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Customer behaviour analytics and data mining

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Abstract

Customer behavior analytics is based on consumer buying behavior, with the customer playing the roles of user, payer and buyer. The concern of many organizations is no longer on the individual buyer but rather on collective or organizational buying behavior which help in determining which customers are worth developing and managing by putting unique strategies in place in order to attract specific customers. Through analysis of customers' behavior, accurate profiles are being generated by specifying needs and interest and allowing business to give customers what they want it, when they want, leading to a better customer satisfaction thereby keeping them to come back for more. While large-scale information technology has been evolving separate transaction and analytical systems, data mining provides the link between the two. Data mining software analyzes relationships and patterns in stored transaction data based on open-ended user queries. Considering previous studies authors' finds out the scope to go for research in market basket analysis using three different algorithms namely Association Rule Mining, Rule Induction Technique and Apriori Algorithm. Authors will make a comparative study of three techniques and adopt the best conclusion.

1. Introduction

In well-run small business organizations, learning relationships with customers is formed naturally; the organizations learn their customer's behavior through personal relationships with each of them. They learn more and more about their customers over time and then use the knowledge to serve them better, as a result of this, customers are loyal to the organizations and the business profit increases. Larger companies with hundreds and thousands or millions of customers do not enjoy this luxury of having personal relationships with each customer, these large organizations must rely on other means of learning customer behavior that will help them predict correctly what customers like, such as, their needs. Evaluating the performance of any organization is an essential part for overcoming this weaknesses.

Customers who visit sites leave behind valuable information about their behavior, customer behavior analysis aims to improve business performance through an understanding for past and present customers so as to determine and identify future customers and their behavior. These organizations also must learn to take advantage of what they have in abundance which is the customer's data that is produced at almost every phase of interaction with these customers. Successful companies need to react to each and every one of these demands in a timely fashion. The market will not wait for your response, and customers that you have today could vanish tomorrow.

Interacting with your customers is also not as simple as it has been in the past. Customers and prospective customers want to interact on their terms, meaning that you need to look at multiple criteria when evaluating how to proceed. You will need to automate:

- The Right Offer
- To the Right Person
- At the Right Time
- Through the Right Channel

The right offer means managing multiple interactions with your customers, prioritizing what the offers will be while making sure that irrelevant offers are minimized. The right person means that not all customers are cut from the same cloth. Your interactions with them need to move toward highly segmented marketing campaigns that target individual wants and needs. The right time is a result of the fact that interactions with customers now happen on a continuous basis. This is significantly different from the past, when quarterly mailings were cutting-edge marketing. Finally, the right channel means that you can interact with your customers in a variety of ways (direct mail, email, telemarketing, etc.). You need to make sure that you are choosing the most effective medium for a particular interaction (Thearling, 2002).It is essential to explore the data base so as to understand the historic behavior and predict the likelihood in the future in order meet the needs and desires of potential customer. The data collected could be of little or no use without intelligence. Intelligence allows us to comb through the memory of data, noticing patterns, devising rules, coming up with ideas, figuring out the right questions and also rightly predicting the future. The tools that add intelligence to the mountain of data and also the techniques that help to exploit the large amount of data generated by interaction with customers and prospect in other to know them better is called Data Mining.

Data mining is the collection of tools and techniques; also one of the several technologies that are required to support customer-centric firms and the E-commerce world is not an exception.

Data mining is also a powerful new technology with great potential to help companies focus on the most important information in the data they have collected about the behavior of their customers and potential customers. It discovers information within the data that queries and reports cannot effectively reveal. It automates the detection of relevant patterns in a database. For example, a pattern might indicate that married males with children are twice more likely to drive a particular sport car than married males with no children. For a marketing manager of an auto mobile industry, this is somewhat surprising pattern might be valuable (Thearling, 2002).

2. Related Works

Leonid Churilov, Adyl Bagirov, Daniel Schwartz, Kate Smith and Michael Dally had already studied about combined use of self organizing maps & non-smooth, non-convex optimization techniques in order to produce a working case of a data driven risk classification system. The optimization approach strengthens the validity of self organizing map results. This study is applied to cancer patients. Cancer patients are partitioned into homogenous groups to support future clinical treatment decisions.

