance measurements can thus form the basis for adaptive RL-based scheduling. The stochastic nature of RL is compatible with that of the on the fly task allocation and assignment, which is an important requirement for dynamic scheduling.

The way, that RL works resembles the operation of a stochastic automaton when performing a search to maximize a payoff or reinforcement function. Fig. 1 shows an RL system that interacts with an environment E. At each instant of time t, E provides the RL system with some pattern $U(t)$. The RL system produces a random output (or action) $Y(t)$. The action gets evaluated by the environment in the context of the input $U(t)$and sends the RL system a reinforcement signal $e(t)$, $e(t)$, with $e(t) = e$ representing maximum reinforcement, According to the goodness (if the error is small) or badness (if the error is large) of the reinforcement signal, the learning system has to produce a better output in order to minimize the error $e(t)$.

In general, the learning system should satisfy several properties. The scheduler must learn to associate with each input pattern an output value for which the reinforcement signal it receives indicates the highest degree of success. In addition, it should be able to improve its performance in cases where it is doing poorly by using greater degrees of exploratory behavior, hence, discriminate between cases in which it's doing poorly and those in which it's doing well. This is important in order not to degrade its performance in cases, which it is doing well by exhibiting behavior that is too random. So, by using the proposed approach, we transform the scheduler design into an optimization problem.

Strategies for solving reinforcement –learning problems

There are two main strategies for solving reinforcement-learning problems. The firrst is to search in the space of behaviors in order to second one that performs well in the environment. as well as some more novel search techniques (Schmidhuber, 1996). The second is to use statistical techniques and dynamic programming methods to estimate the utility of taking actions in states of the world.

Reinforcement learning is the problem faced by an agent that learns behavior through trial-and-error interactions with a dynamic environment. A model of reinforcement learning consists of a discrete set of environment states, a discrete set of agent actions and a set of scalar reinforcement signals. On each step of interaction the agent receives reinforcement and some indication of the current state of the environment, and chooses an action. The agent's job is to find a policy, i.e. a mapping from states to actions, which maximizes some long-run measure of reinforcement. These rewards can take place arbitrarily distant in the future. To obtain a high overall reward, an agent has to prefer actions that it has learned in the past and found to be good, i.e. exploitation, however discovering such actions is only possible by trying out alternative actions, i.e. exploration. Neither exploitation, nor exploration can be pursued exclusively.

Common reinforcement learning methods are structured around estimating value functions. A value of a state or state-action1 pair is the total amount of reward an agent can expect to accumulate over the future, starting from that state. One way to find the optimal policy is to find the optimal value function. If a perfect model of the environment as a Markov decision process is known, the optimal value function can be learned with an algorithm called value iteration. An adaptive version of this algorithm exists for situations were a model of the environment is not known in advance.

For instance the Q-learning algorithm, which is an adaptive value iteration method bootstraps its estimate for the state-action value), (1 *a s Qt* + at time *t+1* upon its estimate for), (*Qt(s',a')*) with *s'* the state where the learner arrives after taking action *a* in state *s*:

$$Q_{t+1}(s,a) = (1-\alpha).Q_t(s,a) + \alpha.(r + \gamma.\max_{a} Q_t(s',a')) \quad (1)$$

With α usual step size parameter, γ a discount factor and *r* the immediate reinforcement.

Limitation in standard reinforcement learning algorithm:

Reinforcement learning has been used successfully in many different application domains. However, there remain large problems with no known optimal policy that are *infeasible* to solve with standard reinforcement learning algorithms. Reinforcement learning is an attractive approach for many problems, especially in situations where providing a reward function is much easier than developing a model of the environment, or where the environment is easily simulated but the principles behind an optimal policy for the environment are poorly understood. Unfortunately, once the space of state-action pairs grows beyond a certain size, the time for standard algorithms to converge becomes too great, and for some situations there can even be difficulties storing the Q-table in memory. Standard algorithms are also based on a *finite* space of state-action pairs, further complications are evident in domains where either the state space or the action space is *continuous*.

The key problem, which arises when reinforcement learning is applied to large-scale problems, is referred to as the *state space explosion*, also described by Bellman (1957) as the *curse of dimensionality*.

The "flat" state space S used by a traditional reinforcement learner can generally be expressed as the Cartesian product of n simpler state variables, X1 x X2 x : : : x Xn. As we scale-up to larger problems by increasing the number of state variables involved, the size of the state space S grows exponentially with n. Since the learning time grows at least as fast as the size of the state space, the learning time will also grow exponentially. Even if these were only binary state variables, |S| would be equal to 2n, and learning would soon become infeasible if n became much larger than about 20.

It is clear that for the fully general case of an MDP with 2n states, there is an inescapable limit on how large we can allow n to grow and still find the optimal policy in a reasonable amount of time.

Despite the widespread success of reinforcement learning algorithms, they display severe limitations when applied to real-life learning domains. . As these problems become more complex and involve more variables, the effects of the *state space explosion* can be observed. The number of possible states of the environment becomes so large that time required to find an optimal (or even near-optimal) solution becomes infeasible large. This is usually because a domain has such a large number of possible states that existing algorithms cannot find an optimal (or even near-optimal) policy in a feasible amount of time. These limitations mean that good solutions cannot be obtained for many useful real-life problems. These limitations prevent good solutions from being found in many useful application domains.

The wide variety of exploration strategies which have been developed demonstrate how fundamental the trade-off between exploration and exploitation is to the reinforcement learning problem. To learn the optimal policy in a reasonable amount of time, a good exploration strategy is vital. The problem of choosing the "best" strategy for a given situation is far from solved. A variety of both simple and complex strategies were surveyed in the previous sections, the more complex ones requiring fewer explorative actions at the expense of greater computational effort.

However, in practice the learning performance obtained using a simple undirected exploration strategy greedy or Boltzmann cannot usually be improved upon with a more sophisticated strategy. The directed strategies only become useful when experience in the environment is extremely sparse or expensive.

Despite the gains that the more complex exploration strategies afford us, there is a limit to how tractable they can make large reinforcement learning problems. Even if the environment is assumed to be deterministic, in theory the worst-case exploration time is that required to visit each state-action pair at least once. The difficulty of large reinforcement learning problems is mainly due to the exponential growth of the state space in the number of state variables. The minimum exploration time required for any reinforcement-learning problem will therefore also increase exponentially. To tackle this problem, we need either to use some technique to reduce the size of the state space, or to generalize between similar states so that it is not necessary to visit all state-action pairs.

The performance can be improved by function approximation method or hierarchical reinforcement learning but function approximation requires prior knowledge to provide a set of good input features for learning and most effective when the target value function has no sharp discontinuities between similar states. Similarly in the hierarchy is constructed to allow the problem to be solved in less time, not to preserve optimality. In general, the true optimal solution can only be found if we solve the problem in the flat state space, which is intractable for large problems.

Distributed Computational Systems based on Cooperative Multi Agents: Although most work on reinforcement learning has focused exclusively on single agents, we can extend reinforcement learning straightforwardly to multiple agents if they are all independent. They together will outperform any single agent due to the fact that they have more resources and a better chance of receiving rewards. However the more practical study is to compare the performance of n independent agents with the one of n cooperative agents and to identify their tradeoffs. How can reinforcement-learning agents be cooperative. Because

- Agents can communicate instantaneous information such as sensation actions or rewards.
- Agents can communicate episodes that are sequences of sensation, action, reward, triples experienced by agents.
- Agents can communicate learned decision policies.

Performance of the clustering method is encouraging in most of load balancing and processing requirements, some effort should be devoted to scaling it up to real-world applications.

The past years have witnessed a steadily growing interest in parallel and distributed information processing systems in artificial intelligence and computer science. This interest has led to new research and application activities in areas like parallel and distributed algorithms, concurrent programming, distributed database systems, and parallel and distributed hardware architectures. Three basic, interrelated reasons for this interest can be identified. First, the willingness and tendency in artificial intelligence and computer science to attack increasingly difficult problems and application domains which often require, for instance, to process very large amounts of data or data arising at different geographical locations, and which are therefore often to difficult to be handled by more traditional, sequential and centralized systems. Second, the fact that these systems have the capacity to offer several useful properties likes robustness, fault tolerance, scalability, and speed-up. Third, the fact that today the computer and network technology required for building such systems is available. A difficulty with parallel and distributed information processing systems is that they typically are rather complex and hard to specify in their dynamics and behavior. It is therefore broadly agreed that these systems should be able, at least to some extent, to self-improve their future performance, that is, to learn. Not surprisingly, today the topic of learning in parallel and distributed information processing systems receives increasing attention. The major property of this kind of learning is that the learning process itself is logically or geographically distributed over several components of the overall system and that these components conduct their learning activities in parallel. The field of parallel and distributed machine learning is of considerable importance, but also is rather young and still searching for its defining boundaries and shape. The basic idea underlying the multiagent learning approach described by Gerhard Wei is that each job is associated with an estimate of the job's influence on the overall completion time, and that these estimates are improved in the course of learning.

As it is described in more detail below, this improvement as well as the execution of the jobs is done by the involved nodes in a parallel and distributed way. A high estimate indicates a significant impact on the overall completion time, and a job being associated with a high estimate therefore is identified as \critical" and should be completed as soon as possible. Learning proceeds in episodes, where an episode consists of the time interval required for completing all jobs.

The basic working steps realized during an episode can be conceptually described as follows:

Until all jobs are completed do

(1) The idle nodes choose among the executable jobs, and this choice is done dependent on the nodes execution times and the job estimates.

(2) The nodes execute their chosen jobs.

(3) If a node completes a job, then it adjusts the estimate of this job.

When an episode t is finished, the next episode t + 1 starts and learning continues on the basis of the adjusted job estimates that are available at the end of episode t. This is iterated for a predefined, maximum number of episodes. The best solution found during these episodes is offered as the solution of the overall learning process. (A solution found

in an episode need not necessarily be as good as the solution found in the preceding episode. Due to its statistical nature this approach does not guarantee a monotonic improvement of the solutions found in the course of learning.

The approach is parallel and distributed in as far as both job execution (2) and estimate adjustment (3) is done by different agents. A synchronization of the agents' activities occurs in step (1). This also shows the potential advantages of this kind of learning over centralized learning approaches:

it is more robust (e.g., failure of an individual node does not damage the overall learning process); it is more flexible (e.g., new nodes can be easily integrated in an ongoing learning process); and it is faster (because of inherent task and result sharing).

Many concrete forms of this conceptual description are possible. It was not the goal of the described work to exhaustively investigate all these forms. Instead, the work aimed at an improved understanding of the potential benefits and limitations of parallel and distributed machine learning in general, and therefore a concretization has been chosen that realizes this type of learning in an intuitive and relatively simple way and at the same time enables a conclusive and efficient experimental investigation.

Learning according to this approach occurs in a parallel and distributed way. In particular, the estimates of different jobs may be adjusted concurrently, and all processors involved in job execution are also involved in the adjustment of the estimates. There are two major characteristics of this approach. First, it realizes a basic form of reinforcement learning. The only available learning feedback is the completion time of the individual jobs.

Conclusion

The applications of artificial Intelligence definitely get speed-up when reinforcement learning implementation by distributed systems. It is relatively powerful and its benefits are obvious for the complex learning applications and highly scalable. Lot of work can be done in the future for it. On the other hand obviously it can increase complexity between exploitation and exploration. With parallel agents sharing information, there is additional pressure for more agents to exploit the same actions instead of diversely exploring. It is very important the amount of information and the frequency communication among the agents.

We hope this study will motivate greater appreciation in emerging field agent-based computational modeling. Still the lot of detail about the identification of conditions under which the generated options are useful requires further study.

The performance of such an implementations will be encouraging; some effort should be devoted to scaling it up to real-world applications.

This research raises several important issues of multi agent reinforcement learning.

- Required number of agents when size of a state space increase exponentially. Generalization techniques to reduce a state space and improve performance for complex noisy tasks
- Information exchanging among agents incurs communication costs
- Cooperative methods need to be explored
- Mapping of required parallel algorithms on the system.

Acknowledgment

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Role of Multi-Agent System in Real Time Business Intelligence

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Abstract:

Business Intelligence enables us to take some action based on the intelligence acquired using BI strategy. BI strategies are intended to utilize knowledge or information properly in the right direction so profitability can be enhanced. A proper business action taken based on the strategies derived with the help of intelligence models. Once everything is done more properly in a way an organization want them to be, then the benefit that comes out of it is priceless. Many data warehouses on which BI solutions are based like financial are loaded overnight. In such cases many of the issues relating to real-time analysis must be address. Conceptually we use reasoning, mathematics on the data at various levels in the enterprise to create business Intelligence. Multi Agent Systems helps BI applications require complex and sheer volumes of data need to be collecting from multiple, disparate sources, Validating and qualifying the results for accuracy, and performance Improvement. Business analytics tools like Traditional query and reporting, OLAP, and Data mining is usable but for effective real time BI solutions include the ability to push information to users. Multi Agent Systems set critical thresholds or triggers and launch a result, report, or note is essential to BI today.

Keywords: Agent, Data Mining, and Business Intelligence

Introduction

Multi-Agent System

The new developments in learning models are based on agent theory. Where,

Agent can be defined to be autonomous, problem solving computational entities capable of effective operation in dynamic and open environments.

Software agents are persistent computations that include percepts, reasoning, action, and communication [Russell & Norvig, 1995]

Agents are autonomous in the sense that they perform their tasks regardless of whether they are required or not. Intelligent agents are computational systems that inhabit in a complex dynamic environment and they can act autonomously and have the capacity to reason by themselves in this environment. This environment can be the network, and the intelligent agent can be seen as a software entity that assist people and gathers information or perform some other services without the immediate presence of a human being.

An intelligent agent could be characterized by the following attributes: autonomy, Reactivity, pro-activity and social ability

An Distributed Intelligent Agent Attributes:

Autonomy: This attribute is one of the most important characteristics that allow us to distinguish the intelligent agents from other type of software. When we say that an agent must have autonomy, we are talking about the capacity of reacting by themselves in an environment using their experience. This means; the capacity of observation and operation without the direct intervention of human beings or other agent.

