ABSTRACT

Data mining applications have been growing tremendously in today’s world. One of the important applications of data mining is its usage in forensic investigation especially when a large amount of data is involved. This project explains why forensic tools such as Forensic Tool Kit and Pro Discover cannot be efficiently used when there is huge amount of data involved in various applications. The main focus of the project is to build a data mining system that can handle large sets of data and make forensic investigation efficient and less time consuming. For this purpose two important data mining tools namely Rapid Miner and Waikato Environment for Knowledge Analysis (WEKA) are studied and the system uses WEKA to demonstrate the data mining methodology and thus retrieve data. The four steps of data mining methodology including Association, Classification, Clustering and Regression are demonstrated on a set of data. Later, data retrieval is also performed using Forensic tool Kit (FTK) and the results are compared. Retrieval of data is performed on storage device using data mining and compared to other forensic tools finally.
# TABLE OF CONTENTS

Abstract ........................................................................................................................................ i

Table of Contents ......................................................................................................................... ii

List of Figures ............................................................................................................................... iii

List of Tables ................................................................................................................................. iv

1. Background and Rationale ....................................................................................................... 1
   1.1 Forensic Tools .................................................................................................................. 3
       1.1.1 Forensic Tool Kit .................................................................................................. 3
       1.1.2 Pro-Discove...”

1.2 Applications of Computer Forensics .................................................................................. 4

1.3 Forensic Techniques ............................................................................................................. 4

1.4 Data Mining as a source of Forensic Investigation (Veena H Bhat 2010) ......................... 7

2. Narrative................................................................................................................................. 9
   2.1 Motivation ....................................................................................................................... 9

   2.2 Data mining .................................................................................................................... 9
       2.2.1 Step by Step Process of Data Mining ................................................................. 9

       2.2.2 Process of Data Mining ..................................................................................... 10
           2.2.2.1 Clustering .................................................................................................... 10

           2.2.2.2 Classification ............................................................................................ 14

           2.2.2.3 Regression .................................................................................................. 15

           2.2.2.4 Association ............................................................................................... 17

   2.3 Levels of Analysis ......................................................................................................... 18

   2.4 Data Mining Applications ............................................................................................ 19
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5</td>
<td>Limitations of Data Mining</td>
<td>20</td>
</tr>
<tr>
<td>2.6</td>
<td>Data Mining Open source tools</td>
<td>21</td>
</tr>
<tr>
<td>2.6.1</td>
<td>Rapid Miner</td>
<td>21</td>
</tr>
<tr>
<td>2.6.1.1</td>
<td>Ways of using Rapid Miner</td>
<td>22</td>
</tr>
<tr>
<td>2.6.1.2</td>
<td>Properties of using Rapid Miner</td>
<td>23</td>
</tr>
<tr>
<td>2.6.1.3</td>
<td>Operator Info</td>
<td>23</td>
</tr>
<tr>
<td>2.6.1.4</td>
<td>Starting Rapid Miner</td>
<td>23</td>
</tr>
<tr>
<td>2.6.1.5</td>
<td>Text mining using Rapid Miner</td>
<td>27</td>
</tr>
<tr>
<td>2.6.1.6</td>
<td>Starting text mining in Rapid Miner</td>
<td>28</td>
</tr>
<tr>
<td>2.6.2</td>
<td>WEKA</td>
<td>29</td>
</tr>
<tr>
<td>2.6.2.1</td>
<td>History</td>
<td>34</td>
</tr>
<tr>
<td>2.6.2.2</td>
<td>Core Classes</td>
<td>35</td>
</tr>
<tr>
<td>2.6.2.3</td>
<td>Learning Schemes</td>
<td>35</td>
</tr>
<tr>
<td>2.6.2.4</td>
<td>Preprocessing Filters</td>
<td>36</td>
</tr>
<tr>
<td>2.6.2.5</td>
<td>User Interfaces</td>
<td>37</td>
</tr>
<tr>
<td>2.6.2.6</td>
<td>Extensibility</td>
<td>37</td>
</tr>
<tr>
<td>2.6.2.7</td>
<td>Standards and Interoperability</td>
<td>37</td>
</tr>
<tr>
<td>2.6.2.8</td>
<td>Download and Installation</td>
<td>38</td>
</tr>
<tr>
<td>2.6.2.9</td>
<td>Application and Interfaces</td>
<td>40</td>
</tr>
<tr>
<td>2.6.2.10</td>
<td>WEKA Function &amp; Tools</td>
<td>40</td>
</tr>
<tr>
<td>2.6.2.11</td>
<td>Advantages and Disadvantages</td>
<td>41</td>
</tr>
<tr>
<td>2.6.2.12</td>
<td>Data Formats</td>
<td>41</td>
</tr>
<tr>
<td>2.6.2.13</td>
<td>Data Retrieval from CSV file</td>
<td>42</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
<td></td>
</tr>
<tr>
<td>----------------------------------------------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>3. Design</td>
<td>45</td>
<td></td>
</tr>
<tr>
<td>4. Implementation</td>
<td>46</td>
<td></td>
</tr>
<tr>
<td>5. Evaluation and Results</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td>6. Future Work and Conclusion</td>
<td>67</td>
<td></td>
</tr>
<tr>
<td>Bibliography and References</td>
<td>68</td>
<td></td>
</tr>
<tr>
<td>Appendix</td>
<td>70</td>
<td></td>
</tr>
</tbody>
</table>
LIST OF FIGURES

