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ON SELECTION OF USER INTERFACE DYNAMICALLY FOR DISPLAYING DATA MINED RESULTS

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ABSTRACT

Many types of mining such as classification mining are being used to discover knowledge hidden in the data. Several methods exist such as mining based on decision tree for carrying classification mining. Each type and method of mining produces different types of mined results when applied on a different database. The mined results also greatly varies when parameters which are used for carrying mining.One of the most challenging issue is to display the mined results such that the user quite understands the results and be able to take decisions that help their business. Choice of a proper interface for displaying the results is most critical for the user to understand and use the mined results for their own decision making. In this paper a method has been presented that helps in finding most appropriate User interface dynamically at runtime that best suits the actual mined result and use the same for displaying the mined results

Keywords: visual display, data mining,user interface.

1. INTRODUCTION

Data Mining can be done using several types of mining which includes classification, clustering, outlier analysis, co-relation analysis, frequent item set mining, rule mining etc. There are many methods that exist in literature for each type of data mining using which mining can be carried. The classification mining can be undertaken for example through the methods that include Decision tree, Bayer's Classifiers, Neural networks etc. The type of mined result that could be obtained depends on the type, method, database and the parameters that are used for carrying Mining.

The initial mining query, the mining process and the mined results both intermediate and final differs greatly from type of mining to mining. The way the mined results are to be displayed also is dependent on the mined data which is dependent on the type of mining carried, method and data base used and the parameters selected for undertaking mining.

There is vast quantity of information out there within the information trade. This knowledge is of no use till it is regenerated and transformed into helpful information. It's necessary to investigate the vast quantity of information and precise and extract helpful information from it. Extraction of information of knowledge involves many data processing steps which include data clean-up, data integration, data transformation, knowledge extraction, pattern analysis etc. Most importantly the way the mined results are presented to the end user such that the user will be able to understand, interpret and be able to take effective decisions related to their businesses.

Data mining issues

Data mining isn't a simple task, because the algorithms used will get terribly advanced and knowledge isn't forever offered at one place. It must be integrated from numerous heterogeneous knowledge sources. These factors conjointly produce some problems. Some of the most difficult issues that must be addressed include Mining Methodology, User Interaction,response time, parametric selection for mining etc. The most important being the ability to display the mined results in most appropriate manner reflecting the meaning of the mined results and the ease of understanding the same by the user. User interaction with the mining system plays a Major role. From Figure-1 one can see that the most critical and important issue is the interaction which is the most key element without which the user will not be able to realise the end outcome achieved out of a mining effort.

Classifications, Clusters, Association rules, frequent item sets, sequences, hierarchical structures, outliers, patterns, and trends are actually mined from different sources of data which include transactional, spatial, temporal, text, WEB etc. Finding proper display method that adequately and properly display the mined results considering type of mining, method used for carrying mining and the kind of database that should be mined is extremely important for the user to understand the mined results in proper meaning and context. The display system must take into account the intermediate mined results and inputs from the user that change the course of mining further. Human knowledge and perception are to be taken into account interactively while mining is in progress in the absence of which no proper mined results could be obtained.

The mined data to be visualised could multi-dimensions (One, two, multi-dimensions, text, hierarchies, graphs, algorithmic and pseudo code. One can use serval visualisation techniques for visualising mined data which include standard 2D/3D, geometrical transformational display, Iconic display, dense Pixel display, stacked display etc. A kind of user interaction is required for undertaking mining through display of intermediate results which should be of a particular data type associated with a Visualisation technique. The dimensional relationship between the types of data to be visualised, the technique to be used for visualisation and the technique to be used for the user to interact with the system is shown in Figure-2.

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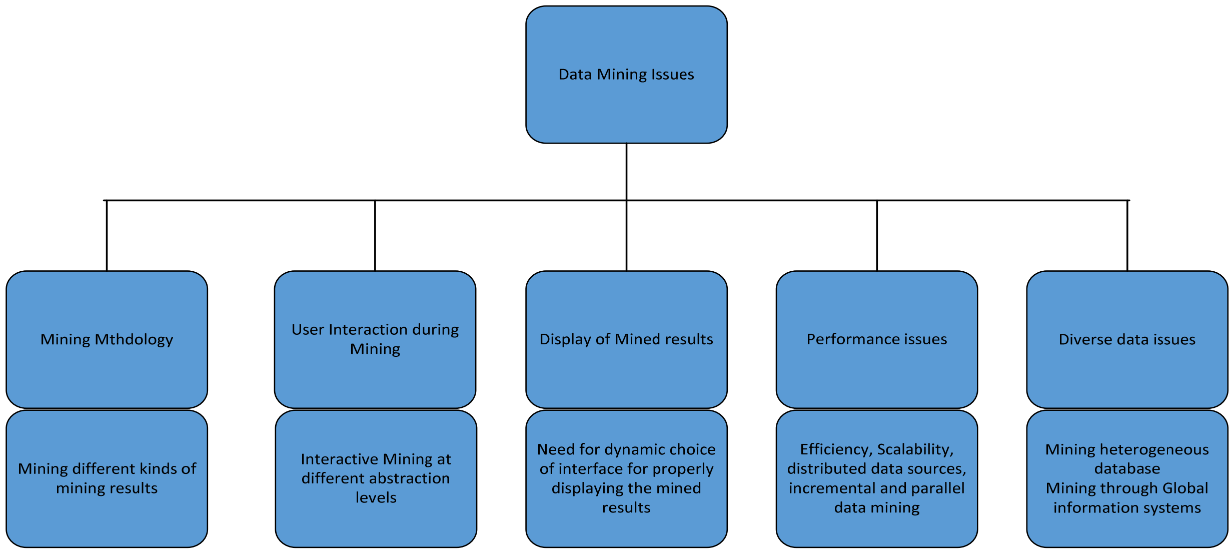