Reactivity: Is the capacity that the agents have to perceive their environment and act depending of the changes that occur in it, in a correct and fast way. Internet can also be one environment where intelligent agents can interact.

Pro-activity: As we had seen before, the agents can react to an environment, but they also have the ability of obtain a goal by taking the initiative. They have a goal-directed behavior without external influences (they are self-sufficient).

Social ability: Sometimes more than one agent is needed to make a task or solve some problems. The social ability is the capacity that one agent have to interact with other agents (or humans), by using some “agent language”, for the possibility to cooperate or negotiate.

Embedded: The agent respects the real time of their environment and act depending on this one.

Distributed: Many different kind of agents can work together in the same system and each one of them can be added or removed without interrupting it.

In the environment agent interact, and maybe co-operate with other agents. Agents may have conflicting aims, such a system is known as a multi-agent system.

Agent architecture is the fundamental engines such an autonomous components that support effective behavior in real-world, dynamic and open environments.

In implementing multi-agent system where agents respond in a rational way to their goals and events that occur in their environment. These agents have a specific set of conditions and associated goals, which indicate the events they should respond to. This architecture stresses the problem of heterogeneous information and knowledge sources.

Durfee [3] indicates that the combination of efforts brings:

- Confidence: Independent derived results can be used to corroborate each other, yielding a collective result that has a higher probability of being correct.
- Completeness: The union of the different subtask results can cover a greater proportion of the overall task.
- Precision: To refine its own solution, an agent needs to know more about the solutions that others have formulated.
- Timeliness: Solving subtasks in parallel can yield an overall solution faster

Business Intelligence and Issues

Business Intelligence is the conscious, methodical transformation of data from any and all data sources into new forms to provide information that is business driven and results oriented. It will often encompass a mixture of tools, databases, and vendors in order to deliver an infrastructure that not only will deliver the initial solution, but will incorporate the ability to change with the business and current marketplace.

Importance of Business Intelligence:

Strategic planning is critical to the ultimate success of any high-impact BI initiative. BI Strategies helps to focus on key goals, minimize risks and plan for a successful BI deployment. By applying an architect approach, it helps:

- Target high-value benefits by identifying your goals, objectives, information needs, and the current approach to resolving these needs
- Leverage overlapping resources, use common technologies and share data by identifying internal and external information producers, availability of data, volumetric of data, and data quality

- Identify risks and dependencies, and develop plans for managing both, ultimately increasing your organization's ROI.

The following steps are generally required to implement Business intelligence.

Data warehouse: In a real time Business Intelligence application the database may consists of a large amount of historical data as well as very current data. It requires building a Data warehouse.

Dimensional Modeling: Dimensional modeling follow a multidimensional in any BI solution that we put in place should ideally be available across the whole company.

Data Integration Process: We can reach the goal of a consistent data warehouses by bring together the many different data sources that contain all your business data.

Analysis Service Database: New data may needs to be available in an OLAP database with every transaction. The OLAP database may be accessible to users continuously, even during updating. Flexible analytical capabilities are required to really take advantage of the integrated information in the data warehouse and move beyond a simple level of understanding such as measuring the increase in income received.

Reporting: Although data warehouses and BI in general are a great way to serve the needs of analysts, an opportunity exists to get even more value by including all the users. Web-based reporting allows you to present information in a useful way without requiring extensive training or complex client software. Reports can be published in Web portals, sent to users via e-mail, or included in applications and dashboards to allow all users to benefit from the information in a data warehouse.

Data Quality: The data warehouse is expected to be the authority for any data it provides. To gain and maintain this position of authority, a data warehouse should only contain data that is complete, correct, and consistent.

Managing Changing Data: When some of the attributes of a dimension record change over time, the dimension is called a slowly changing dimension (SCD).

Scorecards: Many organizations are moving beyond managing their business by focusing completely on the bottom line to include a more balanced set of perspectives in their strategic management system. New management processes and books such as The Balanced Scorecard (Kaplan and Norton) are driving an increased interest in scorecard or dashboard applications to help achieve strategic goals. In Executive Information System (EIS), There is so much talk about "executive dashboards" today. Somewhere beneath the clever graphical interface and presentation lies some data and a corresponding set of values that were produced with a query tool

Data Mining: Analysis Services enables you to build powerful Business Intelligence (BI) solutions that enable users to really understand the business. However, many business problems rely on the ability to spot patterns and trends across data sets that are far too large or complex for human analysts. Data mining can be used to explore your data and find these patterns, allowing you to begin to ask why things happen and to predict what will happen in the future.

Role of Multi Agent System in Business Intelligence Application:

Agent in Data Warehouse Communication: Data Warehouse Agents can perform Communications between Data Warehouse Center servers and warehouse agents. When the Data Warehouse Center server is asked to complete a task that requires the use of a warehouse agent, the server finds an available port on its system and then sends a message to the warehouse agent daemon at the agent site. The message contains the number of the port to which the agent can respond. The warehouse agent daemon receives this message and does some basic validation. After the message is validated, the warehouse agent daemon starts a warehouse agent instance to process the request from the server. The warehouse agent starts and accepts the message sent by the Data Warehouse Center server, finds an available port on its system, and responds to the server, using the port specified in the message from the server. During the response, the warehouse agent also indicates the port on the warehouse agent system that it will use to receive additional requests from the server.

Every time the Data Warehouse Center server needs an agent do a specific task, it must perform a handshake on the ports over which it communicates with the agent. Because the server can handle multiple schedules and client requests at one time, many communication pipes between an agent and a server might be open at the same time.

Agent in Effective Data Mining: To improve the results returned by the searches, intelligent agents and other technology have the potential, when used with existing search and retrieval engines, to provide a more comprehensive search with an improved performance. This research provides the building blocks for integrating intelligent agents with current search engines. It shows how an intelligent system can be constructed to assist in better information filtering, gathering and retrieval. Computational Intelligence Techniques Driven Intelligent Agents for Web Data Mining and Information Retrieval" by Mohammadian and Jentzsch, looks at how the World Wide Web has added an abundance of data and information to the complexity of information disseminators and users alike. With this complexity has come the problem of locating useful and relevant information. Such complexity drives the need for improved and intelligent search and retrieval engines.

Agent in Data Quality: Agent can report about the quality of Data by referring it's knowledge base. In Mozilla Thunderbird they used Mozilla Quality Feedback Agent for reporting the data quality in the data downloading from network connection.

Agent in Analysis Service Database: OLAP Agents are supported by most of the database vendors to ease of operations, like in Oracle. Oracle 9 i providing OLAP Agent service a process that runs continuously in the background.

Agent in Scorecards: Agent-Based Modeling for Competing Firms: From Balanced-Scorecards to Multi-Objective Strategies explains a novel method for agent based modeling in business management domain. Model competing companies with the Balanced Scorecards principle and examines their Value Proposition strategies for customers for agent-based modeling is to explore 'optimal' marketing strategies on given specific markets.

Agent to handle Complexity:

Business Intelligence algorithms, they display severe limitations when applied to real-life learning domains. . As these problems become more complex and involve more variables, the effects of the *state space explosion* can be observed. The number of possible states of the environment becomes so large that time required to find an optimal (or even near-optimal) solution becomes infeasible large. This is usually because a domain has such a large number of possible states that existing algorithms cannot find an optimal (or even near-optimal) policy in a feasible amount of time. These limitations mean that good solutions cannot be obtained for many useful real-life problems. These limitations prevent good solutions from being found in many useful application domains.

Which can be handled by Distributed Computational Systems based on Cooperative Multi Agent.

Conclusion:

Intelligent Agent system has proven it's importance in Information filtering, Information Retrieval, Notifiers, Process Automation, Collaborative Customization, E-Business and OLAP applications. It enables to achieve system automation at a great extends.

The applications of artificial Intelligence definitely get speed-up when Business Intelligence implementation by distributed systems. It is relatively powerful and its benefits are obvious for the complex learning applications and highly scalable.

Multi Agent System is useful in Database, Data Mining Techniques, OLAP, Reporting, Notifying, and Automation, Which are the core parts of any Business Intelligence Application. We hope this study will motivate greater appreciation in emerging field agent-based computational modeling.

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A Comparative Study of Data Mining Techniques and its Selection IssueS

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Abstract

In this paper our objective is to provide comparative study of different Data Mining Techniques like Decision Tree, Neural Network, Genetic Algorithms and K-Means Algorithm. So one can make the decision for proper technique suitable to requirement of application.

This comparison is based on easiness of understanding and implementation of technique, input and output issue, applications, advantages and disadvantages.

As per our opinion this paper should be helpful for those who have started research in data mining and wish to select appropriate algorithm for data mining. We have also tried to discuss the criteria that is helpful for selecting a data mining technique as per learning methodology such as whether learning is supervised or unsupervised, the nature of input and output data, presence of noisy data, time (speed) issue (algorithms for building decision tree and production rules typically execute much faster than NN or GA), classification accuracy.

Keywords: Data Mining, Decision Tree, Neural Network, Genetic Algorithm, K-Means

Data Mining: A Definition

Data Mining is the process of employing one or more computer learning techniques to automatically analyze and extract knowledge from data contained within a database. The purpose of a data mining session is to identify trends and patterns in data.

There are several data mining techniques. We discuss the main data mining techniques: Decision Tree, Neural Network, Genetic Algorithms and K-Means Algorithm.

Decision Trees

The decision tree method of decision analysis uses a tree structure to illustrate the decision process. Probabilities are assigned to events, and the expected value of each alternative is determined. The alternative with the most attractive total expected value is chosen. Depending on the decision, the most attractive expected value may be the highest or lowest number.

DEFINITION 1. A **decision tree (DT)** is a tree where the root and each internal node is labeled with a question. The arcs emanating from each node represent each possible answer to the associated question. Each leaf node represents a prediction of a solution to the problem under consideration.

DEFINITION 2. A **decision tree (DT) model** is a computational model consists of three parts:

1. A decision tree as defined in Definition 1.
2. An algorithm to create the tree.
3. An algorithm that applies the tree to data and solves the problem under consideration.

Let us consider the following example of a recognition problem. During a doctor's examination of some patients the following characteristics are determined.

X_1 - temperature, X_2 – coughing, X_3 – a reddening throat

$Y=\{W_1,W_2,W_3,W_4,W_5\}$ = {a cold, quinsy, the influenza, a pneumonia, is healthy} – a set from the possible diagnoses, demanding more profound inspection.

It is required to find a model, where Y depends on X. The example (figure 1) illustrates such a model, which can be seen as a decision tree.

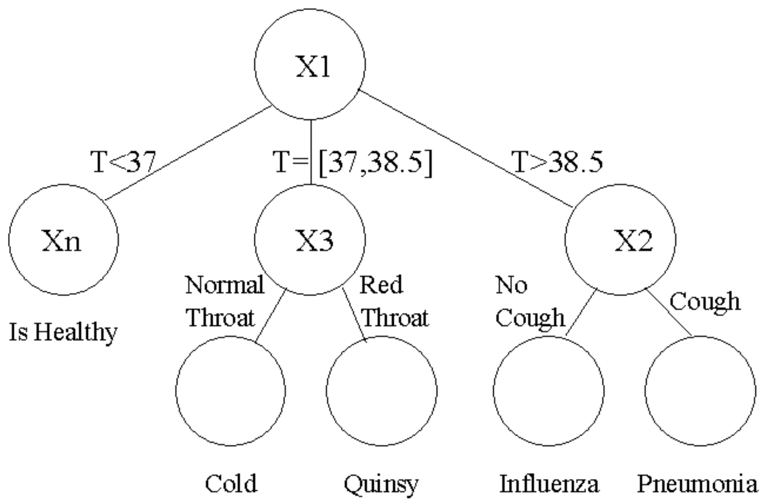

Figure 1: Decision Tree

The ordinary tree consists of one root, branches, nodes (places where branches are divided) and leaves. In the same way the decision tree consists of nodes, which stand for circles, the branches stand for segments connecting the nodes. A decision tree is usually drawn from left to right or beginning from the root downwards so it is easier to draw it. The first node is a root. The end of the chain is called "leaf". From each internal node (i.e. not a leaf) may grow out two or more branches. Each node corresponds with a certain characteristic and the branches correspond with a range of values. These ranges of values must give a partition of the set of values of the given characteristic.

When precisely two branches grow out from an internal node (the tree of such type is called a dichotomic tree), each of these branches can give a true or false statement concerning the given characteristic is shown on figure 2.

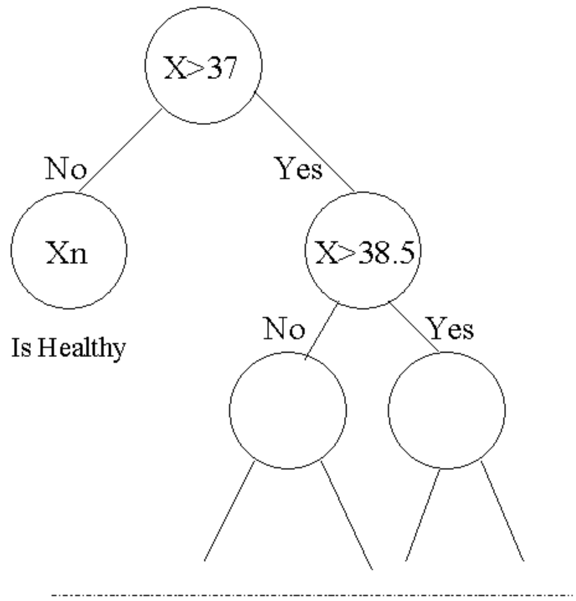

Figure 2: Dichotomic Tree

For any observation of X, using a decision tree, we can find the predicted value Y. For this purpose we start with a root of a tree, we consider the characteristic, corresponding to a root and we define, to which branch the observed value of the given characteristic corresponds. Then we consider the node in which the given branch comes. We repeat the same operations for this node etc., until we reach a leaf. Thus, the decision tree gives the model T of dependence Y from X: Y=T(X).