Most of the different approaches to the problem of clustering analysis are mainly based on statistical, neural network, machine learning techniques. Bagirov et al. propose the global optimization approach to clustering and demonstrate how the supervised data classification problem can be solved via clustering. The objective function in this problem is both non-smooth and non-convex and has a large number of local minimizers. Due to a large number of variables and the complexity of the objective function, general purpose global optimization techniques, as a rule fail to solve such problem. It is very important therefore, to develop optimization algorithm that allow the decision maker to find “deep” local minimizers of the objective function. Such deep minimizers provide a good enough description of the data set under consideration as far as clustering is concerned. Some automated rule generation methods such as classification and regression trees are available to find rules describing different subsets of the data. When the data sample size is limited, such approaches tend to find very accurate rules that apply to only a small number of patients. In the work of Schwarz et al. they demonstrated that data mining techniques can play an important role in rule refinement even if the sample size is limited. For that at first stage methodology is used for exploring and identifying inconsistencies in the existing rules, rather than generating a completely new set of rules. K-mean algorithm lies in the improved visualization capabilities resulting from the two dimensional map of the cluster. Kohonen developed self organizing maps as a way of automatically detecting strong features in large data sets. Self organizing map finds a mapping from the high dimensional input space to low dimensional feature space, so the clusters that form become visible in this reduced dimension ability. The software used to generate the self-organizing maps is Viscovery SOMine (www.eudaptics.com), which provides a colorful cluster visualization tool, & the ability to inspect the distribution of different variables across the map. The subject of cluster analysis is the unsupervised classification of data & discovery of relationship within the data set without any guidance. The basic principle of identifying this hidden relationship is that if input patterns are similar, they should be grouped together. Two inputs are regarded as similar if the distance between these two inputs is small. This study demonstrates that data mining techniques can play an important role in rule refinement, even if the sample size is limited. Leonid Churilov, Adyl Bagirov, Daniel Schwartz, Kate Smith and Michael Dally demonstrated that both self organizing maps & optimization based clustering algorithms can be used to explore existing classification rules, developed by experts and identify inconsistencies with a patient database. As the proposed optimization algorithm calculate clusters step by step and the form of the objective function allow the user to significantly reduce the number of instances in a data set. A rule based classification system is important for the clinicians to feel comfortable with the decision. Decision tree can be used to generate data driven rules but for small sample size these rules tend to describe outliers that do not necessarily generalize to larger data sets.

Anthony D Anna & Oscar H. Gandy develop a more comprehensive understanding of data mining by examining the application of this technology in the marketplace. As more firms shift more of their business activities to the web, increasingly more information about consumers and potential customers is being captured in web server logs. Anthony D Anna & Oscar H. Gandy examine issues related to social policy that arise as the result of convergent developments in e-business technology and corporate marketing strategies. About consumers and potential customers is being captured in web server logs. Sophisticated analytic and data mining software tools enable firms to use the data contained in these logs, to develop & implement a complex relationship management strategy. Individuals whose profile suggest that they are likely to provide a high lifetime value to the firm will be provided opportunities that will differ from those that are offered to consumers with less attractive profiles. Analytic software allows marketers to combine through data collected from multiple customers touch points to find patterns that can be used to segment their customer base.

3. Levels of Analysis Available

Artificial neural networks: Non linear predictive models that learn through training and resemble biological neural networks in structure.

Genetic algorithms: An Optimization technique that uses processes such as genetic combination, mutation and natural selection in a design based on the concept of neutral evolution.

Decision trees: Tree-shaped structures that represent sets of decisions. These decisions generate rules for the classification of a dataset. Specific decision tree methods include Classification and Regression Trees (CART) and Chi Square Automatic Interaction Detection (CHAID). CART and CHAID are decision tree techniques used for classification of a dataset. They provide a set of rules that you can apply to a new (unclassified) dataset to predict which records will have a given outcome. CART segments a dataset by creating 2-way splits while CHAID segments using chi square tests to create multi-way splits. CART typically requires less data preparation than CHAID.

Nearest neighbor method: A technique that classifies each record in a dataset based on a combination of the classes of the *k* record(s) most similar to it in a historical dataset (where *k* 1). Sometimes called the *k*-nearest neighbor technique.

Rule induction: The extraction of useful if-then rules from data based on statistical significance.

Data visualization: The visual interpretation of complex relationships in multidimensional data. Graphics tools are used to illustrate data relationships.

What technological infrastructure is required? Today, data mining applications are available on all size of systems ranging from mainframe, client/server, and PC platforms. System prices range from several thousand dollars for the smallest applications up to $1 million a terabyte for the largest. Enterprise-wide applications generally range in size from 10 gigabytes to over 11 terabytes. NCR has the capacity to deliver applications exceeding 100 terabytes. There are two critical technological drivers:

- Size of the database: the more data being processed and maintained, the more powerful the system required
- Query complexity: the more complex the queries and the greater the number of query being processed, the more powerful the system required.

Relational database storage and management technology is adequate for many data mining applications less than 50 gigabytes. However, this infrastructure needs to be significantly enhanced to support larger applications. Some vendors have added extensive indexing capabilities to improve query performance. Others use new hardware architectures such as Massively Parallel Processors (MPP) to achieve order-of-magnitude improvements in query time. For example, MPP systems from NCR link hundreds of high-speed Pentium processors to achieve performance levels exceeding those of the largest supercomputers.

The term 'Data mining' was introduced in the 1990's, but data mining is the evolution of fields with a long history. Its roots are traced back along three family lines namely;

- Classical Statistics : this is the foundation of most technology upon which data mining are built examples are regression analysis, standard distribution, standard deviation, standard variance, discriminate analysis, cluster analysis and confidence intervals. All of these are used to study data and data relationships.
- Artificial Intelligence: This is built on the heuristics as opposed statistics it attempt to apply human-thought-like processing to statistical problems.
- Machine Learning: This is the union of statistics and artificial intelligence; it could be considered an evolution of artificial intelligence because it blends artificial heuristics with advanced statistical analysis. Machine learning attempt to let computer programs learn about the data they study such that programs make different decisions based on the qualities of the studied data using statistics for fundamental concepts and adding more advanced artificial intelligence heuristics and algorithm to achieve its goals.