Figure-1. Major issues in data mining.

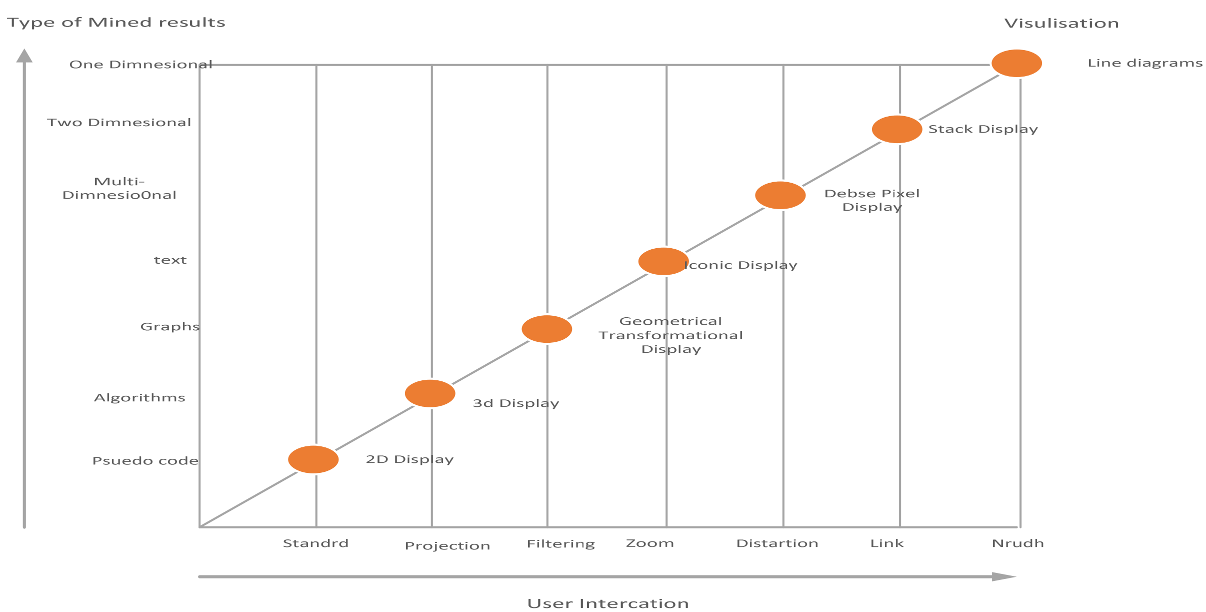

Figure-2. Relationships among type of data, type of user interaction and Visualisation technique.

Thus it is evident that a mechanism is needed that helps in determining most appropriate display method using which the mined results are displayed for easy undertaking of the user who should be able to interpret the results with easiness and take most suitable decisions. The mechanism should help in selecting most appropriate user interface at run time that best suits the mined results obtained by using a type and method of mining undertaken on different types of databases.

2. RELATED WORK

Panuakdet Suwannatat [1] has presented a work to University of California Santa Barbara on "intelligent user interfaces for visual data mining. He has explained that visual data mining is a two-way traffic between the data mining and visualisation techniques. He has made a clear cut definition between data, visualisation and interaction. Intelligent user interfaces requires the use of HCI and AI. Visualisation systems could be static, dynamic or interactive. He has expressed that Visualisation must be closely tied up with data mining and UI research. The focus would be on Multi-User systems, distributed data, semantic based query. He expressed that any automated decision making system is erroneous and decision making require proper visualisation of data.

Most analysts first look at the data at macro level and drill down to micro level so as to set the focus on a particular area of interest. PAM-AND-ZOOM systems are used for carrying MACRO-MICRO approach. MACRO view of large data is difficult and complex and dealing

ARPN Journal of Engineering and Applied Sciences

with many abstract views is much more difficult. Visual abstraction is generally undertaken when data to be processed is very large. The existing system limits an analyst with single abstraction and zooming. Data cubes provide multiple views of a data set. Chri Stolte *et al*., [2] have presented formalisation for describing multiscale visualisation of data presented as data cubes using both data and visualisation abstractions. They have also presented a method for zooming along one or more dimensions through traversing a zoom graph which has nodes described at different levels of details. They have described four different design patterns using the formalism presented. The visualisations achieved through use of the formalism presented are quite effective and efficient.