The building of the tree may be accomplished via an algorithm that examines data from a training sample or could be created by a domain expert. Most decision tree techniques differ in how the tree is created. Algorithm 1 shows the basic steps in applying a tuple to the DT, step three in Definition 2. We assume here that the problem to be performed is one of prediction, so the last step is to make the prediction as dictated by the final leaf node in the tree. The complexity of the algorithm is straightforward to analyze. For each tuple in the database, we search the tree from the root down to a particular leaf. At each level, the maximum number of comparisons to make depends on the branching factor at that level. So the complexity depends on the product of the number of levels and the maximum branching factor.

A set of logic statements about values of characteristics corresponds to decision trees. Each statement is obtained by passing the way from root to leaf. So, for example, for the tree represented on figure 1 the following list of statements corresponds to.

1. If $X_1 < 37$, Y="is healthy".
2. If $X_1 \in [37,38.5]$ and X_3="there is no reddening of throat", then Y="to catch cold";
3. If $X_1 \in [37,38.5]$ and X_3="there is reddening of throat", then Y="angina";
4. If $X_1 > 38.5$ and X_2="there is no cough", then Y="influenza";
5. If $X_1 > 38.5$ and X_2="there is cough", then Y="pneumonia";

Thus, the decision tree represents a logic model of regularities of the researched phenomenon.

ALGORITHM 1

Input:

```
    T       //Decision Tree
    D       //Input database
Output:
    M       //Model prediction
DTProc algorithm:
     //Simplistic algorithm to illustrate prediction
     //  technique using DT
for each t ∈ D do
    n = root node of T;
    while n not leaf node do;
     Obtain answer to question on n applied to t;
      Identify arc from t, which contains correct answer;
      n=node at end of this arc;
    Make prediction for t based on labeling of n;
```

Advantages

Decision trees have several advantages. Here is a list of a few of the many advantages decision trees have to offer.

- Decision trees are easy to understand and map nicely to a set of production rules.
- Decision trees have been successfully applied to real problems.
- Decision trees make no prior assumptions about the nature of the data.
- Decision trees are able to build models with datasets containing numerical as well as categorical data.

Disadvantages

There are several issues surrounding decision tree usage. Specifically,

- Output attributes must be categorical, and multiple output attributes are not allowed.
- Decision tree algorithms are unstable in that slight variations in the training data can result in different attribute selections at each choice point within the tree. The effect can be significant as attribute choices affect all descendent subtrees.
- Trees created from numeric datasets can be quite complex as attribute splits for numeric data are typically binary.

Neural Networks

Neural networks offer a mathematical model that attempts to mimic the human brain. Knowledge is often represented as a layered set of interconnected processors. These processor nodes are frequently referred to as neurodes so as to indicate a relationship with the neurons of the brain. Each node has a weighted connection to several other nodes in adjacent layers. Individual nodes take the input received from connected nodes and use the weights together with a simple function to compute output values.

Why use Neural Networks?

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer “what if” questions.

Network Layers

The NN approach, like decision trees, requires that a graphical structure be built to represent the model and then that the structure be applied to the data. The NN can be viewed as a directed graph with source (input), sink (output) and internal (hidden) nodes. The input nodes exist in a *input layer,* while the output nodes exist in an *output layer.* The hidden nodes exist over one or more *hidden layers.* To perform the data mining task, a tuple is input through the input nodes and the output node determines what the prediction is. Unlike decision trees, which have only one input node (the root of the tree), the NN has one input node for each attribute value to be examined to solve the data mining function. Unlike decision trees, after a tuple is processed, the NN may be changed to improve future performance. Although the structure of the graph does not change, the labeling of the edges may change.

DEFINITION 3. A **neural network (NN)** is a directed graph, F=(V, A) with vertices V= {1,2,….,n} and arcs A={(i,j) | 1<=i,j<=n}, with the following restrictions.

1. V is partitioned into set of input nodes,$V_{I,}$ hidden nodes, V_H and output nodes , Vo.
2. The vertices are also partitioned into layers {1,….,k} with all input nodes in layer 1 and output nodes in layer k. All hidden nodes are in layers 2 to k-1 which are called the hidden layers.
3. Any arc (i,j) must have node i in layer h-1 and node j in layer h.

4. Arc (i,j) is labeled with a numeric value w_{ij}.
5. Node i is labeled with a function f_i.

Definition 3 is a very simplistic view of NNs. Athough there are many more complicated types that do not fit this definition, this defines the most common type of NN.
Figure 3 shows a fully connected feed-forward neural network structure together with a single input instance [1.0,0.4,0.7]. Arrow indicates the direction of flow for each new instance as it passes through the network. The network is fully connected because nodes at one layer are connected to all nodes in the next layer.
The number of input attributes found within individual instances determines the number of input layer nodes. The user specifies the number of hidden layers as well as the number of nodes within a specific hidden layer. Determining a best choice for these values is matter of experimentation. In practice, the total number of hidden layers is usually restricted to two. Depending on the application, the output layer of the neural network may contain one or several nodes.

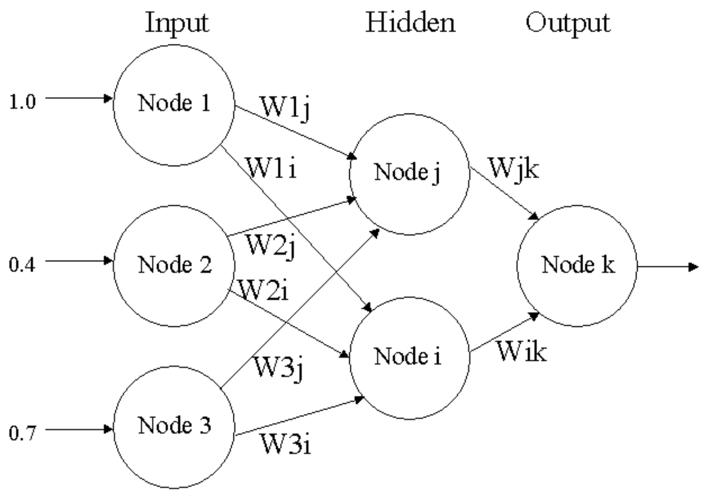

Figure 3 A fully connected feed-forward neural network

Neural Network Input and Output Format

The input to individual neural network nodes must be numeric and fall in the closed interval range [0,1]. Because of this, we need a way to numerically represent categorical data. We also require a conversion method for numerical data falling outside the [0,1] range.

The output nodes of a neural network represent continuous values in the [0,1] range. However, the output can be transformed to accommodate categorical class values.

The Sigmoid Function

The purpose of each node within a feed-forward neural network is to accept input values and pass an output value to the next higher network layer. The nodes of the input layer pass input attribute values to the hidden layer unchanged. Therefore for the input instance shown in figure 3, the output of node 1 is 1.0, the output of node 2 is 0.4 and the output of node 3 is 0.7.

W_{1J}	W_{1I}	W_{2J}	W_{2I}	W_{3J}	W_{3I}	W_{JK}	W_{IK}
0.20	0.10	0.30	-0.10	-0.10	0.20	0.10	0.50

Table 1: Initial Weight Values for the Neural Network Shown in Figure 3

A hidden or output layer node n takes input from the connected nodes of the previous layer, combines the previous node values into a single value, and uses the new value as input to an evaluation function. The output of the evaluation function is a number in the closed interval [0,1]. This value represents the output of node n.

Let's look at an example. Table 1 shows sample weight values for the neural network of Figure 3. Consider node j. To compute the input to node j, we determine the sum total of the multiplication of each input weight by its corresponding input layer node value. That is:

Input to node j= (0.2)(1.0) + (0.3)(0.4) + (-0.1)(0.7) = 0.25

Therefore 0.25 represents the input value for node j's evaluation function.

The first criterion of an evaluation function is that the function must output values in the [0,1] interval range. A second criterion is that the function should output a value close to 1 when sufficely excited. The sigmoid function is computed as:

$F(x) = 1 / 1 + e^{-x}$

Where e is the base of natural logarithms approximated by 2.718282.

Applications of neural networks

Character Recognition – The idea of character recognition has become very important as handled devices like the Palm Pilot are becoming increasingly popular. Neural networks can be used to recognize handwritten characters.

Image Compression – Neural networks can receive and process vast amounts of information at once, making them useful in image compression. With the Internet explosion and more sites using more images on their sites, using neural networks for image compression is worth a look.

Stock Market Prediction – The day-to-day business of the stock market is extremely complicated. Many factors weigh in whether a given stock will go up or down on any given day. Since neural networks can examine a lot of information quickly and sort it all out, they can be used to predict stock prices.

Traveling Salesman's Problem – Interestingly enough, neural networks can solve the traveling salesman problem, but only to a certain degree of approximation.

Medicine, Electronic Nose, Security and Loan Applications – These are some applications that are in their proof-of-concept stage, with the acceptation of a neural network that will decide whether or not to grant a loan, something that has already been used more successfully than many humans.

Advantages

- Neural networks well with datasets containing large amounts of noisy input data. Neural network evaluation functions such as the sigmoid function naturally smooth input data variations caused by outliers and random error.
- Neural networks can process and predict numeric as well as categorical outcome. However, categorical data conversions can be tricky.
- Neural networks can be used for applications that require a time element to be included in the data.
- Neural networks have performed consistently well in several domains.
- Neural networks can be used for both supervised learning and unsupervised clustering.

Disadvantages

- Probably the biggest criticism of neural networks is that they lack the ability to explain their behavior.
- Neural network learning algorithms are not guaranteed to converge to an optimal solution. With most types of

neural networks, the problem can be dealt with by manipulating various learning parameters.

- Neural networks can easily be overtrained to the point of working well on the training data but poorly on test data. This problem can be monitored by consistently measuring test set performance.

Genetic Algorithms

A Genetic Algorithm is heuristic, which means it estimates a solution. We won't know if we get the exact solution, but that may be a minor concern. In fact, most real-life problems are like that: we estimate a solution rather than calculating it exactly.

For most problems we don't have any formula for solving the problem because it is too complex, or if we do, it just takes too long to calculate the solution exactly. An example could be space optimization – it is very difficult to find the best way to put objects of varying size into a room so they take as little space as possible. The most feasible approach then is to use a heuristic method.

Genetic algorithms are different from other heuristic methods in several ways. The most important difference is that a GA works on a *population* of possible solutions, while other heuristic methods use a single solution in their iterations. Another difference is that GAs are probabilistic (stochastic), not deterministic.

Each individual in the GA population represents a possible solution to the problem. The suggested solution is coded into the "genes" of the individual. One individual might have these genes:"1100101011", another has these:"0101110001"(just examples). The values (0 or 1) and their position in the "gene string" tells the genetic algorithm what solution the individual represents.

Where GAs can be used?

GAs can be used where optimization is needed. It means that where there large solutions to the problem but we have to find the best one. Like we can use GAs in finding best moves in chess, mathematical problems, and financial problems and in many more areas.

DEFINITION 4. Given an alphabet A, an **individual** or **chromosome** is a string $I = I_1, I_2, \ldots, I_n$ where $I_j \in A$. Each character in the string , I_j, is called a **gene**. The values that each character can have are called the **alleles**. A **population**, P, is a set of individuals.

Explanation of terms

Fitness: Fitness is the value assigned to an individual. It is based on how far or close a individual is from the solution. Greater the fitness value better the solution it contains.

Fitness function: Fitness function is a function which assigns fitness value to the individual. It is problem specific.

Breeding: Taking two fit individuals and intermingling there chromosome to create new two individuals.

Crossover: The first genetic operator, forms new elements for the population by combing parts of two elements currently in the population.

Mutation: A second genetic operator, is sparingly applied to elements chosen for elimination. Mutation can be applied by randomly flipping bits (or attribute values) within a single element.

Selection: A third genetic operator that is sometimes used. With selection, the elements deleted from the population are replaced by copies of elements that pass the fitness test with high scores.

DEFINITION 5.A **genetic algorithm (GA)** is a computational model consisting of five parts:

1. Starting set of individuals, P.
2. Crossover technique.
3. Mutation algorithm.
4. Fitness function.
5. Algorithm that applies the crossover and mutation techniques to P iteratively using the fitness function to determine the best individuals in P to keep. The algorithm replaces a predefined number of individuals from the population with each iteration and terminates when some threshold is met.

ALGORITHM 2

Input :

    P   //Initial population

Output:

    P'   //Improved population

Genetic algorithm: //Algorithm to illustrate genetic algorithm

```
repeat
N=| P |;
P'= θ;
repeat
    i1, i2 = select(P);
    o1, o2= cross(i1,i2);
    o1 = mutate(o1);
    o2 = mutate(o2);
```

until | P’ | = N;

P = P’;

until termination criteria satisfied;

Algorithm 2 outlines the steps performed by a genetic algorithm. Initially, a population of individuals, P, is created. Although different approaches can be used to perform this step, they typically are generated randomly. From this population, a new population, P’, of the same size is created. The algorithm repeatedly selects individuals from whom to create new ones. These parents,i_1,i_2, are then used to produce two offspring, o_1,o_2, using a crossover process. Then mutants may be generated. The process continues until the new population satisfies the termination condition.

We assume here that the entire population is replaced with each iteration. An alternative would be to replace the two individuals with the smallest fitness. Although this algorithm is quite general, it is representative of all genetic algorithms. There are many variations on this general theme.

Applications of GA

Typical applications of genetic algorithms include scheduling, robotics, economics, biology, and pattern recognition.

Advantages of GA

- The major advantage to the use of genetic algorithms is that they are easily parallelized.
- It can quickly scan a vast solution set. Bad proposals do not effect the end solution negatively as they are simply discarded. The inductive nature of the GA means that it doesn’t have to know any rules of the problem – it works by its own internal rules. This is very useful for complex or loosely defined problems.

Disadvantages of GA

- GAs are difficult to understand and to explain to end users.
- The abstraction of the problem and method to represent individuals quite difficult.
- Determining the best fitness function is difficult.
- Determining how to do crossover and mutation is difficult.

The K-Means Algorithm

The K-Means algorithm (Lloyd, 1982) is a simple yet effective statistical clustering technique. It is an iterative clustering algorithm in which items are moved among sets of clusters until the desired set is reached.