Data mining is as a result of long research and product development process. The origin of data mining lies with the first storage of data on computers and it continues with the improvements in data access until today technology allows users to navigate through data in real time. In the evolution from business data to useful information, each step is built on the previous ones as described .The first step which is data collection involves the individual sites collected data used to make simple calculations such as summations or averages. Information generated at this step answered business questions related to figures derived from data collection sites. Specific application programs were created for collecting data and calculation. The second step is data access and it used database to store data in a structured format, at this stage company-wide policies for data collection and reporting of management information was established. Because every business unit conformed to specific requirements or formats, businesses could query the information system regarding branch sales during any specified period of time. Once the figures were known, questions that probed the performance of aggregated sites could be asked. For example regional sales for specified requirements could be calculated**.** The last step which is the Online Analytics Processing tool (OLAP) which provided real-time feedback and information exchange with collaborating business units (Data mining)**.** The capability of OLAP to provide multiple and dynamic views of summarized data in a data warehouse sets a solid foundation for successful data mining" (Han and Kamber 2001) **.**This capability is useful when sales representatives or customer service persons need to retrieve customer information on-line and respond to questions on a real-time basis.

4. Comparisons

OLAP (Online Analytics Processing) and Data Mining

OLAP is a computer processing that enables a user to easily and selectively extract and view data from different point of view, for example a user can request that data be analyzed to display a spread sheet showing all of a company's beach ball products sold in Abuja in the month of July, compare the revenue figures with those for the same products in September, and also see the compares of other product sales in that same location in the same period. OLAP allows users to analyze database information from multiple data base systems at one time, while relational database are considered two dimensional OLAP data is multidimensional meaning information can be compared in multiple different ways .in other to process database information using OLAP, OLAP server is required to organize and compare the information .clients can analyze different set of data using functions built into OLAP servers.

Comparing OLAP with data mining, it is discovered that both are used to solve different kind of problems .OLAP provides summary data and generates rich calculations .for example OLAP answers questions like how do sales of mutual fund in Florida compares with sales a year ago? What can we predict for the next quarter? Data mining discovers hidden patterns in data and also operates at detailed level instead of summary level. It answers questions like who is likely to buy a mutual fund in the next 6months and what are the characteristics of this likely buyers. OLAP and data mining can complement each other in the sense that OLAP might pinpoint problems with sales of mutual fund in a certain region, data mining can then be used to gain insight about the behavior of individual customers in the region and it can also identify most important attributes concerning sales of mutual funds and those attributes could be used to design the data model in OLAP.

4.1. Data Mining and Customer Behavior

Information system can query past data up to and including current level of business. Often businesses need to make strategic decisions or implement new policies that better serve their customers. For example Grocery store redesigns their layout to promote more impulse purchasing. Telephone companies establish new price structures to entice customers into placing more calls. Both task require an understanding of past customers consumption behavior data in order to identify pattern for making those strategic decisions and data mining is particularly suited to this purpose. With the application of advanced algorithms, data mining uncovers knowledge in a vast amount of data and point out possible relationships among the data. The core components of data mining technology have been developing for decades in research areas such as statistics, artificial intelligence and machine learning .Today technology is mature and when coupled with relational database systems and a culture of data integration they create a business environment that can capitalize on knowledge formally buried within the systems (Berry & Linoff, 2002).

4.2. Data Mining and Data Extraction

With the Advancement in technology, various changes in approaches to organizing and retrieving information have been noticed taking advantage of the available data. Data mining gives us the ability to see patterns, predict the future and make informed decisions based on the evidence in large databases. For example, data mining of categorical and numerical consumer shopping data allow retailer to understand which items are purchased by the same customers, predict sales of seasonal items and more efficiently manage its inventory (McCallum& Jensen, 2005). Primarily the data mining requires a standard process, data store or warehouse, technologies and expertise. The process must be reliable and repeatable by people with little data mining skills. However the standard data extraction process should involve job understanding which determines the job objectives, job background situation assessment etc., followed by the data understanding which collects data , describes data , explore data , and verify data quality .The preparation involves the data set description, selection, assessment, consolidation, data formatting etc. process modeling, process evaluation and deployment (K pal, 2011).

4.3. Data Mining and Customer Relationship Management

Customer relationship management is the process that manages the, technologies between company and its customers. The primary users of customer relationship management software applications are database marketers who are looking to automate the process of interacting with customers' and to be successful with this, the marketers must first identify the market segments containing customers or prospects with high profit potential, then build and execute campaigns that favorably impact the behavior of these individuals. identifying the markets segments requires significant data about prospective customers and their buying behaviors, the more data the better, however massive data stores often impedes marketers who struggle to sift through minutiae to find the nuggets of valuable information.