Aerospace corporations make engineering assessments related to go/no-go decision for launch of space vehicles. The decisions are made by continuously visualising the streaming data. Proper visualisation is crucial for decision making. Jessica Lin *et al*., [3] have introduced that can be used for mining archival data and mentoring incoming telemetry data. A single tool for mining and visualisation helps transferring the mined knowledge to a monitoring task. The approach presented by them transfers' time series data into a symbolic representation and then encoding the data into a modified suffix tree having the nodes mapped with frequency, colours and other properties of patterns.

Spatially referenced data can be mined complimented with visual exploration. The data presented on maps can be mined and visualised through cartographic visualisation. Gennady Andrienko *et al*., [4] have presented an integrated platform for undertaking exploratory analysis of spatial data through a tool that supports variety of data mining tools and provides for mapping of source data to data mined results. They have built the environment based on two platforms that includes Kepler model for data mining, and DESCORATES provides knowledge based visualisation of the mined data. Kepler is an open architecture using which one can incorporate many of the mining tools. DESCARTES allows for automatically selecting presentation method according to the data mining results.

Analysing and exploring huge amount of data is increasingly quite difficult and complex. Flood of information can be handled by combing information visualisation and visual data mining. User is directly involved in visual data mining. Data can be exploited by using number of information visualisation techniques that have been evolved over a period of time. Daniel A. Keim *et al*., [5] have presented classification of visual data mining and data visualization techniques based on the type of data that must be visualised, the visualisation technique, and interaction and distortion technique

Maria Cristina Ferreirade Oliveira *et al*., [6] have presented a survey on different uses of graphical mapping and interaction techniques which can be used for visual data mining of large data sets represented as tabular data. They have presented basic terminology related to data sets, data mining and data visualisation. They have reviewed different categorisation of techniques and systems. They have clearlypresented review on role of interaction techniques and the basis for selection of visualisation technique. A review of a work done which uses visualisation technique in the context of data mining includes visual data exploration and expressing the mining outcomes visually. They have also presented a review on integration of visualisation into the KDD process.

Many visualisation techniques exist in literature. It is confusing to select a visualisation technique that is most suitable and conveys most possible mined results. The most important purpose of a visualisation of data is providing ability to the user to properly interpret the mined results, each visualisation technique convey different level of understanding and suitability for particular presentation. Muzammil Khan *et al*., [7] presented complete information about all the visualisation techniques. They have presented all aspects related to visualisation, visualisation process, the visualisation steps contained, problems that confront visualisation, categorisation of visualisation, categorisation based on different perspectives, common information visualisation techniques, interactive methods for visualisation, interactivity process and the scope of visualisation.

Securing the data at the stage of internet based routing is most essential part of data processing. The data packets that travel on internet could be attacked and as result the packets either do not reach the destination or fall in the wrong hand. Security at the routing stage requires quite an analysis of the data. In the past various visual based, statistical based and signature based techniques have been presented which help in analysing the internet based routing data. Soon Tee Teoh *et al*., [8] have presented the way the visualisation and mining methods can be combined to find anomalies if any existing in the internet routing data. They have presented to find the anomalies existing in the real-time data. The system presented by them is useful for collecting, processing and analysing and visualizing data in real time.

Many tools have come for undertaking visualisation of information. The limitation of these tools can be explained through usability studies and controlled experiments. Catherine Plaisant [9] explained that better tools are required that takes into account long exploratory nature of user tasks, awareness of the users. They also presented that metrics and benchmarks are required to compare tools and they have also opined that case studies required reflecting the use of the tools for solving some specific problems.

3. ANALYSIS OF DISPLAY METHODS

The mined data results can be displayed using several visualisation graphs. Not all graphs suits to every kind of mined result. There should be a way of determining a type of graph and the property of the graph such as X and Y divisions, number of plot points, colours to be used, Text components that must be displayed, statistics that are to be displayed as foot notes and to display as attribute to a graph points and map the same to a type of mining, mining method, parameters used for data

VOL. 12, NO. 11, JUNE 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

mining so that a display method can be chosen dynamically based on the mined results and use the same for effecting the display of mined results. It is necessary to study every type of graph and find the characteristics of the same.

Study of scatter plots

The scatter plot is one of the most effective graphical methods for determining if there appears to be a relationship, pattern, or trends between two numeric attributes. To construct a scatter plot, each pair of values is treated as a pair of co-ordinates in an algebraic sense and plotted as points in the plane shows a scatter plot for the set of data. A scatter plot graphs the actual values of the data against the values predicted by the model. The scatter plot displays the actual values along the x-axis, and displays the predicted values along y-axis. It also displays a line that illustrates the prefect prediction, where the predicted value exactly matches the actual value. The distance of a point from this ideal 45-degree angle line indicates how well or how poorly the prediction is performed. An example scatter plot is shown in Figure-3.