ALGORITHM 3

Input :

$D = \{t_1, t_2, \ldots, t_n\}$ //Set of elements

K_k //Number of desired clusters

Output :

K //Set of clusters

K-means algorithm:

assign initial values for means $m_1, m_2, \ldots, m_k$;

repeat

assign each item to the cluster which has

the closet mean; calculate

new mean for each cluster;

until convergence criteria is met;

EXAMPLE 1

Suppose that we are given the following items to cluster:

{2,4,10,12,3,20,30,11,25}

and suppose that k=2. We initially assign the means to the first two values: m_1=2 and m_2=4. Using Euclidean distance, we find that

for m_1=2	for m_2=4
2 $\rightarrow$ 0	2 $\rightarrow$ 4
4 $\rightarrow$ 4	4 $\rightarrow$ 0
10 $\rightarrow$ 64	10 $\rightarrow$ 36
12 $\rightarrow$ 100	12 $\rightarrow$ 64
3 $\rightarrow$ 1	3 $\rightarrow$ 4
20 $\rightarrow$ 324	20 $\rightarrow$ 256
30 $\rightarrow$ 784	30 $\rightarrow$ 676
11 $\rightarrow$ 81	11 $\rightarrow$ 49
25 $\rightarrow$ 529	25 $\rightarrow$ 441

So we get initially K_1={2,3} and K_2={4,10,12,20,30,11,25}. The value 3 is equally close to both means, so we arbitrarily choose K_1. Any desired assignment could be used in the case of ties. We then recalculate the means to get K_1={2,3,4} and K_2={10,12,20,30,11,25}. Continuing in this fashion, we obtain the following.

m_1	m_2	K_1	K_2
3	18	{2,3,4,10}	{12,20,30,11,25}
4.75	19.6	{2,3,4,10,11,12}	{20,30,25}
7	25	{2,3,4,10,11,12}	{20,30,25}

Note that the clusters in the last two steps are identical. This will yield identical means, and thus the means have converged. Our answer is thus $K_1=\{2,3,4,10,11,12\}$ and $K_2=\{20,30,25\}$.

The time complexity of K-means is O(tkn) where t is the number of iterations. K-means finds a local optimum and may actually miss the global optimum.

Advantages of K-means

- The K-means method is easy to understand and implement.

Disadvantages of K-means

- Although the K-means algorithm often produces good results, it is not time-efficient and does not scale well.
- The algorithm only works with real-valued data. If we have a categorical attribute in our dataset we must either discard the attribute or convert the attribute values to numeric equivalents.
- The K-means algorithm works best when the clusters that exist in the data are of approximately equal size. This being the case, if an optimal solution is represented by clusters of unequal size, the K-Means algorithm is not likely to find a best solution.
- There is no way to tell which attributes are significant in determining the formed clusters. For this reason several irrelevant attributes can cause less than optimal results.

Despite these limitations the K-Means algorithm continues to be a favorite statistical technique.

Selecting a Data Mining Technique

The following are some guidelines that are helpful for selecting an appropriate data mining technique.

- If we require that whether our performance is time (speed) specific then we can opt for decision trees and production rules. Because we know that Algorithms for building decision trees and production rules typically execute much faster than neural network or genetic learning approaches.
- If our data contain several missing values then we can opt for neural networks, because Most data mining researchers agree that, if applicable, neural networks tend to outperform other models when a wealth of noisy data are present.
- If we know which attributes best define the data to be modeled, we can opt for decision trees and certain statistical approaches, because they can determine those attributes most predictive of class membership. As Neural network, Nearest neighbor and various clustering approaches assume attributes to be of equal importance. This is a problem when several attributes not predictive of class membership are present in the data.
- Is our learning whether supervised or unsupervised?
- Is there one set of input attributes and one set of output attributes or can attributes interact with one another in several ways?
- Is the input data categorical, numerical or a combination of both?

- If learning is supervised, is there one output attribute or are there several output attributes? Are the output attribute(s) categorical or numeric?

For a particular problem, these questions have obvious answers. For example, we know neural network is a black-box structure. Therefore this technique is a poor choice if an explanation about what has been learned is required. Also, association rules are usually a best choice when attributes are allowed to play multiple roles in the data mining process.

We can also select data mining technique based on the data mining task we want to perform. In the table below data mining problem types are related to appropriate modeling techniques.

No	Data Mining Task	Data Mining Technique
1	Classification	Decision trees, Neural networks, K-nearest neighbors, Rule induction methods
2	Prediction	Neural networks, K-nearest neighbors, Regression Analysis
3	Dependency Analysis	Correlation analysis, Regression Analysis, Association rules, Bayesian networks, Inductive logic
4	Data description and summarization	Statistical techniques, OLAP
5	Segmentation or clustering	Clustering techniques, Neural Networks,

Conclusion

We have compared the four main Data Mining Techniques i.e. Decision Tree, Neural Network, Genetic Algorithms and K-Means Algorithm.

Decision trees are easy to understand, Neural Networks are difficult to explain to end users, Genetic Algorithms are difficult to understand and to explain to end users, where the K-means method is easy to understand and implement.

Decision trees are able to build models with datasets containing numerical as well as categorical data, Neural networks require input values ranging between 0 and 1 inclusive, in Genetic Algorithms values are usually numeric and may be binary strings, where as K-Means Algorithm only works with real-valued data.

Selection of Data Mining Technique depends on whether learning is supervised or unsupervised, the nature of input and output data, presence of noisy data, time issue (algorithms for building decision tree and production rules typically execute much faster than NN or GA), classification accuracy.

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DATA MINING SUPPORTED INTEGRATED INTELLIGENT ADVISORY MODEL (IIAM) FOR FINANCIAL GROWTH

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Abstract:

Integrated Intelligent Advisory Model (IIAM), recommends switching strategies based on financial market trend analysis to get maximum return on investment (ROI) in Unit Link Insurance Polices. Using IIAM, at the one end ROI improves as it avail maximum opportunity of equity return in bullish trend of financial market and at the other end it tolerate risk of equity by ensuring fixed return based on investment instruments like Debt, money market, if trend is bearish. The forecasting involves attempts to understand the emotions in the financial market by studying the financial market itself. The model works on analysis of financial market psychology and basic assumptions like history repeat itself and financial market moves in the trend. High frequency data may contain additional 'patterns', which are the result of the way that the financial market works; it has given consideration in the IIAM. The implementation of IIAM involves the integration of Expert System, Data Mining, financial econometrics and Agent Technology. Dimensional modeling powered IIAM in a way that information can be organized and enables it to easily formulate. Expert system uses the backward chaining through rule-based data mining to take decisions from its knowledge base. Finally Agent technology can make IIAM self sustainable as data mining agent functions within a data warehouse structure to discover changes in business trends of potential interest, and other agent keeps data warehouse up to date by retrieving and filtering required data, and communicate the recommendations to intended user group.

Key Words: Intelligent Agent, Data Mining, Expert System, Financial Econometrics, Multidimensional Online Analytical Processing, Data Warehouse

1. Introduction

Stock Market is the base of all equity based financial products available. Each product has its own advantages and limitations. ULIP is a combination of financial products like Insurance and Mutual Fund. The main advantage of ULIP over the other investment instrument is that it provides easy control and switching in various available categories. The categories are based on different proportion of equity and related securities, Debt, Money Market (Bond etc) and cash. The other advantage is the cheapest switching among the various categories as most of ULIP provides first 4-5 switches per year free and the additional switches can be performed at very low fixed cost irrespective the present valuation of fund. It is misconception that ULIP is not providing attractive return as equity based mutual funds because it covers Insurance too. The IIAM has proven that ULIP can give attractive return like mutual funds and even in long bearish trend it can give positive returns, if proper switching is performed at right time. IIAM generates the switching recommendations by analysing the financial market at various dimensions like Indices trend, Inflation Rate, Market breath, Volatility, FII activities etc. All these parameters can be determined if we analyse the huge data generated by stock market. Applying concepts of financial econometrics, market technical and fundamentals can perform this analysis.

The IIAM has been tested with various ULIP data available and proved that ULIP can also give good appreciation on the investment even higher than the stock market.

2. Development of Integrated Intelligent Advisory Model (IIAM)

2.1 Generating Recommendations:

The IIAM works on analysis of financial market psychology and basic assumptions like historical trends repeat itself and financial market moves in the trend i.e. the technical analysis of stock market.

The major parameter covers in IIAM are:

- Indices Trend
- Inflation Effect
- Currency Appreciation Effect
- Market Breath
- Market Turnover

- Volatility
- FII Activities
- Product Technical
- Environment Effects
- Commodity Movement etc.

R=f (IT, IE, CAE, MB, MT, V, FA, PT, EE, CM,…)

Where R is recommendation, and f is the function of financial market parameters as shown above. Recommendation is derived using financial econometrics, rules etc.

Detailed technical analysis can help in forecasting the future financial market trend by applying various basic rules like:

1. If **Indices movement=Positive and Total Turnover= High in equity**

Then Market has strength

2. If **index>=Moving average and Volatility = High**

Then Market may have weakness in short term

3. If **Indices movement < Moving Average** of Indices value

Then Market may have further weakness.

4. If **Market Breath=Negative**

Then short to medium term weakness in Market

5. If **FII invested figurer >= Moving average value**

Then Market will remain Bullish

6. The trend in Product technical repeats in historical fashion

7. If **Currency Appreciation=High**

Then overall Market will be bullish

8. If **Govt. Taxation rules relaxed for Capital Gain Tax**

Then Market will have strength

:

:

:

n. If **Market =Significant down from it's Top and Turnover trend is changing**

Then Market will bounce back

All such kind of rules are stored in set of (Fact, Production Rule) in knowledge base.

In IIAM we have given consideration to make knowledge base independent from application.

Expert system uses the backward chaining through rule-based data mining to take decisions from its knowledge base by applying rule through a state space of possibilities. Data Mining is based on rule induction and determines which part of knowledge base will be applied to generate recommendations.

2.2 Further Refinements:

We have used financial econometrics for designing hypotheses concerning the relationships between variables, examining the effect on financial market changes in economic conditions, and forecasting future values of financial variables.

The financial data used in IIAM is Panel data as it has dimensions of both Time Series Data (Data that have been collected over a period of time on one or more variables) and Cross Sectional Data (Data on one or more variables collected at a single point in time).

Volatility and correlation modeling and forecasting is determined by AutoRegressive Conditionally Heteroscedastic (ARCH) and its extensions like GARCH, GARCH-M etc.

Forecasting has also included features of some standard model of stochastic (White noise, moving average, AutoRegressive and mixed AutoRegressive moving average (ARMA))

Multivariate model characteristics are analyzed by simultaneous equation estimation techniques.

Calculating portfolio returns conducted by first estimating the value of portfolio at each time period and then determining the returns.

Over period of time, the various approaches to designing a database schema that is optimized for understanding and querying information have been consolidated into an approach called a dimensional model.

2.3 Recommendation Forecasting:

In IIAM, Backward chaining uses knowledge in the form of a set of rules, rule consequents are examined to find a rule that, when executed, will achieve a goal.

2.4 Automation and Proactive Behavior:

Agent technology can make IIAM self sustainable as data mining agents function within a data warehouse structure to discover changes in business trends of potential interest, and other agent keeps data warehouse up to date by retrieving and filtering required data, and communicate the recommendations to intended user group.

Data Warehouse Agents can perform Communications between Data Warehouse Center servers and Financial Data Source, as new information published at source the agent is supposed to retrieve the information and update the data warehouse accordingly. When the Data Warehouse Center server is asked to complete a task that requires the use of a warehouse agent, the server finds an available port on its system and then sends a message to the warehouse. Agent must perform a handshake when communicates.

Intelligent Agent system has proven its importance in Information filtering, Information Retrieval, Notifiers, Process Automation, Collaborative Customization, E-Business and OLAP applications. It enables to achieve system automation at a great extends.

2.5 Dimensional Modeling:

The information in IIAM data warehouse is organized and presented in a way that enables to easily formulate result, market query, and the answers are returned faster than if similar queries executes in conventional transaction systems. Even IIAM can immediately reformulate further related queries and get more details.

At the center of the dimensional model are the numeric measures that IIAM interested in understanding, such as ULIPID, IndexID etc. Related measures are collected into fact tables that contain columns for each of the numeric measures.

There are usually many different ways that one can look at these measures. These different ways of looking at the information are called dimensions, where a dimension is a particular area of interest. Every dimension table has a number of columns with descriptive text. These descriptive columns are known as attributes; the more interesting attributes you can make available to users, it is considered better dimensional model.

The resulting database schema consists of one central fact table, and a number of dimension tables that can be joined to this fact table to analyze them in different ways. This design is usually known as a star schema.

3. Graphs, Tables, and Photographs

Tables and Graphs:

Fig. 1: Shows the conceptual dimensional modelling used in IIAM.

Fig. 2: Shows the IIAM used for financial recommendation for ULIP switching.

Fig. 3: Shows the Result of IIAM execution

Fig 4: Result in fund value appreciation by IIAM recommendations**,** it is assumed that on 10 Apr 2006 invested amount was 100000 INR. Details of present mode and number of units for each recommendation is shown. It has assumed that all financial charges (for Maintenance, Insurance and additional switching) are negligible.

Fig 5: Shows the success rate of IIAM recommendations for tenure 10 Apr 2006 to 16 Oct 2007.