Figure1 Measures of violent crime .................................................................1
Figure2 Data Storage vs. Time ......................................................................7
Figure3 Data Mining methodology ..............................................................10
Figure4 Example of Clustering ...................................................................11
Figure5 Exclusive Clustering ......................................................................13
Figure6 Demonstrating Classification ..........................................................14
Figure7 Starting Rapid Miner ......................................................................24
Figure8 Download Page of Rapid Miner ......................................................25
Figure9 Download and Install Rapid Miner ..................................................25
Figure10 Registration Window .....................................................................26
Figure11 Start Window of Rapid Miner .........................................................26
Figure12 Text Mining using Rapid Miner ......................................................28
Figure13 Starting WEKA ..............................................................................38
Figure14 Installing WEKA ...........................................................................39
Figure15 Console Window of WEKA .............................................................39
Figure16 WEKA GUI Chooser .....................................................................40
Figure17 WEKA Explorer ..........................................................................42
Figure18 Preprocessing Window of WEKA ....................................................43
Figure 19 Classify Window of Explorer........................................................43
Figure 20 Example of Decision tree .............................................................44
Figure 21 Flow Chart for Data Mining..........................................................45
Figure 22 Preprocessing Window .......................................................... 47
Figure 23 Dialog window for Apriori algorithm ...................................... 49
Figure 24 Running Associate data .......................................................... 50
Figure 25 Classify Tab in WEKA ............................................................ 52
Figure 26 Filtering Capabilities in WEKA ............................................... 52
Figure 27 Result Window of Classification in WEKA ............................. 53
Figure 28 Result J48 tree .................................................................... 53
Figure 29 Decision tree representation in WEKA ................................... 54
Figure 30 Test Instances in WEKA ........................................................ 54
Figure 31 Test Results in WEKA ............................................................ 55
Figure 32 Cluster Window in WEKA ...................................................... 56
Figure 33 Applying Simple k-means Algorithm in WEKA ...................... 56
Figure 34 Simple K-Means Dialog Box .................................................. 57
Figure 35 Result Data Set in Clustering .................................................. 57
Figure 36 Visualization Window in Clustering of WEKA ...................... 58
Figure 37 Visualization threshold curve in Regression .......................... 59
Figure 38 Visualization Margin Curve .................................................... 59
Figure 39 Installing FTK ..................................................................... 62
Figure 40 Case Lop Option .................................................................... 62
Figure 41 Process to Perform using FTK ............................................... 63
Figure 42 Refine Case-Default ............................................................... 63
Figure 43 FTK File Processing ............................................................... 64
Figure 44 FTK Retrieval of Data .......................................................... 64
Figure 45: Retrieving Data using FTK with unavailable Data Sets ........................................65

Figure 46: Resultant Data Set ..........................................................................................65

Figure 47: Data Retrieval using FTK with hard drive .....................................................66
LIST OF TABLES

Table 1.1 Data of Bank Employees .................................................46
Table 1.2 Time taken to Retrieve Data Using WEKA.........................61
1. BACKGROUND AND RATIONALE

Computer Forensics is a branch of digital forensics wherein the evidence in certain criminal investigation is found in computers and other digital media. Forensics is not just about finding data. It is an amalgamation of storing, retrieving, analyzing and presenting data which is a crucial task in forensic investigation. In short data recovery is the main objective. Computer Forensics has become important since 1980’s because that was the peak period when personal computers have started gaining importance and cyber crime started spreading like a disease. Some of the cyber crime activities involved child pornography, piracy of data etc [Wikipedia]. Thus a strong need to attack cyber crime has come into existence and computer forensics has been gradually developing since then. Though many countries have well organized forensic tools and techniques, the developing countries are still facing problems while retrieving data. Figure 1 gives a description of number of crimes and number of arrests in comparison to those crimes.

Figure 1  Relation between number of crimes and number of arrests

Source: Analyzing Huge Data Sets in Forensic Investigations (Kasun and Yasantha)
The number of crimes reported to police is lower when compared to the percentage of violent crimes [Zoysa 2010]. This happens due to various reasons, some of which include collection of evidence in unacceptable manner, evidence damaged due to external conditions which include environmental conditions. Apart from these, the culprit himself could damage the evidence. Developing countries could face these problems due to various reasons such as lack of proper equipment, lack of proper software, procedures and policies are not up to the mark and lack of proper knowledge and training of security personnel. Bank fraud is yet another area where data mining forensics plays a key role.

Fraud in banks can be of various types. A datacenter manager can make online entries to move money to his personal accounts. Fictitious loans can be recorded by bank officers and other lending officials. Apart from that false statements can be submitted by business customers. The annual cost of fraud and abuse has accounted to $994 billion [Zoysa 2010] which is extremely high, out of which 42% recover nothing after fraud is discovered. Thus forensic data mining is important since 30% of all frauds are found by analysis versus tips, unusual discovery of data. Forensic data mining can help find needle in a haystack. Initially well developed computer systems swoop in, brushing away surface dust to excavate potential fraud-experts call this forensic data mining. Some of the professionals who have a good experience in certifying fraud silt through the dirt and much to determine if the data is occupational fraud or sloppy bookkeeping which is termed as forensic data analytic [Deguang 2010]. Every fraud case is unique in nature but any fraud has a common characteristic that any criminal may be caught in at least one context. Data Mining is one of the most upcoming and most successful programs which can help professionals examine fraud based on a set of specific risk areas rather than
searching a whole lot. Forensic professionals can recover data from any computer system which can be a desktop, laptop. Apart from these data can be recovered from storage devices including USB flash drives, cell phones and personal digital assistants. Data mining can be used in various fields including employee payroll, vendors and account payable, and various sales and inventory. Data observed includes data of employees with no deduction, in all working hours, etc. One of the famous quotes says that “Types of fraud has been changing so as the ability to detect it”[Wikipedia].