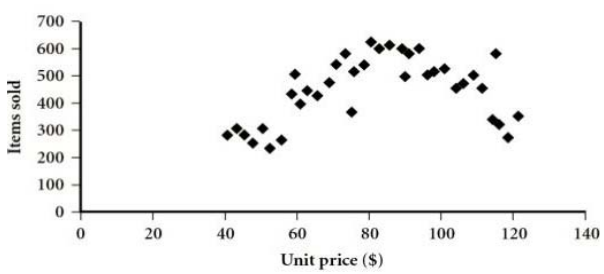

Figure-3. Scatter plot.

Correlations between two sets of data can be represented trough scatter plots. The scatter plot is very useful method for providing a first look at bivariate data to see clusters of points and outliers, or to explore the possibility of correlation relationship. Two attributes x,y are correlated if one attributes implies the others. Correlations can be positive, negative, or null (uncorrelated) correlations between two attributes. If the plotted points pattern slopes from lower left to upper right, this means that the values of y increases, suggests a positive correlation. A typical positive correlation is shown in Figure-4.

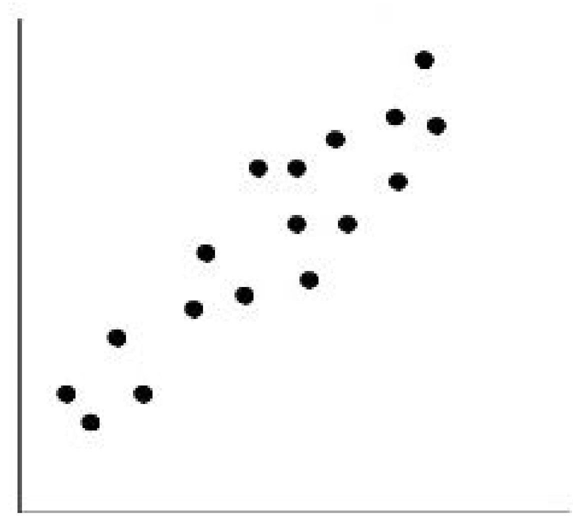

Figure-4. Positive correlation.

If the pattern of plotted points slopes from upper left to lower right, the values of x increase as the values of y decrease, suggesting a negative correlation. A typical negative correlation is shown in Figure-5.

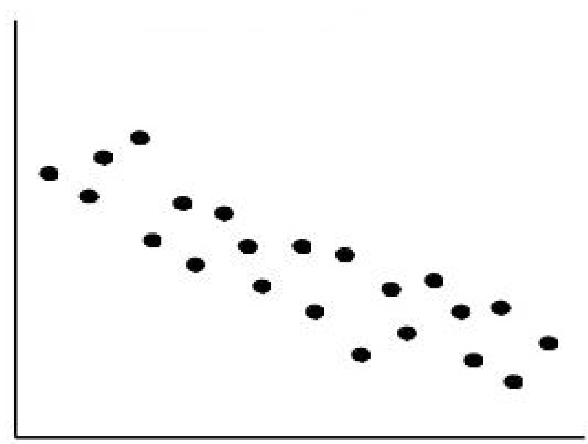

Figure-5. Negative correlation.

A line of best fit can be drawn to study the correlation between two variables. Statistical tests or correlation are computed to find the kind pf correlations that exists. The scatter plots can be extended to n attributes, resulting in a scatter-plot matrix. Three cases where there is no observed correlation between the two planes plotted attributes in each of data sets are shown in Figure-6.