Fig 6: Shows the Comparative Return of IIAM Vs BSE

Fig 7: Shows the Comparative Return of IIAM Vs other ULIP categories

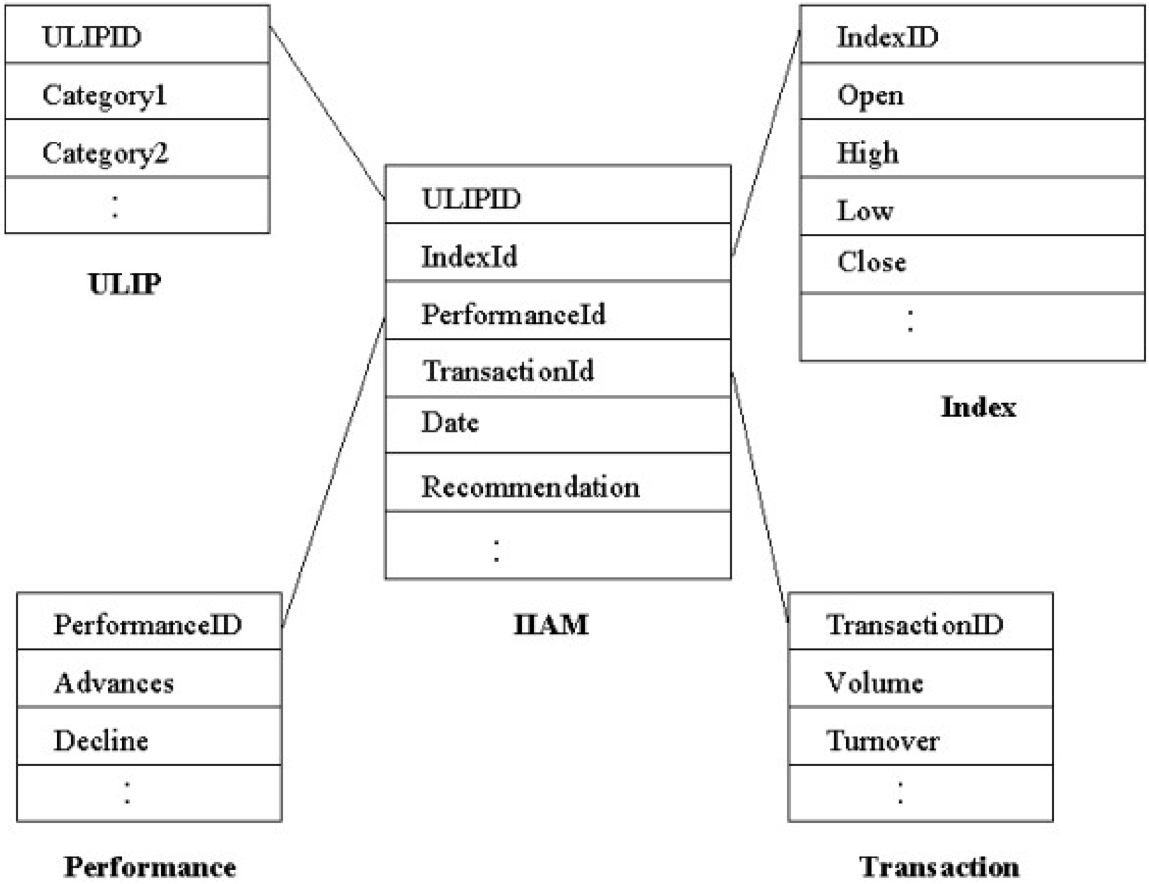

Fig: 1 Dimensional Modeling : Star Schema

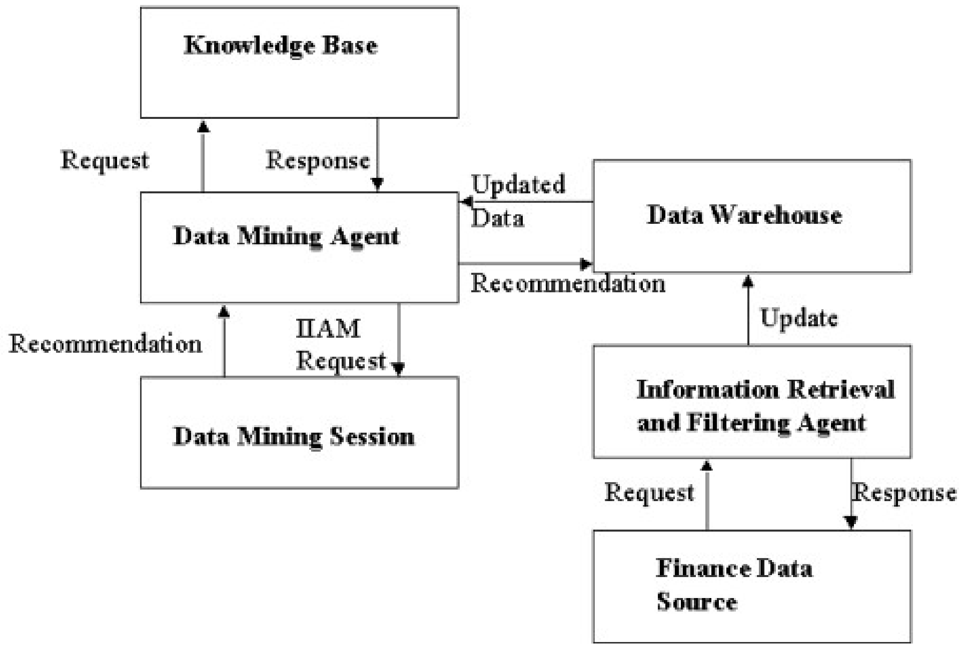

Fig-2 An Agent Based Model for Financial Recommendation

Oracle SQL*Plus

File Edit Search Options Help

UDATE	PRESERVER	PROTECTOR	BALANCER	MAXIMIZER	RESULT
16-APR-07	10.76	10.59	10.91	11.54	Maximiser
13-APR-07	10.75	10.58	10.82	11.31	Maximiser
12-APR-07	10.75	10.58	10.74	11.08	Maximiser
11-APR-07	10.75	10.58	10.77	11.15	Maximiser
10-APR-07	10.74	10.58	10.77	11.17	Maximiser
09-APR-07	10.74	10.58	10.77	11.18	Maximiser
05-APR-07	10.73	10.57	10.66	10.91	Maximiser
04-APR-07	10.73	10.56	10.63	10.83	Maximiser
03-APR-07	10.73	10.55	10.6	10.74	Maximiser
31-MAR-07	10.72	10.55	10.78	11.13	Maximiser
30-MAR-07	10.71	10.55	10.78	11.13	Maximiser
29-MAR-07	10.71	10.55	10.75	11.03	Maximiser
28-MAR-07	10.71	10.55	10.72	10.96	Maximiser
26-MAR-07	10.7	10.54	10.79	11.16	Maximiser
23-MAR-07	10.69	10.53	10.79	11.29	Maximiser
22-MAR-07	10.69	10.53	10.78	11.26	Maximiser
21-MAR-07	10.69	10.52	10.66	10.95	Maximiser
20-MAR-07	10.69	10.52	10.59	10.77	Preserver
16-MAR-07	10.68	10.51	10.49	10.52	Preserver
15-MAR-07	10.67	10.51	10.53	10.64	Preserver
14-MAR-07	10.67	10.51	10.53	10.62	Maximiser
13-MAR-07	10.67	10.51	10.64	10.93	Maximiser
12-MAR-07	10.67	10.52	10.6	10.82	Maximiser
09-MAR-07	10.66	10.5	10.63	10.8	Preserver
08-MAR-07	10.66	10.51	10.68	10.94	Preserver
07-MAR-07	10.66	10.51	10.55	10.55	Preserver
06-MAR-07	10.66	10.5	10.58	10.64	Preserver
05-MAR-07	10.65	10.5	10.49	10.4	Preserver
02-MAR-07	10.65	10.5	10.63	10.81	Preserver
01-MAR-07	10.64	10.5	10.74	11.11	Preserver
28-FEB-07	10.64	10.49	10.69	10.97	Preserver
27-FEB-07	10.64	10.5	10.83	11.4	Preserver
26-FEB-07	10.64	10.5	10.87	11.5	Preserver
23-FEB-07	10.63	10.5	10.86	11.49	Preserver
22-FEB-07	10.63	10.49	10.96	11.76	Preserver
21-FEB-07	10.63	10.5	11.02	11.93	Preserver
20-FEB-07	10.63	10.49	11.03	11.97	Maximiser
19-FEB-07	10.62	10.49	11.07	12.1	Maximiser
15-FEB-07	10.62	10.49	11.07	12.11	Preserver
14-FEB-07	10.61	10.48	10.95	11.76	Preserver
13-FEB-07	10.61	10.49	10.97	11.81	Preserver

Oracle SQL*Plus

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UDATE	PRESERVER	PROTECTOR	BALANCER	MAXIMIZER	RESULT
16-OCT-07	11.26	11.13	12.97	16.18	Maximiser
15-OCT-07	11.25	11.13	12.97	16.22	Maximiser
12-OCT-07	11.25	11.12	12.81	15.73	Maximiser
11-OCT-07	11.24	11.12	12.92	16.06	Maximiser
10-OCT-07	11.24	11.12	12.85	15.88	Maximiser
09-OCT-07	11.24	11.11	12.73	15.53	Maximiser
08-OCT-07	11.24	11.11	12.56	14.99	Maximiser
05-OCT-07	11.23	11.1	12.63	15.21	Maximiser
04-OCT-07	11.23	11.1	12.6	15.11	Maximiser
03-OCT-07	11.22	11.1	12.6	15.12	Maximiser
01-OCT-07	11.22	11.08	12.49	14.81	Maximiser
28-SEP-07	11.21	11.08	12.53	14.87	Maximiser
27-SEP-07	11.21	11.07	12.51	14.83	Maximiser
26-SEP-07	11.2	11.07	12.47	14.66	Maximiser
25-SEP-07	11.2	11.07	12.48	14.69	Maximiser
24-SEP-07	11.2	11.07	12.45	14.6	Maximiser
21-SEP-07	11.19	11.06	12.36	14.37	Maximiser
20-SEP-07	11.19	11.06	12.3	14.19	Maximiser
19-SEP-07	11.19	11.05	12.26	14.11	Maximiser
18-SEP-07	11.18	11.04	12.07	13.62	Maximiser
17-SEP-07	11.18	11.04	12.03	13.51	Maximiser
14-SEP-07	11.17	11.03	12.05	13.57	Maximiser
13-SEP-07	11.17	11.02	12.06	13.61	Maximiser
12-SEP-07	11.17	11.02	12.01	13.49	Maximiser
11-SEP-07	11.16	11.02	12.02	13.51	Maximiser
10-SEP-07	11.16	11.02	12.04	13.55	Maximiser
07-SEP-07	11.15	11	12.01	13.53	Maximiser
06-SEP-07	11.15	11	12.02	13.58	Maximiser
05-SEP-07	11.15	10.99	12	13.51	Maximiser
04-SEP-07	11.15	10.99	12.02	13.56	Maximiser
03-SEP-07	11.14	10.99	12	13.52	Maximiser
31-AUG-07	11.14	10.98	11.96	13.42	Maximiser
30-AUG-07	11.13	10.98	11.91	13.3	Maximiser
29-AUG-07	11.13	10.98	11.86	13.17	Maximiser
28-AUG-07	11.13	10.98	11.83	13.1	Maximiser
27-AUG-07	11.12	10.99	11.78	12.96	Maximiser
24-AUG-07	11.12	10.98	11.67	12.67	Preserver
23-AUG-07	11.11	10.98	11.59	12.46	Preserver
22-AUG-07	11.11	10.98	11.6	12.49	Preserver
21-AUG-07	11.11	10.97	11.52	[illegible]	Preserver

Report on Value Appreciations as per IIAM Recommendations								
Product: ICICI Prudential Life Link Super					Tenure: 10-Apr-2006 to 16-Oct-2007			
Date(DD/MM/YY)	Life Preserver III	Life Protector III	Life Balancer III	Life Maximiser III	IIAM Recommendations	Value in INR	Unit-Maximiser	Unit-Preserver
16/Oct/07	11.255	11.1327	12.97	16.18	Maximiser	206078.1263	12736.59619	0
27/Aug/07	11.1241	10.9851	11.78	12.96	Maximiser	165066.2866	12736.59619	0
06/Aug/07	11.0693	10.9824	11.8	13	Preserver	164253.1302	0	14838.61945
15/Jun/07	10.909	10.738	11.27	12.06	Maximiser	152376.3654	12634.85617	0
07/Jun/07	10.8884	10.7256	11.25	12.02	Preserver	152088.6257	0	13967.9499
21/Mar/07	10.6895	10.5243	10.66	10.95	Maximiser	138549.9543	12652.96387	0
15/Mar/07	10.6747	10.5121	10.53	10.64	Preserver	138358.1269	0	12961.31291
12/Mar/07	10.6678	10.5152	10.6	10.82	Maximiser	140698.7719	13003.58335	0
21/Feb/07	10.628	10.4953	11.02	11.93	Preserver	140146.1483	0	13189.10852
19/Feb/07	10.6239	10.4897	11.07	12.1	Maximiser	142171.2933	11749.69366	0
12/Feb/07	10.6092	10.5026	11.02	11.93	Preserver	141974.5748	0	13382.21306
26/Dec/06	10.5071	10.468	10.89	11.61	Maximiser	138166.3716	11900.63493	0
19/Dec/06	10.494	10.4641	10.8	11.32	Preserver	137994.1091	0	13149.81028
15/Dec/06	10.4846	10.4543	10.89	11.59	Maximiser	141285.488	12190.29232	0
11/Dec/06	10.477	10.4681	10.84	11.44	Preserver	141183.074	0	13475.52487
25/Jul/06	10.207	10.1705	9.72	9.08	Maximiser	112057.8944	12341.1778	0
10/Jul/06	10.1811	10.1416	9.84	9.47	Preserver	111773.5504	0	10978.53379
16/Jun/06	10.1189	10.0745	9.5	8.78	Maximiser	103629.543	11802.90923	0
12/May/06	10.0921	10.0355	10.4	11.09	Preserver	103355.0792	0	10241.18659
10/Apr/06	10.0301	9.9972	10.28	10.73	Maximiser	100000	9319.664492	0