1.1 Forensic Tools

Forensic Tools are very crucial in performing forensic analysis. Some of the widely known forensic tools include

1.1.1 Forensic tool kit (FTK) [Wikipedia]

FTK is one of the most recognized software. It is one of the court validated software’s and thus it has become crucial software in cyber forensic investigations. FTK is an encapsulation of decryption and password cracking. FTK 3 is one of the most important and latest technologies available in many organizations so that they could detect any sort of fraud. FTK performs various operations like restoring deleted images and scan a disk for text strings. FTK also has special software named as FTK imager. Though FTK is the most widely used forensic tool it has certain limitations and one of the biggest FTK is one of the most recognized software. It is one of the court validated software’s and thus it has become crucial software in cyber forensic investigations. FTK is an encapsulation of decryption and password cracking. FTK 3 is one of the most important and latest technologies available in many organizations so that they could detect any sort of fraud. FTK performs various operations like restoring deleted images.
and scan a disk for text strings. FTK also has special software named as FTK imager. Though FTK is the most widely used forensic tool it has certain limitations and one of the biggest limitation is it can be used only if a certain amount of data is being searched. But if large amounts of data (for example if terabytes of data) is considered, FTK decreases in efficiency.

### 1.1.2 PRODISCOVER

Pro Discover is another efficient tool in forensic investigation since it scans data from the sector level itself. It does not delete existing files and in turn recovers data from the sector level. It performs Boolean search on the entire hard drive and recovers data. Moreover hash functions can also be used in this type of search. Some of the advantages of Pro discover include creating bit stream copy of disk to be analyzed while keeping the data intact without any modifications. Though pro-discover has its own advantages, it suffers from limitations such as it cannot be used efficiently when large amounts of data is considered. Apart from these, some of the forensic tools include Sleuth Kit, PyFlag, PTK, Autopsy etc. These tools are not widely used due to their complexity and time consumption.

### 1.2 Applications

Forensics can be utilized in Genetics, DNA technology, e-forensics and many other applications.

### 1.3 Forensic Techniques [google]

A number of techniques are used in forensic investigations:
• **Cross-Drive analysis**: An important forensic technique that correlates information on various hard drives.

• **Performing anomaly detection**: Corresponds to discovery of events that typically do not confirm to normal behavior.

• **Live Analysis**: Live analysis is the process of examining computers from within the operating system using some of the existing tools to extract evidence from a computer. This sort of technique is useful when dealing with encrypting file systems, when encryption keys are collected and in some cases the hard drive volume can be imaged before the system shuts down.

• **Deleted Files**: Deleted Files can be recovered using computer forensics. Recent forensic tools have inbuilt tools for recovering deleted files. In many operating systems physical data is not deleted which enables data to be reconstructed from physical disk sectors. A technique known as file carving involves searching for known files headers within a disk image and reconstructing deleted materials. Apart from that there are various other forensic techniques which vary from those on computer networks and other computer systems. On computer networks three types of basic computer forensic techniques include packet Sniffing, IP address tracing and Email address tracing.

• **Packet Sniffing**: Packet sniffing is the process of removing out important packets of data from the network. The data can contain crucial data including user names and passwords, email information and any other important data that is transmitted in the network. IP Address tracing: This technique is
important to trace an IP address from which data is being transmitted. IP address tracing involves counting number of servers which exist between client and server which are termed as hops.

- **Email address tracing**: This technique is useful since it detects where an email has come from. Emails have an e-mail header which in turn consists of the source from where email has originated.

Though the above techniques are well useful for computer networks, computer systems have a set of forensic techniques which are very popular. Some of them are as follows:

- **File Structure**: File structure is analyzed and the files which are not normal are collected and subjected to digital evidence. Such type of files may include encrypted files which may give the examiner a wrong view or any file with an attached hash algorithms. This is done using automated tools which makes it a easier process.

- **Storage Media**: Storage devices include physical or removable disks like hard drive, thumb drive etc. The data might be deleted due to various reasons. There are various tools and techniques which are helpful in recovering such deleted data. The recovered data may or may not of the form it was originally, thus all the fragments of data are combined so as to get it back to normal form.

- **Steganography**: It is the process of hiding information in any other format than the original format. Data can be hidden by sending it through sound files or other files across the internet which makes it very difficult for the
examiners to detect. In such cases the encrypted data format can be decrypted using some of the existing techniques or some methods such as steg-analysis are performed to recover the data

1.4 Data mining as a source of Forensic Investigation [Veena H Bhat 2010]

Data Retrieval in large storage devices has been gaining tremendous importance now in recent days. Storage capacity is growing with time since new technologies have been emerging. One of the major problems is that tremendous effort and time are taken to analyze huge data sets and today most of the forensic tools analyze single drive at a time which makes it more complex. Thus data mining provides a better approach in solving the problem. It is a solution to handle massive volumes of data. A diagrammatic approach of how storage capacity grows over time is as shown in Figure 2.

Figure 2 Storage Capacity over Time

The advantages of data mining include reducing complexity of investigator, increasing the speed of investigation, improving the quality of data retrieved and data mining is also economic when huge volumes of data is involved. Data mining is different from knowledge discovery in databases. Knowledge discovery in databases is the process of finding useful information and patterns in data whereas data mining makes use of algorithms to extract useful information and patterns derived by the KDD process. Data mining is useful in many ways. The results obtained from data mining include forecasting future events, classification of data into various groups based on their properties, clustering data based on attributes, associating events that might occur and sequence them so that they can be used by future events.
2. NARRATIVE

2.1 Motivation

Data Mining is a growing area of research in today’s world and one of the emerging field in forensic investigation. Data mining plays a crucial role when a large amount of data is involved. Thus the main objective of this project is to study open source data mining tools and implement a data mining tool by using all the four steps involved in data mining.

2.2 Data Mining

Data mining is the process of extracting patterns from huge datasets using a combination of statistics and artificial intelligence with database management. To understand data mining in detail, one needs to get a clear understanding of various steps involved in data mining. They are as follows:

2.2.1 Steps of Data Mining [Veena Bhat 2010]

The following is a step by step methodology to demonstrate the process of data analysis.