ARPN Journal of Engineering and Applied Sciences

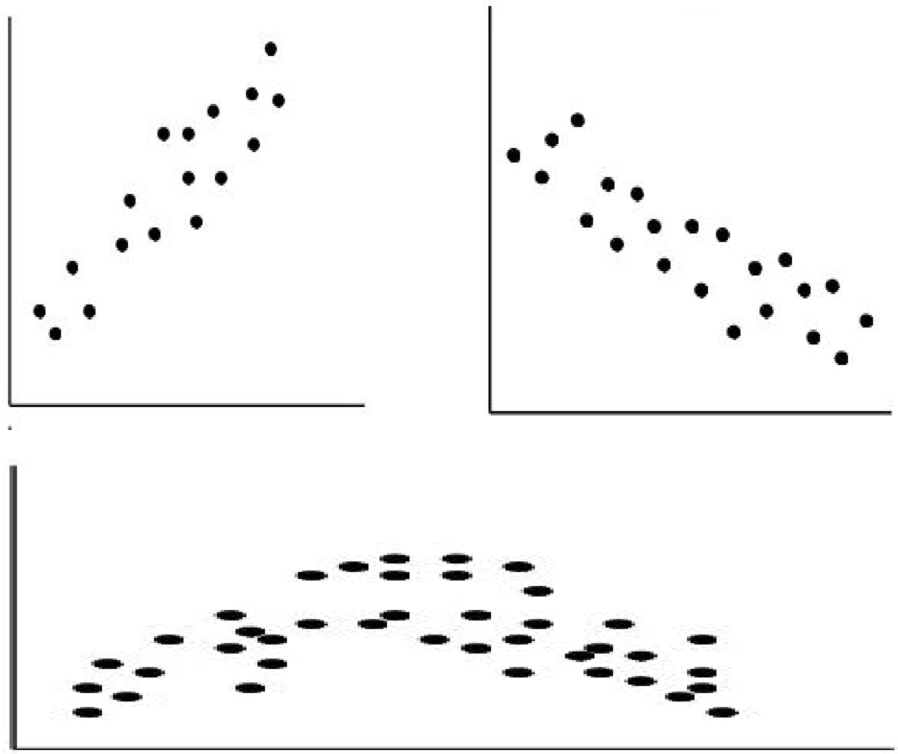

Figure-6. Scatter diagrams that show no observed correlations.

Study of Histogram

It is a graphical method for summarizing the distribution for a given attribute. Histograms Partitions the data distribution into disjoint sets that can be referred as a buckets or bins. Each bucket consists of a single attribute and it is used for separating continuous data. It consists of an overlapping and non-overlapping horizontal bars and with the horizontal bars we can represent the data within the increase or decrease. A typical Histogram is shown in Figure-7.

data mining method | classification method | type of method used | decision induction tree | Attribute used for participationing | Age

elements	yes	no	total
students	200	300	500
middle aged	800	0	800
seniors	1200	200	1400
total	2000	500	2700

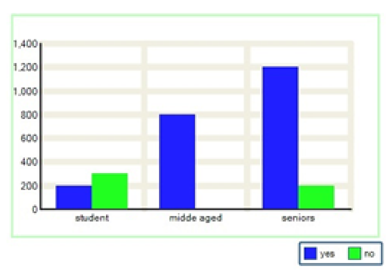

Figure-7. Typical Histograms.

Study of PIE graph

A space filling curve is a curve within a range it covers the entire dimensional data. It is also called as cyclic graph and is used to determine the size of data segment that it will compare to another data segment. The PIE model is ok for two or three categories. If more than two categories exist it is hard to visualize and the user get confused while seeing a display. A typical PIE diagram is shown in Figure-8.

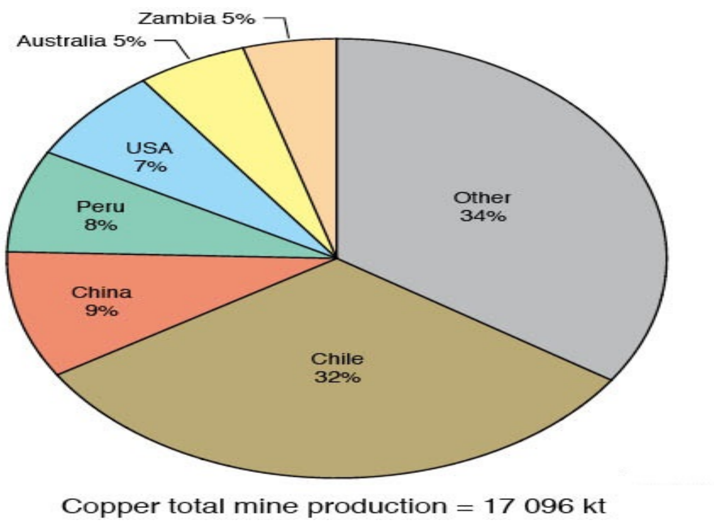

Figure-8. Typical PIE diagram.

Study of line graphs

The data items selected through data mining could be continuous and the pattern of those continuous points can be represented through line diagram. Line diagrams can also be used for displaying clusters, classes and rules and the connectivity is a kind of proximity between the mined data elements. Line diagram is a kind of extension of scatter plot. Data can be focused on symbols or images. Line diagrams can also be used for showing trends over a time interval and the same can be used to show the inclination in the information set and show the progression of a particular interval of time. Figure-9 shows a typical Line diagram.

Figure-9. Typical line diagram.

Scatter plot

It is a graphical showcase of set of information that can be represented using Cartesian products. It demonstrates the relationship between two variables, while one variable shows the horizontal separation the other shows vertical separation and the Graph generally helps in spotting out the outlier existing in the mined results. Figure-10 shows a typical scatter plot.