Fig 4: Result in Value appreciation by IIAM recommendations

Success of IIAM Recommendations							
Product: ICICI Prudential Life Link Super				Tenure: 10-Apr-2006 to 16-Oct-2007			
Date	IIAM Recommendations	Fund Value in INR	Result	Date	IIAM Recommendations	Fund Value in INR	Result
10/Apr/06	Maximiser	100000		19/Feb/07	Maximiser	142171.2933	
11/May/06	Maximiser	104287.0457	Success	20/Feb/07	Maximiser	140643.8331	Failure
12/May/06	Preserver	103355.0792		21/Feb/07	Preserver	140146.1483	
15/Jun/06	Preserver	103602.9159	Success	09/Mar/07	Preserver	140605.1292	Success
16/Jun/06	Maximiser	103629.543		12/Mar/07	Maximiser	140698.7719	
07/Jul/06	Maximiser	110121.1431	Success	14/Mar/07	Maximiser	138098.0552	Failure
10/Jul/06	Preserver	111773.5504		15/Mar/07	Preserver	138358.1269	
24/Jul/06	Preserver	112039.2309	Success	20/Mar/07	Preserver	138517.551	Success
25/Jul/06	Maximiser	112057.8944		21/Mar/07	Maximiser	138549.9543	
08/Dec/06	Maximiser	145749.3098	Success	06/Jun/07	Maximiser	152974.3331	Success
11/Dec/06	Preserver	141183.074		07/Jun/07	Preserver	152088.6257	
14/Dec/06	Preserver	141257.1894	Success	14/Jun/07	Preserver	152340.0488	Success
15/Dec/06	Maximiser	141285.488		15/Jun/07	Maximiser	152376.3654	
18/Dec/06	Maximiser	141651.1968	Success	03/Aug/07	Maximiser	166148.3587	Success
19/Dec/06	Preserver	137994.1091		06/Aug/07	Preserver	164253.1302	
22/Dec/06	Preserver	138073.0079	Success	24/Aug/07	Preserver	164950.5453	Success
26/Dec/06	Maximiser	138166.3716		27/Aug/07	Maximiser	165066.2866	
09/Feb/07	Maximiser	145901.7843	Success	16/Oct/07	Maximiser	206078.1263	Success
12/Feb/07	Preserver	141974.5748					
15/Feb/07	Preserver	142061.5592	Success		Total Recommendation		19
					Success		17
					Failure		2
					Percentage Success		89.47368421

Fig 5: Success Rate of IIAM recommendations

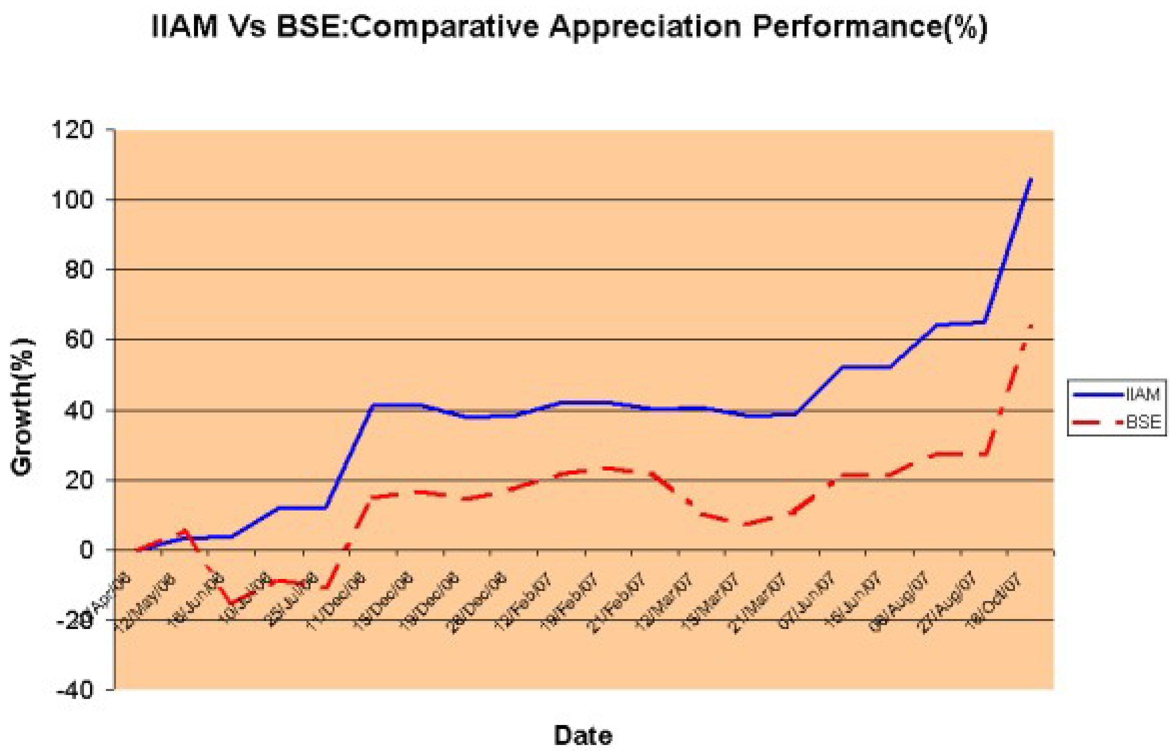

Fig 6: Comparative Return of IIAM Vs BSE

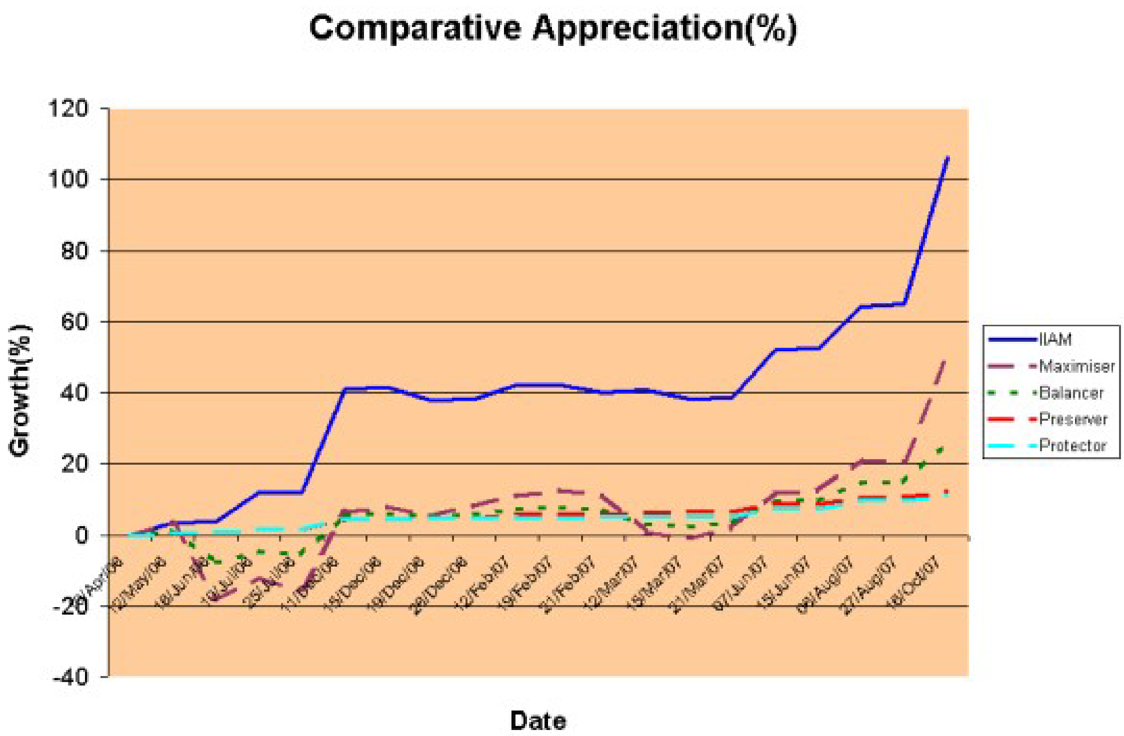

Fig 7: Comparative Return of IIAM Vs other ULIP Categories

4. Conclusions:

Using IIAM recommendation we can maximize the profit as it picks maximum financial market opportunity in bullish trend and tolerate risk of financial market by ensuring fixed return based on Debt, money market in bearish trend.

IIAM performs technical analysis successfully so it can be used for index future trading too.

The superiority of IIAM can be verified from the benchmark return of all ULIP categories over a period of approximate 18 months. The percentage return from IIAM is more than 100 %, while next highest return of BSE index is about 63% for the same tenure. Switch accuracy of IIAM is about 90%, which shows the strength of IIAM.

In other ULIP product also the return is almost comparable with the result shown in paper.

As ULIP is relatively new product and limited data are available, still IIAM has to prove in future with new changing trend in financial market.

As it has tested with ULIP data available for India only, and past long term trend is bullish only, it has to test for long-term bearish trend too.

If financial market contains high volatility for long term and does not indicate any clear-cut trend, the number of recommendation will increase and performance may reduce significantly.

We can improve existing algorithm by applying back propagation neural networks, as it can be better at handling noisy data.

5. Acknowledgements

The authors would like to thank the referees for some very helpful comments on the original version of the manuscript.

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DERIVING BUSINESS INTELLIGENCE THROUGH COLLABORATIVE COOPERATIVE MULTI AGENT MODEL FOR MUTUAL FUND ASSET ALLOCATION

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ABSTRACT:

Intelligent technologies became strengthens as a result of advancement in processing power, connectivity and data management techniques. Business Intelligence exploits high-level software intelligence for business applications. This research paper is an attempt to derive Business Intelligence along with Multi agent technology in asset allocation for mutual fund portfolio management. Business Intelligence facilitates us to use of high-level software intelligence for assistance in complex decision of asset allocation. At the same time use of Agent technology is very good candidate when we wish to automate different essential business process using intelligent techniques. Agent Technology empowers the business intelligences through atomicity, proactive, reactive intelligence characteristics along with automation. The model proposed in the paper is based on data

driven automated market analysis activities and disproves the Random walk hypothesis and efficient market hypothesis. Collaborative intelligent agent based model suggest asset allocation for fund portfolio by considering the different parameters like market trend, market volatility, turnover, market breath etc., and as a result it normally beats the benchmark indices. This model can be enhance business intelligence to make different finance decisions Stock & Equity management, Prediction of commodity prices, Cash flow management etc, which finally minimize the risk and maximize the returns in a longer run. We have tested the model for approximately 3years with live market data, and return from recommended fund allocation strategy is compared with BSE-30 Sensex return for the same period.

KEYWORDS: Intelligent Agent, ROI, Data Mining, Financial Econometrics, Data Mart

1. INTRODUCTION:

1.1 Business Intelligence: Business Intelligence uses the software intelligence for business applications in the right direction. Software intelligence achieved by using intelligent technologies (like Data mining, Agent Technology etc.) Processing power, and connectivity available to interact with environment. The acceleration in development of e-commerce application will create opportunities for business intelligence in future.

Definition of Business Intelligence: *Business intelligence (BI) is a broad category of applications and technologies for gathering, storing, analysing, and providing access to data to help enterprise users make better business decisions. BI applications include the activities of decision support systems, query and reporting, online analytical processing (OLAP), statistical analysis, forecasting, and data mining." (WHATIS.COM, 2001)*

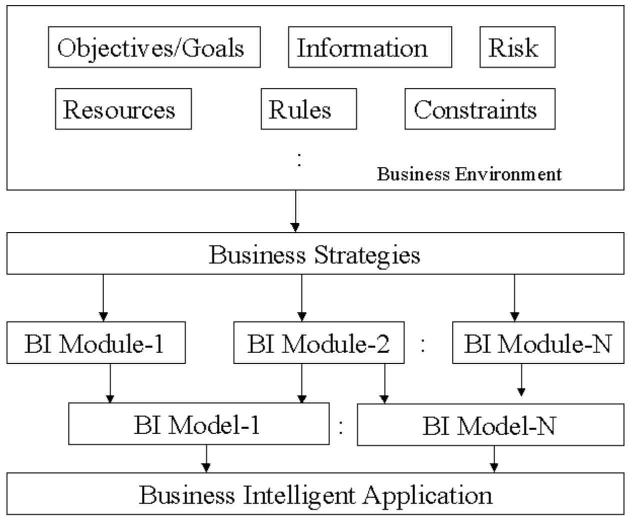


Figure: Business Intelligence Application Architecture

Business Intelligence applications are based on Business Intelligence Models. These models are created by number of business intelligence software modules; these software modules incorporated the BI strategies in order to develop intelligence. Business Intelligence applications utilized this knowledge or information properly in the right direction so organization enhances the profitability.

Business Intelligence is *the use of high-level software intelligence for business applications*. More specifically, business intelligence can be defined by the collection of progressive technologies that help to make systems more intelligent. This includes:

- Representation, communication, execution and retrieval of business policies, rules, and processes
- Data mining and visualization
- Machine learning and knowledge discovery
- Competitive intelligence/analysis
- Dynamic pricing
- Agents and the Semantic Web
- Recommendation and reputation systems

Automated contracting, brokering, and negotiation

Business intelligence in financial system the model helps to removing uncertainties, calculating and managing risks and optimizes the returns on investment.

1.2 Agent Technology:

The new developments in learning models are based on agent theory. Where, Agent can be defined to be autonomous, problem solving computational entities capable of effective operation in dynamic and open environments.

Software agents are persistent computations that include percepts, reasoning, action, and communication [Russell & Norvig, 1995]

Agents are autonomous in the sense that they perform their tasks regardless of whether they are required or not. Intelligent agents are computational systems that inhabit in a complex dynamic environment and they can act autonomously and have the capacity to reason by themselves in this environment. This environment can be the network, and the intelligent agent can be seen as a software entity that assist people and gathers information or perform some other services without the immediate presence of a human being.

An intelligent agent could be characterized by the following attributes: autonomy, Reactivity, pro-activity and social ability

An intelligent agent attributes:

Autonomy: This attribute is one of the most important characteristics that allow us to distinguish the intelligent agents from other type of software. When we say that an agent must have autonomy, we are talking about the capacity of reacting by themselves in an environment using their experience. This means; the capacity of observation and operation without the direct intervention of human beings or other agent.

Reactivity: Is the capacity that the agents have to perceive their environment and act depending of the changes that occur in it, in a correct and fast way. Internet can also be one environment where intelligent agents can interact.

Pro-activity: As we had seen before, the agents can react to an environment, but they also have the ability of obtain a goal by taking the initiative. They have a goal-directed behavior without external influences (they are self-sufficient).

Social ability: Sometimes more than one agent is needed to make a task or solve some problems. The social ability is the capacity that one agent have to interact with other agents (or humans), by using some "agent language", for the possibility to cooperate or negotiate.