- **Data Integration**: Data is collected and integrated from different sources
- **Data Selection**: Useful data is selected while putting aside the data which is not of any use to the user
• **Data Cleaning**: Data which is selected may not be perfect. It may contain some disturbances which include noise, errors or unspecific data. Some techniques are applied to get rid of such data

• **Data transformation**: Though data is clean, it is not ready for use. It needs to be transformed to the form in which it serves the purpose. Some of the techniques include smoothing of data, normalization etc

• **Data mining**: Now the data is ready to be mined. Techniques like clustering or association analysis are then used to mine interesting patterns of data

• **Pattern evaluation and knowledge representation**: In this step, redundant data is removed. It involves visualization also. After this the data is ready and decisions are taken finally based on the requirement.

![Figure 3 Data Mining Methodology (Source: Oracle.com)](image)

Data mining can be demonstrated using figure 3.

**2.2.2 Process of Data Mining:**

Data Mining can be performed using the following:
Data mining commonly involves four classes of tasks namely clustering, classification, regression and association rule mining.

### 2.2.2.1 Clustering [Shi Na, 2010]

Clustering is the task of discovering groups and structures in the data that are in some way or another "similar", without using known structures in the data. A formal way of clustering is it is considered to be the most important unsupervised algorithm which finds a structure in a collection of unlabeled data. Clustering differentiates similar data and dissimilar data which say it is different to data in other clusters. [Shi Na, 2010].

Clustering can be described using Figure 4.

![Image of Clustering](source: google)

**Figure 4  Example of Clustering (Source: google)**

In figure 4, a set of four clusters are taken into consideration. Clusters are of same kind if the distance between them is same. If clustering is based on the distance between the clusters, it is called distance based clustering. If objects belong to the same cluster and have a concept in common, they are said to be conceptual clustering. Applications of Clustering

Clustering can be used in various applications some of which are listed as follows:
• Marketing: In marketing, clustering can be used to find a set of clients who share a common pattern based on their habits and past purchases

• Biology: In classifying plants and animals based on their characteristics

• Libraries: A set of books are ordered which have similar data

• Insurance: In identifying frauds, by the high probability of crime happened previously

Apart from these, clustering can be useful in various other applications including city-planning, earthquake studies etc. To understand clustering in detail, there is a strong need to understand goals of clustering, requirements of clustering and clustering algorithms.

• Goals of clustering: The main aim of clustering is to determine the intrinsic grouping in a set of unlabeled data. Good clustering is based on how the user supplies the requirements. Any clustering mechanism makes use of clustering algorithm.

• Clustering Requirements: The main requirements that a clustering algorithm should satisfy include scalability, dealing with different types of attributes, discovering clusters with arbitrary shape, minimal requirements for domain knowledge to determine input parameters, ability to deal with noise and outliers, insensitivity to order of input records, high dimensionality, interpretability and usability.

Clustering Algorithms: Clustering algorithms are classified as follows
• **Exclusive clustering:** Data is grouped in an exclusive way, in the sense that if data belong to a certain group, it cannot be included in another group. An example of exclusive clustering is demonstrated using the figure 5. Figure 5 shows two sets of data separated by a straight line on a two dimensional line.

![Figure 5 Exclusive Clustering](Source: google)

• **Overlapping Clustering:** The overlapping clusters use fuzzy sets to cluster data. This type of clustering is useful when a point may belong to two or more clusters. In overlapping clustering, data is associated to an appropriate membership value.

• **Hierarchical Clustering:** This algorithm is used when union between two clusters is considered. Initially every datum is set as cluster and after a few iterations the final clusters which are required are obtained.

• **Probabilistic Approach:** Clustering is performed based on a probabilistic approach.

Some of the popular algorithms include K-means, fuzzy C means, Hierarchical clustering and mixture of Gaussians. Each of these algorithms belongs to one of the clustering types. As per the listing above, K-means [Shi Na, 2010] is an exclusive
clustering algorithm, Fuzzy C-means is an overlapping clustering algorithm, Hierarchical clustering and finally Mixture of Gaussian is a probabilistic clustering algorithm.

2.2.2.2 Classification [Christian, 2007]

Classification is the task of generalizing a known structure to apply to new data. For example, an email program might attempt to classify an email as legitimate or spam. Common algorithms include decision tree learning, nearest neighbor tree learning, nearest neighbor, naïve Bayesian classification, neural networks and support vector machines. For classification, a model is found for class attributes as a function of values of other attributes. Classification of data involves two data sets which are called training set and the test set. The training set is given as input to the data mining process and the test set is used to determine the accuracy of the model. The test set is used to test after the model is built using the training set. Figure 6 illustrates the classification process of data mining.

![Figure 6 Demonstrating classification (google)](image-url)
Examples of classification include:

- Classifying cancer cells as working or damaged
- Classifying any card transactions as authorized or unauthorized
- Classifying food items as vitamins, minerals, proteins or carbohydrates etc
- Classification of news into sports, weather, stocks etc

Classification Techniques include:

The following are various classification techniques

- Decision tree techniques
- Rule based method
- Neural networks based method
- Naive bayes method
- Support vector machines abbreviated as SVM

2.2.2.3 Regression

Regression – Regression analysis is the process of predicting of continuous dependant variable from a number of independent variables. It attempts to find a function which models the data with the least error. Regression analysis can be used on data which is either continuous or dichotomous. Regression analysis cannot be used to determine causal relationship. To understand regression in detail, the assumptions of regression should be understood.

The various assumptions of regression are:
• **Number of cases**: The ratio of cases to independent variables (IVs) ratio should be 20:1. The minimum ratio should be 5:1.