But recently the marketers have added a new class of software to their targeting strategies; data mining applications automate the process of searching the mountains of data to find patterns that are good predictors of purchasing behaviors, after mining the data marketers must feed the result into campaign management software which manages the campaign directed at the defined market segments. The requires significant data about prospective customers and their buying behavior of these individuals.

4.4. Stages in Data Mining

Data mining is an analytic process designed to explore data (usually large amounts of data) in search of consistent patterns and or systematic relationship between variables and then to validate the findings by applying the detected patterns to the new subset (Warner&misra,1996).data mining is often considered as a blend of artificial intelligence and statistics(Pregibon ,1997) .The process of data mining consist of three stages which are

(a) The initial exploration
(b) Model building or pattern identification
(c) Deployment

4.4.1. The Initial Exploration

This stage usually begins with data preparation which may involve cleaning data, data transformation, selecting subsets of records. This first stage of data mining may involve anywhere between a simple choice of straight forward predictors for a regression model to elaborate exploratory analyses using wide variety of graphical and statistical methods in order to identify most relevant variables and determine the complexity and or the general nature of models that can be take into account in the next stage.

4.4.2. Model Building or Pattern Identification

This stage involves considering various models and choosing the best one based on their predictive performance i.e. explaining the variability in questions and producing stable results across samples, this may sound simple but it involves an elaborate process. There are several techniques that can be applied to achieve that goal many of which are based on applying different models to the same data set and comparing their performances to choose the best.

4.5. Deployment

This involves using the model selected as the best in the previous stage and applying it to the data in order to generate predictions or estimate the expected outcome.

Data mining techniques involves:
(a) Neural Networks
(b) Association rule
(c) Decision tree

The above techniques can be combined during the mining process of the data. One technique can be applied at one phase and the other at another phase.

4.5.1. Neural Networks

These are analytic techniques modeled after processes of learning in the cognitive system and the neurological functions of the brain and capable of predicting new observations on specific variables from other observations from the same or other variables after learning from existing data. The first step of the neural network is to design the specific network architecture, the size and the structure of the needs to match the nature of the investigated phenomenon. This is so because the phenomenon is usually not well known at the early stage, this task may involve multiple trail and errors but however there is neural network software's that apply artificial intelligence technique to assist in the tedious task and find the best network architecture. The new network is subjected to training, where the neuron apply an iterative process to the number of inputs to adjust the weight of the network in order to optimally predict, after the learning phase the new network is ready.

4.5.2. Association Rule

This technique describes the process of discovering interesting and unexpected rules from large data sets (Peter & Venansius, 2006). This approach makes strong simplifying assumptions about the form of the rules and limits the measure of rule quality to simple properties. A typical and most running example of association rule is market base analysis, this process analyses customer buying habits by finding association between different items that customers place in their shopping baskets. The discovery can help retailer develop marketing strategies by gaining insight into which item is frequently purchased together by customers and which items bring them better profits when placed in close proximity. Researcher has the following transaction data from an organization and the number of transaction for one day is limited as shown below:

Table 1.0. *(Yen,Kwei, Ren-Jie&Ya-Han,2005)*

Transaction ID	Items from the customer who bought more than one item
1	Sugar, wheat, pulses, Rice
2	Pulses, sugar
3	Wheat, pulses
4	Pulses, wheat ,rice
5	Wheat, pulses
6	Sugar, wheat
7	Sugar, rice ,pulses

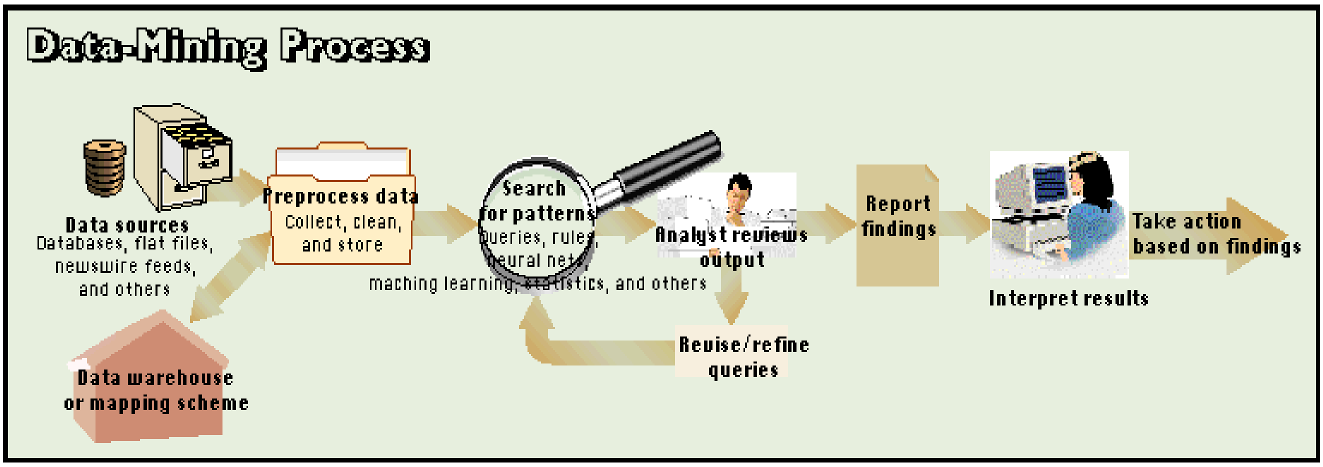

Figure 1. *(Yashpal &Alok,2005-2009)*

Table 1.1. *(Yen, Kwei, Ren-Jie &Ya-Han,2005)*

People who bought this item	People who bought the following items	Support	Confidence
Wheat	Pulses	57%	80%
Rice	Pulses	43%	100%

Based on the above researcher derive the following output of association rule using basket analysis.