1.3 Market Hypothesis:

The Efficient Market Hypothesis (EMH) given by Fama 81(1965-1970) was most accepted in the financial community (Malkiel82 1987, Tisibouris & Zeidenberg83 1995). According to EMH, The all traders are using efficiently the information available and all news is promptly incorporated in prices in very short period of time. As it is not possible to predict news by nature, the past prices cannot help in forecasting future price changes (Malkiel11, 1989). According to EMH the best prediction for a price is the current price and the actual prices follow is called a random walk as new information occurs randomly. Thus, investors cannot devise an investment strategy to yield abnormal profits on the basis of an analysis of past price patterns.

[81] Fama, Eugene (1970), 'Efficient Capital Markets: A Review of Theory and Empirical Work', Journal of Finance, 25, 383-417.
[82] Malkiel, B. G. (1996), '*A Random Walk Down Wall Street*', New York
[83] Tsibouris, G. & Zeidenberg, M. (1995). 'Testing the efficient markets hypothesis with gradient descent algorithms'.

1.4 Model Introduction:

Distributed co-operative multi agent-learning model in the area of Business Intelligence helps to achieve business intelligence in term of maximizing profit and speed-up the finance decisions. The model acts as a true advisor, which suggests how to manage financial assets and liabilities in a best possible way. The finance management is basic need of all human being. Lot of hypothesis is given to understand the market movement like Random walk hypothesis and efficient market hypothesis. Still it is a great challenge to predict the market. Since 1993, the disciplines like Computational Economics and Computational Finance attract the researchers and occupy their place in field of Artificial Intelligence, Finance Modeling and related research areas. The high-speed computers along with intelligent techniques like Expert Systems, Artificial Neural Networks, and Evolutionary Algorithms make it possible to achieve new milestones. As these methods are utilizing thoughts and reasoning; they have proven far better as compare to traditional statistical and engineering methods. There are so many products available in finance market based on different requirement (need and liquidity), risk and return scenarios.

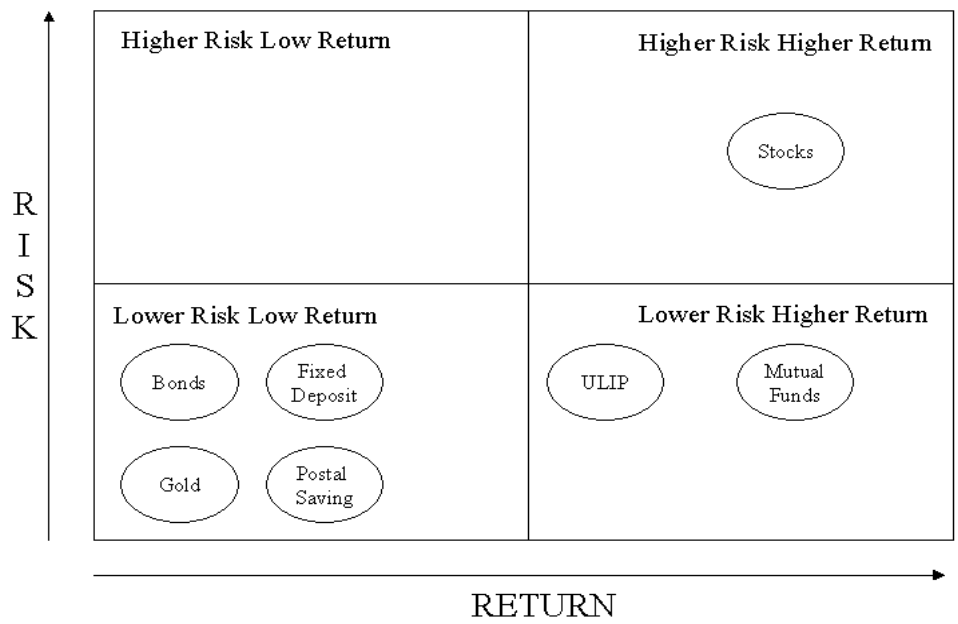
Our model presented in the paper is confined to use Business Intelligence using cooperative multi agent model for the asset allocation decision based on market movement in the financial product mutual fund.

We have selected Distributed Co-Operative Multi Agent System for modeling purposes. As it fulfillment of requirement of software with time, technology, User friendly as well as programmer friendly, reusability and supports higher granularity in software development process. The evaluation and invention of the Agent Oriented methodologies is opted as it can better handle application and it's environment issues like heterogeneity, heave interaction, complexity, Distribution ability, openness, dynamics and unpredictability.

Multi Agent Systems helps BI applications require complex and sheer volumes of data need to be collecting from multiple, disparate sources, Validating and qualifying the results for accuracy, and performance Improvement Business analytics tools like Traditional query and reporting, OLAP, and Data mining is usable but for effective real time BI solutions include the ability to push information to users.

Mutual Fund is a financial Product, which is categorized as a low risk high return asset. The management of mutual fund is in the hands of experienced and knowledgeable fund managers.

Risk Return Matrix



There are various types of mutual fund available. Each one has some special characteristics particularly in assets in their portfolio.

In our model we have opted equity index growth kind of equity fund with the objective to seek long-term capital appraisal.

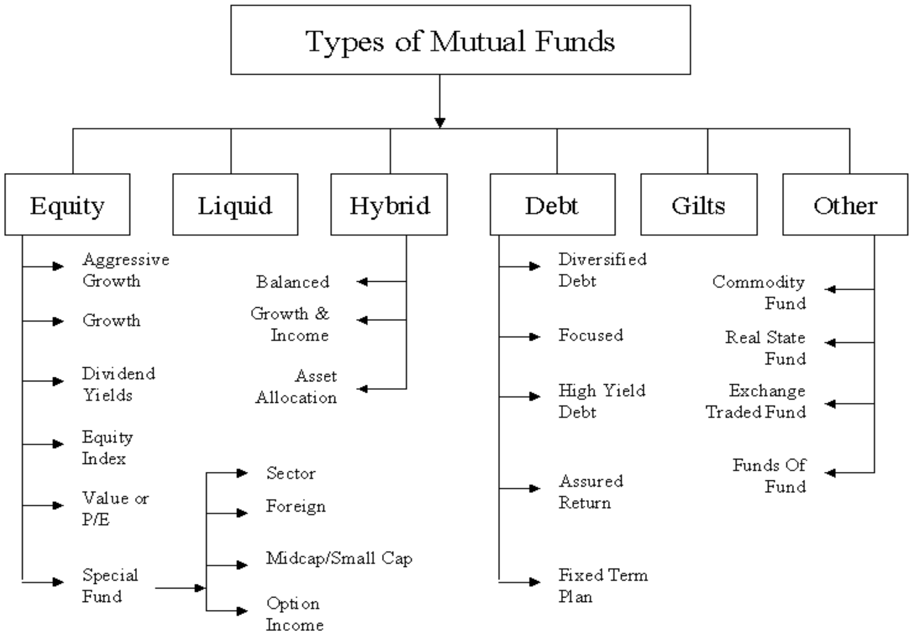


Figure: Types of Mutual Fund

Our model generates the asset allocation recommendations by analyzing the financial market at various dimensions like Indices trend, Inflation Rate, Market breath, Volatility, Market turnover, Currency exchange trend etc. All these parameters determined by analyze the huge finance and economy data generated over different periods. Applying concepts of financial econometrics, market technical and fundamentals can perform this analysis.

Multi Agent Systems helps BI applications require complex and sheer volumes of data need to be collecting from multiple, disparate sources, Validating and qualifying the results for accuracy, and performance Improvement Business analytics tools like Traditional query and reporting, OLAP, and Data mining is usable but for effective real time BI solutions include the ability to push information to users. Multi Agent Systems set critical thresholds or triggers and launch a result, report, or note is essential to BI today.

2. DEVELOPMENT OF ASSET ALLOCATION MODEL FOR MUTUAL FUND PORTFOLIO:

We are proposing a Multi agent cooperative model to perform the asset allocation, to automate one of the most tedious activities of fund management. We have Multiple Agent allocated their dedicate role like Data Gathering, Knowledge Discovery, and fund operation. Different agents collaboratively perform their functions and then finally settle on the asset allocation activity.

Benchmark Data Fetcher gathers the required index data stream and store in to Finance Data Mart. Different knowledge discovery agents' process on this stream and generate the knowledge about market movement, Fund allocation agent using data mining techniques collectively process this knowledge and try to estimate future trend of market with the derived knowledge and suggests asset allocation for the fund. Presently our model is allocating fund either in index fund or equity arbitrage fund. Based on different market movement estimation model select a particular fund for allocating asset, like index fund allocation is chosen, if market movement is estimated positive in near future term, otherwise fund allocation is shifted in to equity arbitrage fund.

The Table 1: Characteristics for Bull and Bear Market shows some of the basic rule to determine trend of market, which has given consideration in the model.

We have taken BSE-30 as a benchmark index for index fund allocation, and Kodak Equity Arbitrage fund for arbitrage allocation. The reason to select this fund is fund age as only this equity arbitrage fund is 3 years older and actual NAV of this fund can be taken as a base to calculate NAV of the Fund for our model. The estimate about the market movement helps to protect loss in sharp downside movement, while offer the opportunity to take full benefit of equity in upward movement.

Automation and Proactive Behavior:

Agent technology can make model self sustainable as data mining agents function within a data warehouse structure to discover changes in business trends of potential interest, and other agent keeps data warehouse up to date by retrieving and filtering required data. Intelligent Agent system has proven its importance in Information filtering, Information Retrieval, Notifiers, Process Automation, Collaborative Customization, E-Business and OLAP applications. It enables to achieve system automation at a great extends.

Salient Features taken care in the model

- Benchmark index values and turnover will be base to calculate trend of market. It is classified in to different categories like Instantaneous term, Short bullish term, Medium bullish term, Long bullish Term, Short bearish term, Medium bearish term, long bearish term etc. For example 3 days moving averages are base for Instantaneous term, 50 Days moving average consider as a base to determine short term trend, 100 days moving average is consider as a base to determine Medium term trend, and 200 Days moving average is considered as a base to determine Long term trend.
- Volatility of market has taken in account by GARCH (Generalized Autoregressive Conditionally Heteroscedastic) Model developed by Bollerslev and Taylor(1986)
- In all bullish trends up to most of asset value will be allocated in equity instrument.
- In transition from Long Bearish to Short Bullish, Short Bullish to Medium Bullish, Medium Bullish to long Bullish trend allocation from equity to debt or cash is performed.

- In transition from Long Bullish to Short Bearish trend allocation from cash to equity is performed, In transition from Short Bearish to Medium Bearish trend allocation from equity to cash is performed, and In transition from Medium bearish to long Bearish trend allocation from equity is shifted in debt or cash instruments until the transition period is over.
- Instantaneous tread transition with large turnover with global or fundamental change must be consider as it may cause reverse of trend in longer run too.
- The data used in model are real and model performance is based on the accuracy of market estimation by analyzing future trend.
- Agent Technology empowered autonomy, proactive, reactive, and social ability to the model.
- Expected ROI is based on future profit of the benchmark companies, Market Risk is a function of various parameters like Inflation, local/Global demand supply, Global Parameters like Crude price. The following table shows impact of Expected ROI and Risk on Price movement. The effect is shown in Table: 2

3. TABLES:

Table 1: Characteristics for Bull and Bear Market

Table 2: Impact of Expected ROI and Risk on Price movement

Parameter	**Bull Market**	**Bear Market**
Moving Average	Bar Graph of Daily Prices are above 200 Days Moving Average	Bar Graph of Daily Prices are below 200 Days Moving Average
Interest Rates	Interest Rates are Steady or Decline	Interest Rates are increasing
Inflation	Inflation Rates are Steady or Decline	Inflation Rates are Rising

Earnings	Earning Reports shows gain in profit compared to past results	Earning Reports shows decline in profit compared to past results
Advance/ Decline	Advanced/Decline Ration Constantly Rising (More Gainer than losers)	Advanced/Decline Ration Constantly falling (More losers than Gainer)
Closing Trend	Market Closing is towards the high of the day	Market Closing is towards the low of the day
Turnover	Strong Volume on the up days, and rallies for several days in row	Weak volume on the up days, and rallies fails due to the selling pressure
Trend line	Trend Line is clearly positive	Trend Line is clearly negative
Sentiment	Fear or pessimisms Exist	Greed or Optimisms Exists

TABLE 1: CHARACTERISTICS FOR BULL AND BEAR MARKET

<table>
<tr><th colspan="2">Expected ROI</th><th>Risk</th><th>Price Change</th></tr>
<tr><td colspan="2">Increase</td><td>Unchanged</td><td>Increase</td></tr>
<tr><td colspan="2">Increase</td><td>Decrease</td><td>Increase Significantly</td></tr>
<tr><td colspan="2">Unchanged</td><td>Decrease</td><td>Increase</td></tr>
<tr><td colspan="2">Unchanged</td><td>Increase</td><td>Decrease</td></tr>
<tr><td colspan="2">Unchanged</td><td>Unchanged</td><td>Unchanged</td></tr>
<tr><td colspan="2">Decrease</td><td>Unchanged</td><td>Decrease</td></tr>
<tr><td colspan="2">Decrease</td><td>Increase</td><td>Decrease Significantly</td></tr>
<tr><td rowspan="3">Increase Compared to Risk</td><td>Increase Greater than</td><td>Increase</td><td>Increase</td></tr>
<tr><td>Increase less then</td><td>Increase</td><td>Increase Significantly</td></tr>
<tr><td>Increase equal to</td><td>Increase</td><td>Unchanged</td></tr>
<tr><td rowspan="3">Decrease Compared to Risk</td><td>Decrease Greater than</td><td>Decrease</td><td>Decrease</td></tr>
<tr><td>Decrease less then</td><td>Decrease</td><td>Increase</td></tr>
<tr><td>Decrease equal to</td><td>Decrease</td><td>Unchanged</td></tr>
</table>

TABLE 2: IMPACT OF EXPECTED ROI AND RISK ON PRICE MOVEMENT

4. FIGURES AND DATA

Fig. 1: Collaborative Multi Agent Model for Fund Allocation

Fig. 2: Shows the sample statistics generated by model.