• **Accuracy of data**: Data entered should always be checked for accuracy. Though every entry is not verified, the minimum and maximum value of each variable should be verified.

• **Missing data**: Missing data can also be verified using regression analysis. Some of the variables miss certain values and the user may not be sure if he can or cannot use those values in his experimentation. After examining data, the user may want to replace the missing values with the existing values. The mean value is used as the replacement value.

• **Outliers**: Outliers are extreme values on a particular item. An outlier is a value which is at least 3 standard deviations above or below the mean.

• **Normality**: Normality is used to show how the data is normally distributed. Normalization of data can be done using histograms. The histogram consists of a line which conveys how the shape looks like compared with the original normalized data.

• **Scatter plot**: Results can be examined statistically using scatter plot.

• **Linearity**: An important assumption of regression analysis is linearity. Linearity defines a straight line relationship between Independent variables and dependant variables. Only linear relationship is considered ignoring the non-linear relationship. For a linear relationship, the scatter plot is oval.

• **Homoscedasticity**: The residuals are approximately equal to all predicted dependant variables. Data is said to be homoscedastic if residual plots are of
same width as the predicted dependant variable. To represent homoscedasticity, cluster of points are taken into consideration.

- **Multicollinearity and Singularity**: Multicollinearity is a situation where independent variables are highly correlated. Singularity refers to the situation where the independent variables are perfectly correlated and the dependant variable is obtained from the independent variables.

- **Transformations**: Transformations are used to normalize data. There are various types of transformations which vary depending on the requirement. To choose which type of transformation is to be applied, trial and error method is used. The transformation produces best results for whose distribution is normal. For data which is not normal, log transformation is used.

To understand linear regression in detail, one needs to understand simple linear regression and standard multiple regression. Simple linear regression is used when values of one variable is to be predicted given values of another variable.

Standard Multiple Regression is the linear regression where different dependant variables are used to predict another variable while in multiple regressions several independent variables predicting the dependant variable.

### 2.2.2.4 Association Rule Learning [Sean 2008], [Du 2010]

Association rule learning searches for relationships between variables. It is a method for discovering interesting relations between variables in large databases. Association rules are used to satisfy a user-specified minimum support and a user-specified minimum confidence at the same time. Initially association rules are generated using two separate steps, [Sean 2008]. In the first step, minimum support is applied to
find all frequent items in a database. In the second step, the frequent data sets are taken and minimum confidence constraint is used to form rules. Association rule types are categorized into three types namely actionable rules, trivial rules and inexplicable rules. Actionable rules are those which convey the actionable information. Trivial Rules are those in which information is already familiar with the business and market. Inexplicable Rules are that which have no explanation and does not have any suggested action [Du 2010]. An important terminology in associative rule mining is termed as lift. Lift conveys how better a rule is when predicting a result than just assuming the result in the first place. Creating Association rules is one of the crucial tasks in data mining. The following is a step by step procedure to create association rules [Du 2010].

- Initially the data that is to be mined is taken into consideration
- Generate rules by deciphering the counts in co-occurrence matrix. “A co-occurrence matrix is a matrix or distribution that is defined over an image to be distribution of co-occurring values at a given offset” according to Wikipedia.
- Overcome practical limits imposed by unique items.

For data mining to be understood various levels of analysis are to be understood.

### 2.3 Levels of Analysis

Different levels of analysis are available which are listed as follows:

- **Artificial neural networks**: They indicate the non-linear predictive models that are similar to biological neural networks in structure
• *Genetic algorithms*: Genetic algorithms are optimization techniques which use processes such as genetic combination, mutation and natural selection in a design based on the concepts of natural evolution.

• *Decision trees*: They provide a rule base which can be useful in predicting an outcome for a new data set

• *Rule Induction*: Obtaining a set of useful if-then rules from huge sets of data based on statistical significance

• *Nearest neighbor*: Classify records based on k-most similar records

• *Data visualization*: Visual interpretation of complex relationships in multidimensional data

2.4 Data Mining Applications

Data mining applications can be categorized into 4 types including classification, numerical prediction, and association and clustering. Some of the examples include automatic abstraction of data, financial forecasting, targeted marketing, fraud detection, and weather forecasting and health sectors. Data mining is used to detect fraud and remove waste initially. But recently it is being used in measuring and improving performance. Veteran Affairs department uses data mining to predict demographic changes in the constituency. The airlines department used data mining to analyze flight crash details. Data mining is also being used in serving a country’s security purposes. Data Mining is used in games such as chess, dots and boxes wherein human usable strategies are extracted from these oracles. In customer services data mining plays a crucial role. Especially when a company wants to start marketing, instead of randomly
selecting a customer, data mining can be performed on selecting the most likely customers based on their previous sales. Data mining can also be used in human resources department in identifying characteristics of their most successful employees. In genetic sciences, data mining can be applied to analyze DNA cells and its risk to develop cancer. This would be very useful to prevent and treat the disease. The data mining technique used for such purpose is called multifactor dimensionality reduction. Engineering is yet another field which utilizes data mining.

2.5 Limitations of Data Mining [Yan Li 2010]

Though data mining has many applications and advantages, it has equal number of drawbacks. The limitations of data mining are as follows:

• *Privacy issues*: Privacy is a major concern in any country. In recent years, internet usage has been increasing and thus privacy has been decreasing. Selling of private data without the consent of the customers is also termed as violating privacy law.

• *Security Issues*: Though many organizations have a lot of private data online, no proper security measures are being followed.

• *Misuse of information*: Trends obtain through data mining intended to be used for marketing purpose or any other purpose is misused. Unauthorized organizations may obtain data which is extracted through data mining and use it for illegal purposes.
• **Connection between behaviors and variables**: Though data mining identifies connections between behaviors and variables, it does not identify a causal relationship.