Output Association Rule

The association rule will have the form X → Y, meaning people who bought item X often also bought item Y.

Support and confidence are two measures of association rules; support is the frequency of transaction to have all the items on both sets Y are bought together. In formula support can be computed as the probability of the union set X&Y

Support (X → Y) = p (XUY) = n (XUY) /N where n is the number of frequency of the set union and N total number of transaction for the analysis.

Confidence(X Y) = P(X/Y) = n (XUY) / n (X) where N is total frequency.

To obtain the association rules researcher usually apply two criteria:

1 Minimum support

2 Minimum confidence

(Yen,Kwei, Ren-Jie&Ya-Han,2005)

4.5.3. Decision Tree

Once the clusters and the associated statistical summaries data are made, the decision tree inducer assist to create, verify customer profiles, obtain tables with attributes, character attributes and continuous attributes. These attributes may contain irrelevant attributes which must be removed for the purpose of creating more accurate customer profiles; for the purpose of reserving the relatively important attributes neural network is used, one hidden layer network is sufficient to model a complex system with desired accuracy.

5. Case Study

Being an online retail company, it is of utmost importance to keep our main sources of power up and running all day, seven days a week; so one can wonder its financial implications on the business and how we manage to stay competitive with our pricing. It’s simple; as a company driven by targets and customer satisfaction we have built a mesh network of top local and international brands with a mission to bringing best quality products to our customers at the best price deals anywhere in the country, this in turn has helped us see a steady increase in our customer base, giving us the capacity to manage this challenge.

5.1. Jumia’s Type of Business

Nigeria's largest online store for fashion, electronics & mobile phones which has become well known through the homes of people Since you are not luckily landed at Jumia but still on Jumia.com.ng, you can shop in peace and pay on delivery from home or wherever you are with the easy to navigate category tree, you are definitely convinced you are in the right place. Step out in style with Jumia Fashion and

Style, with top brands such as Zara, Fever London, Blot, top quality shirts from David Wej and Max. Also you get classy women shoes from Launch, Posh Collection and other amazing options. Beautify yourself with beauty products from Mary Kay, House of Tara & Sleek. Jumia makes online shopping fun with our stress-free online store.

6. Result and Interpretation

The charts below are drawn from the data collected through the analysis of customer behavior and reactions / responses to questionnaire filled in an online survey. This will help the organization in providing high quality level service to customers' compared to the traditional method of learning customers' behavior which was to have one on one relationship with the customers over time, then use the derived knowledge to serve them better. This brings about customers loyalty and consistency to the organization.