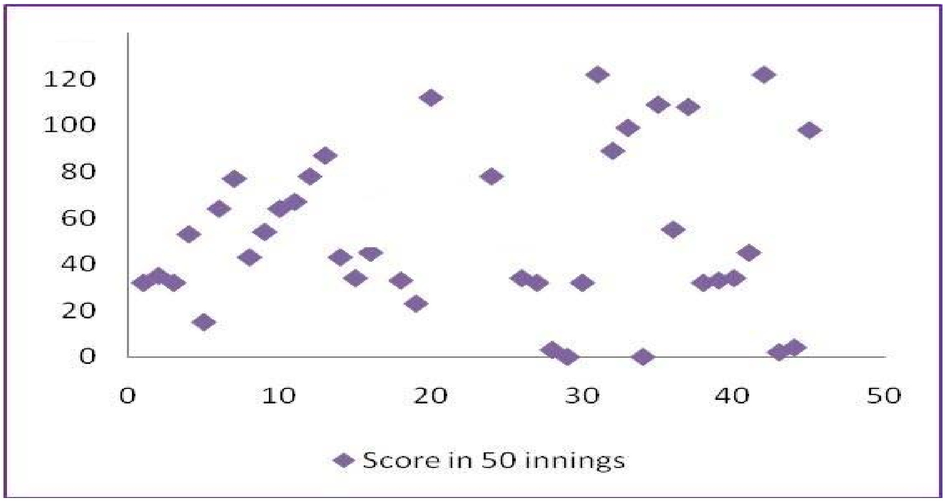

Figure-10. Typical scatter plots.

Other plots

There are a number of other displays which can cater in respect of a particular type of mining done having some characteristics. The diagram used must reflect very clearly the nature and extent of the mined results. Other frequently used displays include quantile plots and quantile - quantile plots, Quantile plots can be used to display data that has univariate distribution. Entire data of an attribute can be displayed using this graph covering overall behaviour and unusual occurrences. The plot displays the quantile information about the attribute. Quantile - quantile graphs plots distributions of two different univariate variables.

3. ANALYSIS OF VISUALISATION METHODS

Data can be visualised using number of methods that include pixel oriented visualisation, Geometric visualisation, Icon based Visualisation, Hierarchical visualisation and many other visualisation techniques exists for displaying complex data. Pixel oriented visualisation shows the colour shading to represent density, size etc. Many pixel shadings are used for display based on number of dimensions of the data. Geometric visualisation display number of projections related to multi-dimensional data. Geometrical visualisations help visualisation of high dimensional data in 2D space. Scatter plot, a scatter plot matrix, a 3D scatter plot matrix, display of parallel coordinates can be used for displaying the geometrical projections related to the data.

In the ICON based visualisation, small Icons are used to represent multi-dimensional data. The data is represented cartoon like human faces. Chertoff faces and stick figures are the most frequently used methods to display multi-dimensional data.

Hierarchical visualisation methods partitions n-dimensional data into n sub-spaces with each space nested into another. Worlds-within-worlds are a hierarchical visualisation technique that is used quite frequently. Using these methods the effect of changing one dimension with reference to the changes in some other dimension can be displayed. 2D plots or three 3D plots are used to shows how one dimension behaves with reference to other dimensions. Tree-Maps are another visualisation method that displays multiple dimensional data as nested rectangles each containing display of a single dimension of the data.

Visualising text, social network related data and WEB data is a challenge. Quite recently many techniques have been presented to present visualisation of such a data. A tag-cloud is visualisation of statistics of user defined tags. A tag-cloud as such tags or combines various types of web based contents such as images, audio, video, text, graphics and displays the same for better understanding of the user.

4. ANALYSIS OF DATA MINING TYPES AND METHODS

Several types of objects can be mined from different types of data sources. The objects that can be mined include frequent patterns, associations, and co-relations. Several methods are in existence for mining frequent item sets / patterns which include Apriori, Pattern growth, vertical data formats and mining association rules from frequent data items. Many other types of objects can also be mined form data that includes classifiers, predictors, clusters, outliers, correlations etc. Each type of objects can be mined through several methods.

Classification mining

Classifiers can be mined by using the methods such as Decision tree induction, neural network, Bayesian classifiers, rule based classification, back propagation using numeral networks, support vector machines, pattern analysis, lazy learners (Learning from neighbours), genetic algorithms, Rough sets, fuzzy sets, Binary classification, Multi classification, semi-supervised classification, active learning etc. Each method requires supply of certain input parameters. Entire data mining process involves learning a model and use the model to mine the objects.

ARPN Journal of Engineering and Applied Sciences

Determining the most important parameters is the key for classification mining. Choice of values for the parameter becomes equally important for undertaking classification mining. The kind of mined results that one will get is generally are based on the choice of parameters and the values that are chosen for those parameters for undertaking the mining. Most appropriate method of display method must be chosen to display the mined results. The display method must clearly reveal the uses of the mined results especially in terms of accuracy and effectiveness. Prior knowledge of the classes contained in the data is necessary for carrying classification mining. Most of the display and visualisation methods described above could be used for displaying mined results through undertaking classification mining.

Mining clusters

Cluster mining is resorted when no prior knowledge of the classes exists. Data elements which are similar in nature are grouped and placed in the same cluster. Clustering is useful when data elements that have same features and likelihood exists. Clustering is an un-supervised learning. Many algorithms are in use for undertaking cluster mining which includes K- means (Means, Means++, Filtering), K- Medoids (PAM, CLARA, CLARANS), agglomerative hierarchical clustering(DIANA, AGNUS, BIRCH, CURE ROCK, Probabilistic Hierarchical), density based methods (DBSCAN, OPTICS, DENCLUE, Grid based (STING, wave cluster), Scalable methods, fuzzy methods, High dimensional clustering (Apriori based dimension - growth clustering - CLIQUE, Stream clustering (clustering streams, K-medians, clustering evolving data streams, clustering high dimensional data Strems. The mined cluster can be presented by using many display and visualisation methods. Choice of most essential display or visualisation is not important for the users to properly interrupt the mined results. A kind of mapping of the mined results produced by each of the algorithm is needed to dynamically selecting the display and visualisation method and then generates the display dynamically making the mining system as a whole more effective and useful.