The project initially starts with understanding the forensic tools FTK and pro discover. Later on the data mining process is studied in detail and the methodology involved is understood. For this purpose some of the open-source data mining tools including Rapid Miner is focused mainly to understand the process of data mining. A data miner module is used in this project to retrieve data from a specific drive. It is further extended to retrieve data from a storage device which can be a hard drive or a thumb drive. As the data mining process is completed and data retrieval is performed, it is finally compared with the results obtained from FTK and pro discover. The results are presented finally after comparison between data mining with other forensic tools in data retrieval. The main objective of this project would be to study the drawbacks of forensic tools such as FTK and pro discover. One of the drawbacks of these tools is that they cannot be used when large amounts of data is involved. Common areas in which data mining is used include employees and payroll, vendors and accounts payable, expense reimbursement, loans (for financial institutions), sales and inventory. The data examined includes employees with no deductions, no sick/vacation/time off, payroll activity subsequent to termination and employee vs. department vs. company baselines (dollars and hours).

### 2.6 Data Mining Open Source Tools

#### 2.6.1 Rapid Miner [rapid-i.com]
The knowledge discovery process consists of the various steps which include visualization of data, machine learning and evaluation and also data preprocessing. Hence a data mining platform should allow complex nested operator chains or trees, provide transparent data handling, comfortable parameter handling and optimization, be flexible, extendable and easy-to-use. Depending on the task a user has to perform, he may want to perform highly automated data mining process, or continuously inspect intermediate results. RAPIDMINER which was initially termed YALE, is an environment for machine learning, text mining, predictive analysis and business analytics. Rapid miner is used to mine huge amounts of data which includes data preprocessing, visualization and deployment. Rapid miner is the most widely used tool by researchers due to its nature of handling transparent data. Rapid miner is used in research areas and also for real-world implementation. Rapid Miner is currently available in 2 versions including the community edition which is an open source version and also the enterprise version which is an upgrade of community edition. Enterprise edition has enhanced features, services and also has a guarantee period. Process Modeling is yet another important feature that helps Rapid Miner reach end users. A clear GUI is used and XML scripting language also plays a key role in machine learning. In Rapid Miner, the leaves indicate simple steps of the modeled process while the inner nodes correspond to complex or abstract steps. The root corresponds to the whole process. Rapid Miner uses XML, a widely used language for describing structured object used in data mining process. XML configuration files define a standardized interchange format in data mining process.
2.6.1.1 Ways of Using Rapid Miner [rapid-i.com]

Rapid Miner can be used in 2 ways. It can either be started off-line or Rapid Miner GUI can be used to design XML description of the operator tree. Process configuration is provided as XML file. Break points in rapid miner can be used to check intermediate results. The other ways of using Rapid miner include invoking rapid miner from the program instead of GUI. This can be done using Java API or a clear command line version. To understand Rapid Miner, there is a strong need to understand the properties of Rapid Miner.

2.6.1.2 Properties of Rapid Miner

The following are various properties of Rapid Miner

- Rapid Miner is completely written in Java.
- Operator trees describe the process of knowledge discovery
- Usage of XML representation ensures a standard for large and automated experiments
- Graphical User Interface, Command line mode and JAVA API are three important modes through which rapid miner can be implemented
- A huge set of visualization schemes are available in data miner which is obtained by the plotting facility available
- Some of the applications of data mining include text mining, multimedia mining, feature engineering, data stream mining etc.

2.6.1.3 Operator Info [rapid-i.com]

A large set of operators are available in Rapid Miner. One of the important operators supported by Rapid Miner is OLAP operators. OLAP stands for online
analytical processing. OLAP is an approach to swiftly answer multi-dimensional analytical queries. An OLAP operators are further categorized as aggregation operators, group by operators, attributes set pivot operators, group by, grouped ANOVA, post processing operators can be usually applied on models in order to perform some post processing steps like cost-sensitive threshold selection.

2.6.1.4 Starting Rapid Miner

Two ways exist to start Rapid Miner on any platform. The user can adapt the amount of memory which is allowed for usage using any of these ways. The method that is used makes use of installing Rapid Miner along with Java and then the executable is run on the system.

- For Rapid Miner to be downloaded, initially the user needs to download Java. For using rapid miner, the user needs to run a java run time environment (JRE) version 1.5 (officially 5.0) or higher

![Figure 7 Starting Rapid Miner](Source:rapid-i.com)

- In the second step, Rapid miner is downloaded and extracted
To download and install Rapid Miner, initially go to rapidminer.com as stated in Figure 7.

Figure 8 Download page of rapid miner [source:rapid-i.com]

Go to downloads tab and download as shown in Figure 8.

Figure 9 Download and Install rapid miner
Click on the download option based on the Windows system varying if it is 32 bit or 64 bit or any other system and this will take the user to the login or register page as shown in Figure 10.

**Figure 10 Registration window**

Rapid miner is now downloaded, and now needs to be installed. The installation guide will take the user through various steps of installation process. Finally an icon of Rapid miner5 can be seen on the desktop which is similar to the one shown in Figure11.
Figure 11 Start window of Rapid Miner

The Rapid Miner has the following tabs including a menu, edit, process, tools, and view and helps which enables the user to have a good user interface. One of the major uses of Rapid Miner is text Mining.

2.6.1.5 Text Using Rapid Miner

Text Mining is the process of deriving important data from large amounts of data. High quality data retrieval is called text mining. High quality data represents novel, interesting data which is relevant. The process of text mining initially starts with structuring the input text, and then proceeds with deriving patterns of structured data and finally obtaining the required output. Text mining is one of the recent applications of data mining which comprises of data mining, information retrieval, computational logistics. Text mining is gaining importance since most of the data is stored in the form of text itself. Thus the exact technical definition for text mining is as follows:”The discovery by computer of new, previously unknown information from a large amount of data resources” as per Wikipedia. To understand the definition, initially one has to know the meaning of previously unknown which stands for genuinely new. Text mining makes use of repositories.