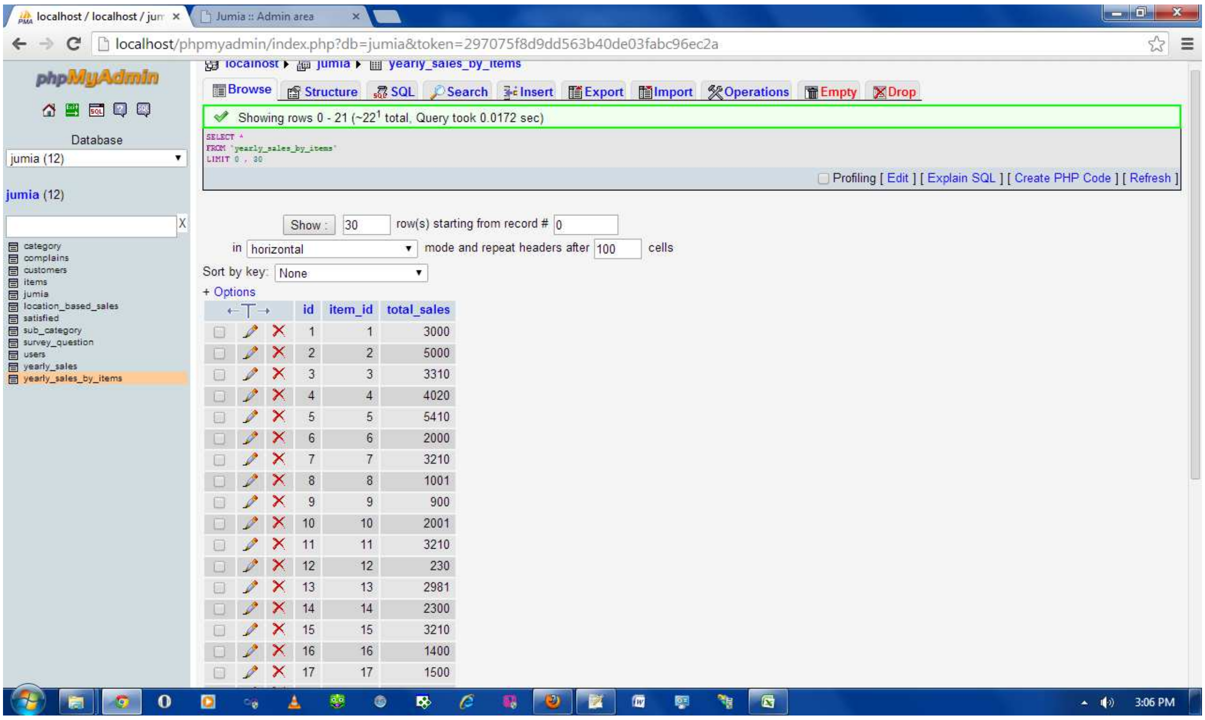

Figure 2. *(Overall Sales as per each Item)*

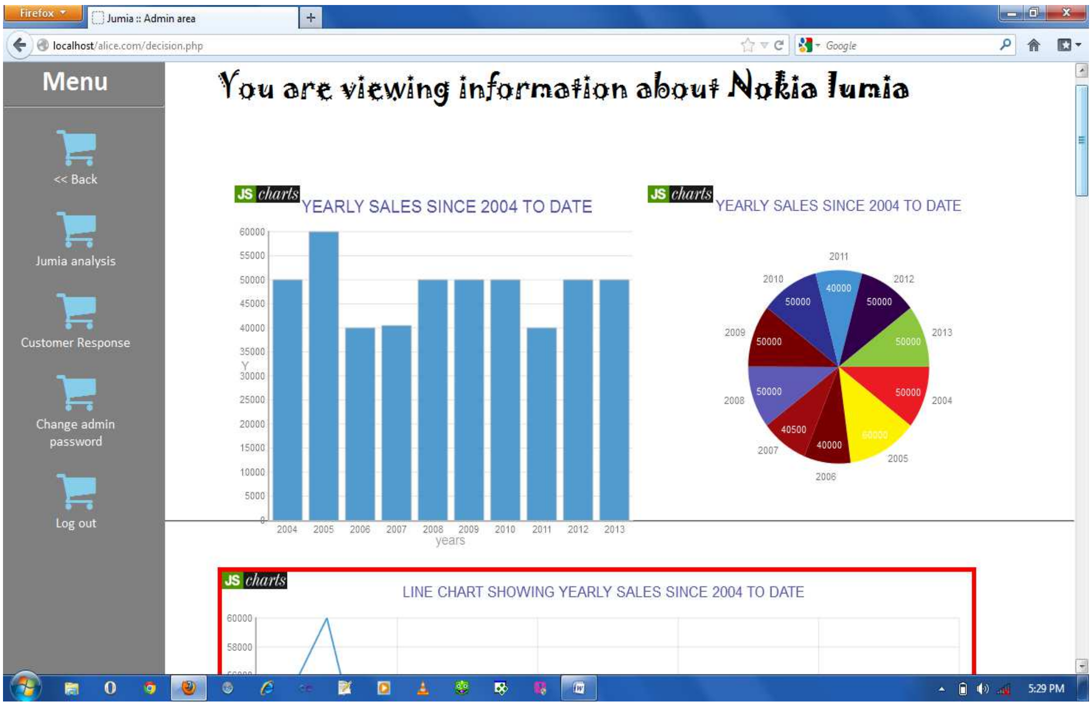

Figure 3. *(Graph of Nokia Lumia yearly Sales from 2004 to date)*

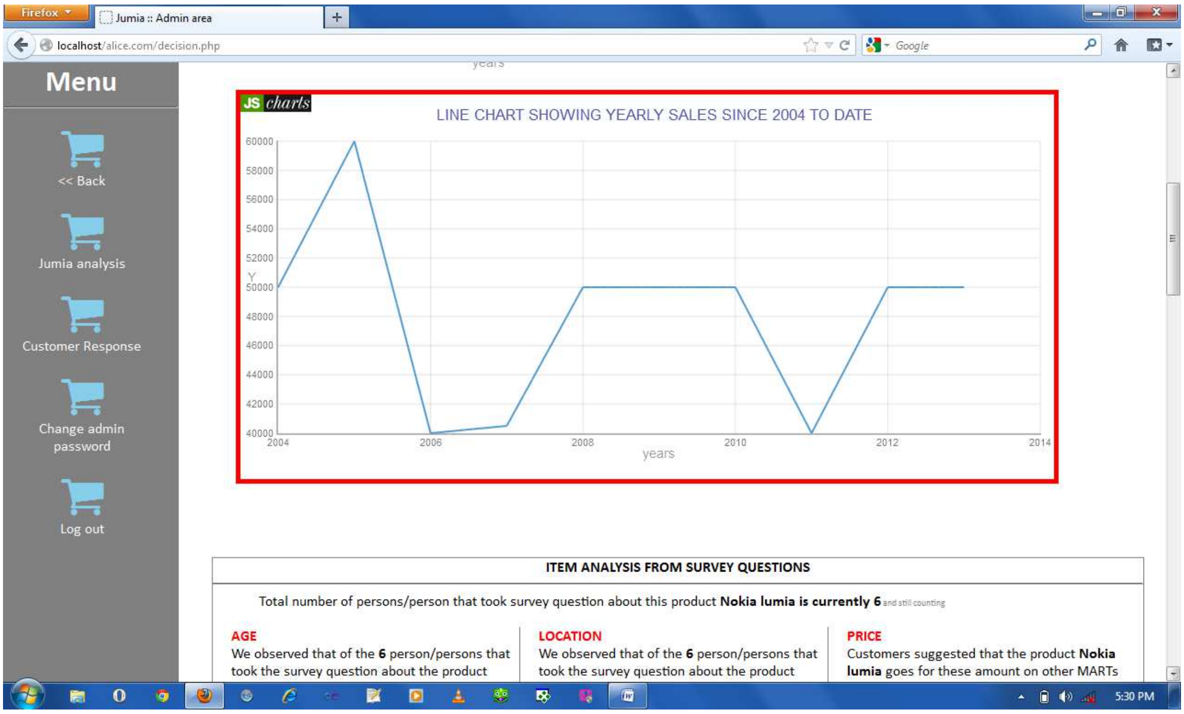

Figure 4. *(Line Chart and Analysis of each Item from 2004 to date)*

7. Summary and Conclusion

This has given us the opportunity to develop an application that analyses the database and extract valuable information which will help management with decision making as regards customer behavior, sales pattern and possibly predict future sales accurately.

Comparism of online analytics processing (OLAP) and data mining, we described OLAP as a computer process that enables users to easily extract and view data from different point of view and also OLAP server is required to organize and compare information. OLAP provides summary but data mining gives insight and details about the behavior of individual customer. However Data mining and customer behavior, both require an understanding of past customers consumption behavior and data extraction made possible by technological advancement. We mentioned Customer relationship management as a technology that manages the relationship between organizations and their customers, the key people being the database marketers. Also mentioned in this work are the stages of data mining beginning with the initial exploration, followed by model building or pattern identification and lastly deployment. We also discussed different methods of data mining techniques like neural networks, decision tree and association rule citing some examples of their application.

References

[1] Abdul-salam .S.O.adewole, K. b. (2004). In Data mining techniques for knowledge discovery. finance institute database.

[2] Abhijit, R. &. (1994). A source for consumer behavior analysis. In Data Mining Technique. VivekanandTarabai Park: .