Advanced cluster mining

In simple cluster mining, an object can be included into one cluster based on fulfilment of certain criteria as defined by a mining method. But in reality the same object can be placed in more number of clusters. More advanced clustering techniques are being used to solve some special problems that need clustering of the same object into many number of clusters. Some of the techniques that help in doing advanced clustering include fuzzy clustering, model based clustering, mixture models, EM algorithm, CLIQUE, PROCLUS, Bi-clustering, δ-p Cluster, spectral clustering, SCAN- clustering graph, COP-k-means, CVQE, constrained based clustering etc. The results produced by these methods require different types of visualisation of data mined results. Most suitable display objects needs to be selected and grouped to form an interface that can be used to display mined results.

Outlier mining

Outliers or the objects that are situated outside the boundary of a distribution. Outliers are defined from a statistic angle. Several methods are used for either detecting or mining the outliers. Some of the methods used include semi-supervised-outlier detection, Gaussian distributions, Boxplots, Grubbs test, Grubs test for determining multi- variate outliers, χ^2 – statistic, Gaussian mixture models, Histograms, Distance based outliers (Index based, nested loop based, grid based) database scanning, Density based outliers, Find CBOLF, bootstrap, Multi-class classification in network intrusion detection, etc. In these cases of mining also appropriate display and visualisation methods are to be identified for proper understanding of the end users.

5. NOVEL APPROACH TO FINDING THE DISPLAY / VISUALISATION METHOD SUITABLE FOR DISPLAYING MINING RESULTS

Many display and visualisation methods exist in literature using which the mined results can be displayed. A specific display or visualisation method could be suitable for displaying the mined results or sometimes a combination of the methods may be considered for displaying the mined results. The display and visualisation characteristics of a particular type can be pre-identified as a set of attributes of that particular type. Table-1 shows characteristics of some type of display and visualisation methods. Any interface output to be visualised by the end user can be captured as a repository of different characteristic with each characteristic defined with different attributes of a variable that is considered for displaying the output of mined results. The type of variable is also captured for computational purpose. Table-1 can be modified whenever more number of attributes of variables or more number of variables is to be added.

ARPN Journal of Engineering and Applied Sciences

Table-1. Characteristics of display or visualisation method.

Serial number	Type of user interface	Interface name	Characteristic name	Type of attribute	Data element	Number of variable groups	Data element type
	Display	XY-Plot	X-Axis	Length Number of divisions Division value Legend	Var-1	1	Integer/Float/ Double
			Y-AXIS	Length Number of divisions Division value Legend	Var-2	1	Integer/Float/ Double
	Display	XYZ Plot	X-Axis	Length Number of divisions Division value Legend	Var-1	1	Integer/Float/ Double
			Y-AXIS	Length Number of divisions Division value Legend	Var-2	1	Integer/Float/ Double
			Z-AXIS	Length Number of divisions Division value Legend	Var-3	1	Integer/Float/ Double

ARPN Journal of Engineering and Applied Sciences

Serial number	Type of user interface	Interface name	Characteristic name	Type of attribute	Data element	Number of variable groups	Data element type
	Display	Histogram	X-Axis	Length	Var-1	3	Integer/Float/ Double
				Number of Bar positions			
				Number of simultaneous bars			
				Legend			
				Bar Colour			
			Y-AXIS	Length	Var-2	1	Integer/Float/ Double
				Number of divisions			
				Division value			
				Legend			
	Visualisation	Scatter plot	X-Axis	Length	Var-1	1	Integer/Float/ Double
				Number of Divisions			
				Legend			
			Y-AXIS	Length	Var-2	1	Integer/Float/ Double
				Number of divisions			
				Division value			
				Legend			

It has been explained at the earlier instance that there are many data mining types and each type of mining can be undertaken using many methods. However each of the mining methods generates output of a particular type. Classification mining generates a set of classes each class contain certain number of tuples of the database included in it. Similarly cluster mining generates some clusters each cluster represented by a mean, median, medoid etc. Certain numbers of tuples are included into each of the cluster. Table-2 shows the details of a mined output of a student database. The mining done is related to different levels of the students who take some term classes.

Table-2. Mining results of student data base.