A rapid miner repository can help the user organize the analysis projects, data and the methods of data mining process. Data from a location can be simply imported to the repository by drag n drop. Three main components of Rapid miner include flow design, Data transformations and repositories. Data Miner allows setting a new repository. A new repository prompts the user to enter parameters to create a new local or remote repository. A new local repository is created. The next step is setting a repository where
the root directory needs to be specified and click on next, so that the specified directory is selected. To initialize a new project, a repository location is selected in the repository browser. This step directs the user to the process perspective. The process perspective is where the actual repositories and operators are found. Operators in rapid miner are yet another crucial attributes that are important for data mining process. The operators in rapid miner define their expected inputs and delivered outputs as well as their parameters. Rapid Miner has more than 400 data mining operators. Rapid Miner is used to add operators and connect operators.

2.6.1.6 Starting Text Mining [rapid-i.com]

To start text mining in rapid miner, rapid miner needs to be updated and text mining needs to be installed. For this, initially one needs to go to the help menu, then update rapid miner and then select text mining and finally install it.

![Figure 12 Text Mining using rapid miner][rapid-i.com]

The user should start a new process, select a repository and specify a process name. On the left side of rapid miner screen one can observe two tabs namely repositories...
and operators. When the user clicks on the operators tab, the following elements can be seen. They include process control, utility, repository access, import, export, data transformation, modeling, evaluation and text processing. To select document, one of the tabs namely “process doc from files” is selected which retrieves data from a specific file. To get a system view, it is dragged into the design view and parameters are specified. To read documents from, one should know where they should be read from. Selection of specific directories can be performed and internal names can be given to those parameters. A waiting scheme can be selected. They are taken as unstructured list and converted to document vector model. Documents are represented as vectors where each position specifies each word. For each document, each word occurring number of times is known. If one wants to find relative term frequency, “term frequency” is used to specify it. Term occurrences correspond to number of times a word occurs.”TF-IDF” is one of the most important frequencies. Apart from that various separators or regular expressions can be used in text mining. Though Rapid Miner is useful, it has various drawbacks and thus not widely used.

2.6.2 WEKA [Waikato.ac.nz]

WEKA, an abbreviated form of Waikato Environment for Knowledge Analysis, is an open source machine learning tool written in Java developed at the University of Waikato which is a place in New Zealand. Initially, when the project was developed, several machine learning algorithms were available which were available on a large variety of data formats. WEKA is used to compare various machine learning methods. The WEKA tool kit is flexible and easily extendable. WEKA has various advantages such as availability under GNU general public license, easily portable due to its
implementation in Java, allows data preprocessing and modeling techniques, simple to use. Various data mining tasks are supported including data preprocessing, clustering, classification, regression, visualization and feature selection. WEKA provides access to SQL databases using Java Database Connectivity, the result is returned by a database query. Some of the features of WEKA are it has forty nine data preprocessing tools, seventy six classification or regression algorithms, eight clustering algorithms, fifteen attribute/subset evaluator and ten search algorithms for feature selection.3 algorithms for finding association rules and three graphical user interfaces.

The graphical user interfaces are “The Explorer”, ”The Experimenter”, ”The Knowledge Flow”. Explorer has a panel based interface which consists of various panels. The preprocess panel in WEKA can be used to load data and transform data. Data can be loaded in various types of file formats like Comma Specified Value (CSV), Attribute related file format (ARFF) etc. The preprocess panel is used to filter data using preprocessing tools [Remco 2009]. WEKA allows the following such as preprocessing, visualization, classification, feature selection. Preprocessing allows loading data, analyzing data and filtering data. Visualization includes comparing pairs of attributes and plotting matrices. Classification is the process of diving data into algorithms such as Naïve Bayes etc. Feature Selection is the process of forwarding feature subset selection etc. The main interface is the Explorer which has various panels.

The various panels including the preprocess panel, classify panel, select attributes panel, visualize panel provides access to main components of the work bench. The preprocess panel is a crucial panel which provides an opportunities for importing data from a database or CSV file. This panel is helpful to visualize prediction errors and also
evaluates data via threshold curves. For preprocessing to take place, a filtering algorithm is applied on the data which is imported. The second panel is used to classify data using classification and regression techniques [Remco 2010]. After filtering, the resultant dataset is sent through certain classification and regression algorithms. Regression is one of the important and easiest techniques to use since it involves a single input and output variable but can become more complex if large data sets with more number of inputs are taken into consideration [Remco 2010]. The regression model is helpful to predict the unknown dependant variable if a set of independent variables are taken into consideration. For data to be passed through regression phase, data should be loaded initially. The data should be of the format that WEKA understands well. Most probably ARFF type of files is considered. In this file each column can be defined and the information what each column contains. The regression models can be used to define numeric or data column. Initially data is loaded using the preprocessing function explained above. Visualization of data is performed so that the data set is observed. Now the classify tab is selected and choose button is selected and the functions branch is expanded. Now the Linear Regression leaf is selected. Thus the desired model is chosen, and other choices are “supplied test” which is useful to supply data set to build the model. The other choice is “cross validation” which is helpful to build a subset model. Apart from that percentage split is yet another process to build a model based on supplied data set. For WEKA, “use training set” is the option to perform regression for a certain data set. Though there are various supervised algorithms, a wide variety of unsupervised algorithms also exist which are termed as clustering algorithms. The next important panel is termed as cluster panel where in clustering techniques of data mining are applied. Clustering allows grouping
data into patterns. Clustering of data is advantageous over classification because every attribute is used in grouping of data. Cluster panel provide simple statistics. WEKA’s clustering techniques are not very extensive compared to the classification and regression techniques. Yet clustering of data might be complex and disadvantageous in many circumstances since the user needs to know in advance how to create data groups. Attributes are adjusted using simple K means algorithm [Shi 2010].