[3] AC Yeo, KA Smith, RJ Willis and M Brooks, Journal of the operation research society: 2002, A mathematical programming approach to optimize insurance premium pricing within a data mining framework.

[4] AkashRajak & Mahendra Kumar Gupta (2012).Association rule mining: application in various area. Krishna institutes of engineering and technology, Delhi-Merrut highway, Ghaziabad-201206, (U.P.).

[5] Alex Berson, Stephen Smith, Kurt Thearling(2000).Building data mining applications for customer relationship management CRM.McGraw Hill.

[6] Al-Radaideh, Q., Al-Shawakfa, E. & Al- Najjar, M. (2006), Mining Student Data Using Decision Trees, International Arab Conference on Information Technology (ACIT'2006), and Yarmouk University, Available on:

[7] Ana Cristina, Bicharra Garcia, Inhauma Ferraz and Adriana S. Vivacqua, Artificial Intelligence for engineering design, analysis and manufacturing: 2009, from data to Knowledge Mining

[8] Anthony Danna, Oscar H. Gandy, and Journal of business ethics: 2002, all that glitters is not gold: Digging Beneath the surface of data mining.

[9] Available on: http://www.cs.waikato.ac.nz/ml/weka/[accessed December 15, 2011]

[10] Baglin, C. A. (2001). Linking eligibility for early intervention services to school age educational disability. Unpublished doctoral dissertation, Johns Hopkins University, Baltimore, Maryland.

[11] Balaji Padmanabhan and Alexander Tuzhilin, Institute for Operation Research and Management Science: 2011, On the use of optimization for data mining: Theoretical Interaction and e-CRM opportunities.

[12] Barry, M. (2000). In M. d. mining. New york: wiley computer.

[13] Che-Chern Lin, Hung-Jen Yang, Lung-HsingKuo, (2009) "Behaviour analysis of internet survey completion using decision trees: An exploratory study", Online Information Review, Vol. 33 Iss: 1, pp.117 – 134.

[14] Chung, H. .. (1999). Data mining. In journal of management informatiuon system. (pp. 11-17).

[15] Daniel Lowd & Jesse Davis (2002).learning markov network structure with decision tree, university of Oregon, Eugene, Belgium.