Serial number	Variable-1				Variable-2			
	Variable divisions (Class labels)	**Variable groups (Branches)**	**Variable type**	**Variable values**	**Variable divisions (Class labels)**	**Variable groups (Branches)**	**Variable type**	**Variable values**
1	UG Students	CSE	Numeric	0	1	3	Numeric	23
		ECE	Numeric	0			Numeric	12
		EEE	Numeric	0			Numeric	8
2	PG Students	CSE	Numeric	0	1	3	Numeric	13
		ECE	Numeric	0			Numeric	12
		EEE	Numeric	0			Numeric	15
3	Doctoral students	CSE	Numeric	0	1	3	Numeric	12
		ECE	Numeric	0			Numeric	11
		EEE	Numeric	0			Numeric	13

VOL. 12, NO. 11, JUNE 2017 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

These mined results have to be presented to the end user. There could be several ways of representing the mined results. To show these results one has to determine the most effective way of presenting the data to the end user. Similarity of the mined results with the display characteristic has to be ascertained and the display / visualisation that have the highest similarity have to be selected. As can be seen from Table-1 that every display / visualisation is represented as number of axis's which related to number of variables that must be presented on the graph. Each variable point may be presented in one or more values which are being called as variable groups. The type of values represented by the variables can be used for determining whether they should be representing as horizontal or vertical dimension. If there are only numeric values represented by a variable, the same are to be represented on a Y axis. Comparing Table-1 with Table-2 a similarity table (Table-3) has to be ascertained form which the most effective display / visualisation method can be determined and the same is used for affecting the display. Similarly of the display / visualisation can be determined through number of characteristic variables, number of divisions that every characteristic variable must be represented, minimum and maximum number of decisions, and type of variable and variable values that must be used for displaying the mined output. The Histogram representation has the highest similarity when compared to the attributes of the mined results. Therefore Histogram based display can be chosen for display of mined results. The mined results show that they are two variables. While one variable has three divisions and the other variable have 0 divisions or nil divisions. Similarity of 5 has been assigned to Histogram as all the mappings (Number of variables, number of variable's having divisions, minimum number of divisions, variable type) have been matched with the mined results. Thus it can be determined dynamically the Histogram is the right way to represent the mined results

Table-3. Similarity matrix.

Serial number	Type of user interface	Interface name	Number of variables	Number of variables having divisions	Minimum number of divisions	Number of maximum number of divisions	Variable type	Similarity with the mined results
1	Display	X-Y Plot	2	0	0	0	Numeric	2
2	Display	XYZ Plot	3	0	0	0	Numeric	2
3	Display	Histogram	2	1	1	3	Numeric	5
4	Visualisation	Scatter plot	2	0	0	0	Numeric	2

After selecting the type of display the same can be generated dynamically and displayed. The display produced for the perusal of end customer looks like the way it is shown in Figure-11.

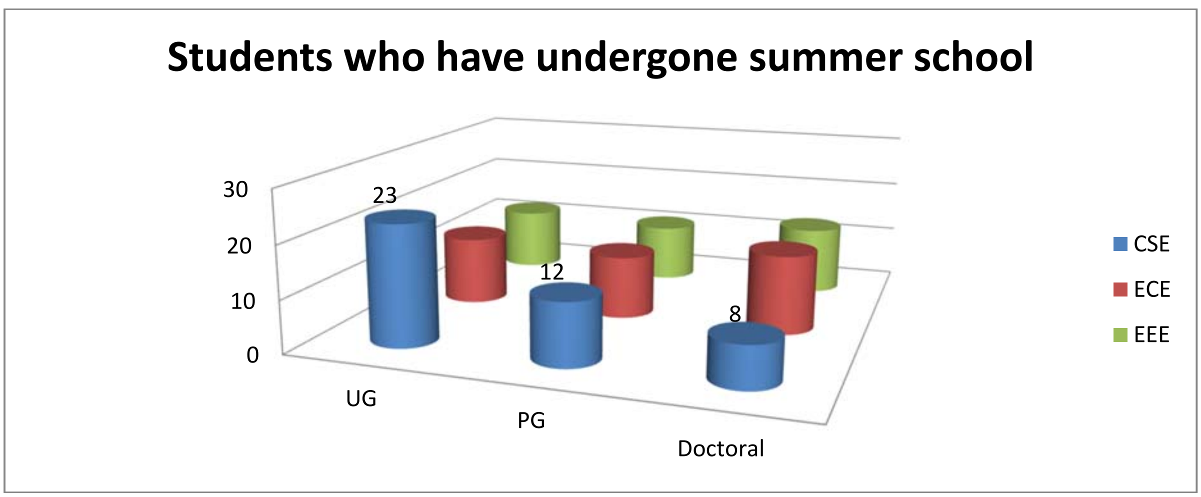

Figure-11. Display of mined results.

6. CONCLUSIONS

Variety of data mining can be done, each done through several methods. The mining output generated is generated based on type of mining, method of mining and the parameter used for mining. Users must be provided with mined output using different kinds of displays or visualisation which are most apt to the mined results and also for the better understating of the results by the end user. There should be a way to determine the kind of display / visualisation that must be used for displaying the mined results at run time that truly represent the mined results and the output display is quite easy to understand by the user. The repository based similarly mapping would be one of the best ways to determine the display that must be used for displaying the mined result.

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