Fig. 3: Fund Performance Comparison At Regular Interval

Fig. 4: Shows the Performance Comparison with benchmark.

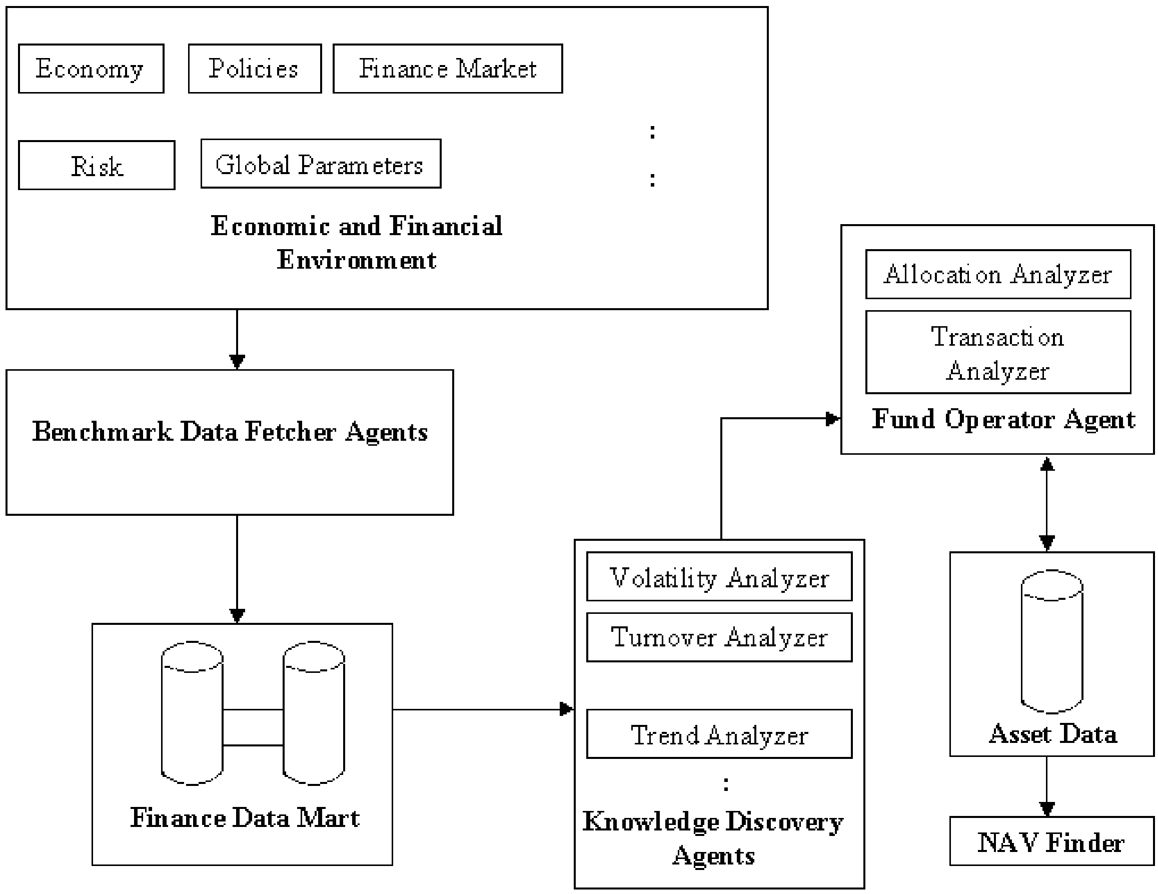


FIGURE.1 COLLABORATIVE MULTI AGENT MODEL FOR FUND ALLOCATION

FIGURE 2: SAMPLE STATISTICAL DATA OF FUND

Date	Arbitrage NAV	Allocation Mode	Volatility	Turnover	Short Trend	Medium Trend	Index	Breath	Breath Avg	Fund NAV
30-06-2006		Index	0.3012	47.3333	1.5034	0.9886	10609.25	0.6272	0.0888	10.00
03-07-2006		Index	0.1319	-30.0000	1.8436	0.7390	10695.26	-0.0325	0.1963	10.08
04-07-2006		Index	0.1436	-70.6667	1.6338	0.6067	10662.22	-0.2396	0.1183	10.05
05-07-2006		Index	0.3093	20.6667	0.9720	0.9856	10919.64	0.1598	-0.0375	10.29
06-07-2006		Index	0.1260	1.3333	0.2388	0.6579	10767.97	-0.3402	-0.1400	10.15
07-07-2006		Index	0.4140	63.3333	-0.4582	0.2263	10509.53	-0.6302	-0.2702	9.91
10-07-2006		Index	0.2318	-86.0000	-0.7087	0.2665	10684.3	-0.1302	-0.3669	10.07
11-07-2006		Index	0.1242	-38.0000	-0.4639	0.5209	10614.35	-0.1213	-0.2939	10.01
12-07-2006		Index	0.3676	46.0000	1.3276	0.6927	10930.09	-0.0148	-0.0888	10.30
13-07-2006		Index	0.1146	20.0000	0.3966	0.6091	10806.55	-0.0858	-0.0740	10.19
14-07-2006		Index	0.2033	-12.6667	0.2190	0.4720	10678.22	-0.3018	-0.1341	10.07
17-07-2006		Index	0.3613	-50.6667	-1.9744	-0.2558	10293.22	-0.6746	-0.3540	9.70
18-07-2006	10.59	Arbitrage	0.2482	-0.6667	-1.8128	-0.3881	10226.78	-0.6391	-0.5385	9.64
19-07-2006	10.59	Arbitrage	0.4200	48.0000	-2.1322	-0.5551	10007.34	-0.8018	-0.7051	9.64
20-07-2006	10.5945	Arbitrage	0.1799	28.0000	0.2208	-0.4606	10352.94	0.3284	-0.3708	9.64
21-07-2006	10.5954	Arbitrage	0.2913	2.6667	-0.4238	-0.5689	10085.91	-0.7426	-0.4053	9.64
24-07-2006	10.5994	Arbitrage	0.3758	-30.6667	0.7193	-0.2340	10215.37	-0.2781	-0.2308	9.65
25-07-2006	10.60	Index	0.1152	-40.0000	0.2215	-0.2070	10415.61	0.4793	-0.1805	9.65
26-07-2006		Index	0.2732	-10.6667	1.7266	0.0286	10617.27	0.5414	0.2475	9.83
27-07-2006		Index	0.1621	12.6667	1.6891	-0.1354	10741.59	0.1716	0.3974	9.95
28-07-2006		Index	0.1704	14.0000	0.8453	-0.0846	10680.23	0.0976	0.2702	9.89
31-07-2006		Index	0.1335	-26.6667	0.3985	0.0776	10743.88	-0.1124	0.0523	9.95
01-08-2006		Index	0.1218	-40.6667	0.0625	0.4201	10761.36	-0.2485	-0.0878	9.97
02-08-2006		Index	0.1500	4.0000	0.6086	0.5758	10876.19	0.3964	0.0118	10.07
03-08-2006		Index	0.1881	32.0000	0.5539	0.8101	10923.16	0.2012	0.1164	10.12
04-08-2006		Index	0.2094	4.6667	0.3268	0.4490	10866.51	-0.3136	0.0947	10.06
07-08-2006		Index	0.0000	-57.3333	-0.1942	0.6384	10812.64	-0.2071	-0.1065	10.01
08-08-2006		Index	0.1739	-24.6667	0.2856	0.6919	11014.97	0.4083	-0.0375	10.20
09-08-2006		Index	0.2218	25.3333	0.8525	0.6211	11145.18	0.3373	0.1795	10.32
10-08-2006		Index	0.1443	8.6667	1.0297	0.4484	11149.17	0.3107	0.3521	10.33
11-08-2006		Index	0.1537	18.6667	0.5354	0.3772	11192.46	0.3994	0.3491	10.37
14-08-2006		Index	0.0966	-46.6667	0.5003	0.5270	11312.99	0.4083	0.3728	10.48
16-08-2006		Index	0.1088	-9.3333	0.8871	0.5816	11448.31	0.4231	0.4103	10.60
17-08-2006		Index	0.1497	41.3333	0.8426	0.5900	11477.48	-0.4704	0.1203	10.63
18-08-2006		Index	0.0861	-14.6667	0.4495	0.4837	11465.72	0.0148	-0.0108	10.62
21-08-2006		Index	0.1355	-55.3333	0.1844	0.4808	11511.68	0.1538	-0.1006	10.66
22-08-2006		Index	0.1376	-29.3333	0.0732	0.5208	11502.62	-0.0533	0.0385	10.65
23-08-2006		Index	0.1176	6.0000	-0.1707	0.4901	11406.65	-0.4497	-0.1164	10.56
24-08-2006		Index	0.2372	34.6667	0.0618	0.4198	11531.95	0.0473	-0.1519	10.68
25-08-2006		Index	0.0770	33.3333	0.2044	0.3441	11572.2	0.1775	-0.0750	10.72
28-08-2006		Index	0.0699	-60.6667	0.6188	0.3780	11619.52	0.1775	0.1341	10.76
29-08-2006		Index	0.0754	20.6667	0.5032	0.4110	11706.85	-0.1302	0.0750	10.84
30-08-2006		Index	0.0960	-12.6667	0.4354	0.3264	11723.92	-0.3462	-0.0996	10.86
31-08-2006		Index	0.1015	39.3333	0.2284	0.1983	11699.05	-0.5237	-0.3333	10.84
01-09-2006		Index	0.1103	-35.3333	0.2029	0.2365	11778.02	0.1331	-0.2456	10.91
04-09-2006		Index	0.0977	-36.6667	0.5397	0.3510	11914.21	0.3669	-0.0079	11.03

Fund Performance Comparison at 6 Month Interval							
Sr. No	Period	Index-Start	Index-End	Index Gain	NAV-Start	NAV-End	Gain(%)
1	July-Dec 2006	10695.26	13786.91	28.91	10.00	12.54	26.95
2	Jan-June 2007	13786.91	14650.51	6.26	12.54	14.40	12.31
3	July-Dec 2007	14650.51	20286.99	38.47	14.40	20.47	40.76
4	Jan-June 2008	20286.99	13461.6	-33.64	20.47	16.70	-19.80
5	July-Oct 2008	13461.6	8509	-36.79	16.70	16.89	-0.62
	Total	**10695.26**	**8509**	**-20.44**	**10.00**	**16.89**	**68.93**

FIGURE 3: FUND PERFORMANCE COMPARISON AT REGULAR INTERVAL

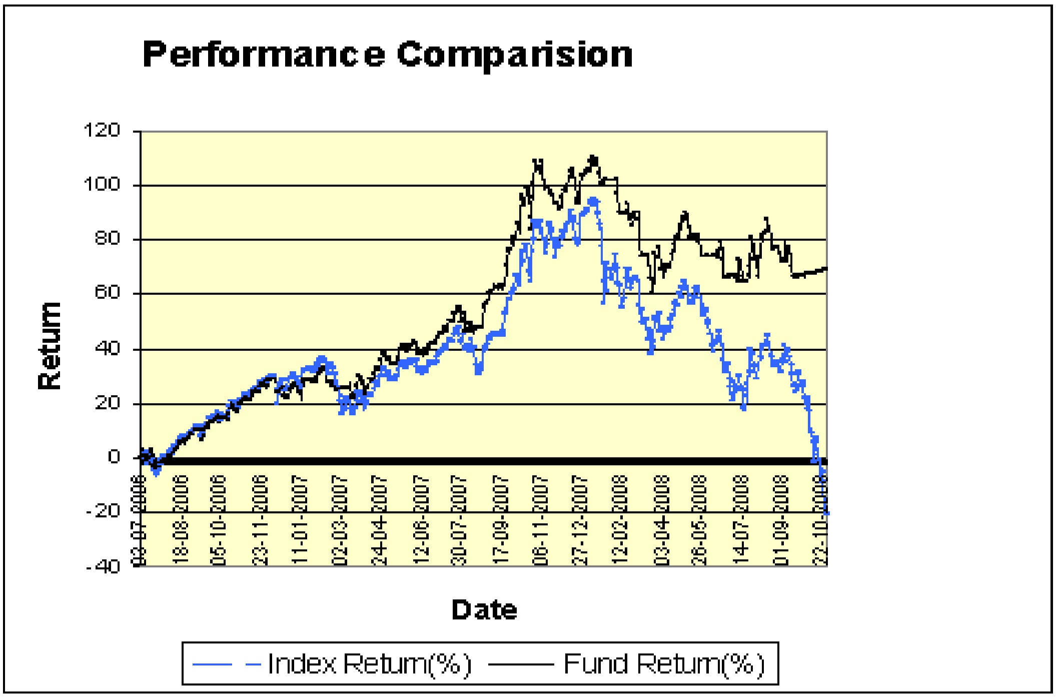


FIG. 4: SHOWS THE PERFORMANCE COMPARISON WITH BENCHMARK

5. CONCLUSION:

Using Model Asset allocation we have checked the performance for 2.5 Years real data and it has proven usefulness. This period contains almost all type of cycles of stock market e.g. Bullish Trend, Bearish

Trend, Volatility etc. The prepared model has proven its usefulness by maximize the profit as it picks maximum financial market opportunity in bullish trend and tolerate risk of financial market by ensuring fixed return based on Debt, money market in bearish trend. Model has performed technical analysis which make decision successfully most of the time hence disproves the efficient market hypothesis. The superiority of model can be verified from the benchmark return for experimental duration. The percentage return generated by model asset allocation is very exciting. We can strengthens the model by implementing the supporting activity for its commercial use like

- Maintaining and running unlimited number of funds
- Support for investment plans and structured products
- Investment limitations calculation, applied to asset components.
- Assets and expenses valuation through various methods
- Reporting regarding the net asset value, portfolio composition, unit value, number of units in circulation, other reports required by government institutions (security commission, central bank, etc.)
- Automated bookkeeping and financial reporting
- Automated communication with fund members (web, e-mail, IVR, SMS)
- Compliance with local legislative and regulations
- Integrated authorization system

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