[16] El-Halees, A. (2008), mining students' data to analyze learning behavior: a case study,

[17] Fayyad, U. (2001). communications of the ACM. In The Digital Physics of mining (pp. (44:3),62-65.).

[18] Glymour, C. &. (1996). Communications of the ACM. In Statiscal Inferenceand Data mining.

[19] Han, J. (2001). In Data mining: concept and techniques. Morgan-kaufmann Academic Press.

[20] Hand, D. (1998). The American Statistician. In Data mining:Statistic and more (pp. (52:2)112-118).

[21] Himanshu, S. (2008). In Consumer Behavior.

[22] http://titania.addu.edu.ph/researches/DECISION/SUPPORT/Mining/Student/DataUsing decision Trees.pdf [pristup 10.january 2012.]A

[23] http://uqu.edu.sa/files2/tiny_mce/plugins/filemanager/files/30/papers/f158.pdfaccessed January 10 2012]

[24] http://www.psychology.about.com

[25] http://www.webnoxcorp

[26] Jianning Dong, William Perrizo & Qin Ding (2006).The application of association rule mining to remotely sensed data. Fargo.

[27] Kotsiantis, S.B. & Pintelas, P.E. (2005), Predicting Students Marks in Hellenic Open University, ICALT 2005. Fifth IEEE International Conference on Advanced Learning Technologies, Kaohsiung, pp. 664– 668.

[28] Kumar S. A. & Vijayalakshmi M. N. (2011), Efficiency of Decision Trees in Predicting Student's Academic Performance, First International Conference on Computer Science, Engineering and Applications, CS and IT 02, Dubai, pp. 335-343.

[29] Kurt Thearling (2002). Data mining and customer relationships. AICCSA (2009).Computer systems and applications, IEEE/ACS International conference on 10-13 May 2009.

[30] Leonid Churilov. Adyl Bagirov, Daniel Schwarta, Kate Smith, Michael Dally , Journal of management information system : 2005, Data mining with combined use of optimization techniques and self organizing maps for improving risk grouping rules : application to prostate cancer patients

[31] Machine Learning Group at University of Waikato,

[32] Minaei-Bidgoli, B. Kashy, D.A., Kortemeyer G. & Punch WF (2003), Predicting student performance: an application of data mining methods with the educational web-based systems LON-CAPA, 33rd ASEE/IEEE Frontiers in Education Conference, Boulder, pp.13-18.

[33] Minaei-Bidgoli, B., Punch, W.F. (2003), Using Genetic Algorithms for Data Mining Optimization in an Educational Web-based System, GECCO 2003 Genetic and Evolutionary Computation Conference, Chicago, pp. 2252-2263.

[34] Nan-Chen, H. &.-C. (2011). In Enhancing consumer Behavior analysis by data minin. ROC. Taipei.

[35] Peacock, P. (1998). In Data mining in marketing (pp. 9-18). marketing management,winte.

[36] Rachid Anane, Computer and the humanities: 2001, Data mining and serial documents.

[37] Romero C. Ventura S. Espejo, P.G. & Hervás C. (2008), Data mining algorithms to classify students, I International Conference on Educational Data Mining (EDM). Montreal, pp. 8-17.

[38] Romero, C. & Ventura, S. (2007), Educational Data Mining: a Survey from 1995 to 2005, Expert Systems with Applications, Elsevier, pp. 135-146.

[39] Shakil Ahmed, Frans Coenen, Paul Leng, Knowledge Information System: 2006, Tree based partitioning of data for association rule mining

[40] smyth.R, f. (1996). In the KDD Process for Extracting usefull knowledge from volumes of data (pp. (39:11),pp27-34). communications of the ACM.

[41] Sreekumar Pulakkazhy & R.V.S Balan (2006).Data mining in banking and its applications-A review,Noorul Islam university, Tamil Nadu,India.

[42] Sreekumar Pulakkazhy (2013).Journal of computer science 9(10):1252-1259, 2013. Noorul Islam university, Tamil Nadu, India.

[43] Superby J.F, Vandamme J.P. & Meskens N. (2006), Determination of Factors Influencing the Achievement of the Firstyear University Students using Data Mining Methods, Proceedings of the 8th international conference on intelligent tutoring systems, Educational Data Mining Workshop, (ITS`06), Jhongali, pp. 37-44.

[44] Timothy T. Rogers, James L. Mcclelland, Behavioral & Brain Sciences: 2008, Precis of Semantic Cognition: A Parallel Distributed Processing Approach.

[45] Ulaanbaatar (2012). Developing a cost-benefit analysis of mining sites in Mongolia, annual report -2011.

[46] Vijaylakshmi, S. &. (2010). In Mining of users' access behavior for frequent sequential pattern.

[47] William's.S. (2004). In the promise and pitfall of datamining. Newyork.

[48] Yen-Liang, C. T.-J. (2005). In Market basket Analysis in multiple store environment. Elsevie.

[49] Zekic-Susac M., Frajman-Jaksic A. & Drvenkar N. (2009), Neuron Networks and Trees of Decision-making for Prediction of Efficiency in Studies, Ekonomski vjesnik, Vol.No.2, pp. 314-327.