The select attributes panel is useful for selecting the most probable attributes in a large set of data. Select attributes panel is a means of having access to large variety of algorithms and evaluation criteria for identifying the most important attributes in a data set. Since combining various search methods with different evaluation criteria plays a key role, large number of candidate techniques is configured. Cross validation is an important approach to validate robustness of attribute sets. The last panel called the Visualize panel is helpful for visualization of data. Here data is plotted as a matrix called a scatter plot matrix. In this panel, data plots can be selected and studied for later purposes. In short visualization panel provides color-codes scatter plot matrix [Remco 2010] which allows drilling down of data by selecting individual plots of the matrix and re-selecting parts of those plots to visualize.

The main aim of designing “The Explorer” phase is for batch-based data processing. Batch-based data processing is that process where the training data as a whole is loaded into the memory and then processed. Though this sort of a process is advantageous for small data sets, it may not be suitable for large data sets. WEKA allows implementation of some algorithms which allows incremental model building making it a popular data mining tool.
The Explorer interface does not provide a good graphical interface for incremental model building. In such a case, another set of WEKA’s graphical user interfaces have been proven successful. This interface is termed as “Knowledge Flow”. Though most of the activities performed by the explorer interface are performed by knowledge interface, the knowledge flow interface is highlighted for its data flow model which enables incremental updates in addition to batch based training. In this interface, the incremental updates with the processing nodes can load data and pre process individual instances prior to serving as inputs to machine learning algorithms which in this case are the incremental learning algorithms. The knowledge flow interface provides a set of nodes for visualization and evaluation of data.

The third important graphical user interface is the “Experimenter”. This interface provides a mechanism to facilitate experimental comparison of predictive performance of algorithms based on various evaluation criteria. These experiments may include various algorithms running on a large number of data sets, for example using repeated cross validation. The experimentation can be conducted on a single node or extended to large number of nodes on a distributed network which enables reducing computational load to the individual nodes. As soon as the experiment is set up, it can be saved to either XML or binary form so as to retake it when necessary. Though WEKA GUI interface provides a means of accessing the saved experimental data, it can also be accessed through the command line. According to practitioners, whatever interface is chosen for the data mining process, it is important for the user to provide java virtual machine which runs WEKA, with a good and enough heap space. Memory should be pre specified but the
basic requirement is it needs to be lower than the amount of physical memory of the machine the user is handling.

2.6.2.1 History [Remco 2010]

WEKA was a project which was funded by New Zealand Government since 1993. The main aim of the project was stated as follows [Christian 2007]

“The program aims to build a state-of-the-art facility for developing techniques of machine learning and investigating their application in key areas of the New Zealand economy. Especially, a work bench is created for machine learning, to determine the factors that contribute towards its successful application in the agricultural industries, develop new methods of machine learning and ways of assessing their effectiveness.” Initially WEKA implementation was started in C language and some routines were written in Prolog. The initial version of WEKA use only Attribute Relation File format(ARFF) and was released in 1994. The first official releases of WEKA were in 1996 and 1997 which were termed WEKA 2.1 and WEKA 2.2. Initially eight learning algorithms, were used in WEKA. WEKA 2.2 also supported UNIX Make files which were used for large scale experimentation. At a certain point of time, it had become very difficult to handle large data sets. It was at this point of time, that the system was entirely written in Java. The complexity factors included changes to supporting libraries, management of dependencies and complexity of configuration that made the data mining task a difficult procedure. Thus Java provided a better option to handle such large data sets since it had unique feature named “Write Once, Run anywhere”. The next version of WEKA was released in 1998 May termed WEKA 2.3 and finally in 1999 a complete version of WEKA 3.0 was released. A stable version of WEKA was released in 2003
called WEKA 3.4. The latest version of WEKA until present is WEKA 3.6 which given the even-odd version numbering scheme is considered a feature-stable version. A wide variety of features make WEKA the most popular tool of data mining. The following are some of the features in WEKA 3.6

2.6.2.2 Core classes [Remco 2010]

One of the major changes to WEKA’s core classes is the inclusion of relation-valued attributes which helps the user to support problems involving multiple instances. These attributes allow each of its values to refer to a set of instances of a different set. XML format is yet another data format for ARFF files [Holmes 1994]. An important update to the core class of WEKA is the “capabilities” meta-data function. Data characteristics are decided based on the algorithms and filters that are an important part of this framework. This framework is helpful to the end user since it provides a feedback about its applications. “Technical Information” class is another set of classes added to the core classes which allows citing of details for a particular algorithm. Central log file has been an added important feature which enabled logging into WEKA. Central log file is one which captures all the information written to any graphical logging panel in WEKA along with any output to standard out and error.

2.6.2.3 Learning schemes [Christian Kraetzer 2007]

Since WEKA 3.5 has been released, various learning schemes have been developed and added to WEKA which enabled its popularity. Apart from that some of the existing schemes have been developed one of which is the instance based learning. Instance based learning has been improvised and new data structures have been added to
improve its performance and efficiency. A set of classification algorithms which have been added in WEKA 3.6 are listed as follows:

- **Bayesian Logistic Regression**: It is an algorithm which is used for text categorization, with Gaussian and Laplace priors.
- **Best first Decision Trees**: An algorithm which uses best first algorithm in building a decision tree
- **Decision table naïve Bayes hybrid**: An algorithm specifically hybrid learner which is a combination of building decision tree and naïve Bayes
- **Functional Trees**: Functional trees are a type of decision trees with oblique splits and leaves represent linear functions.

Apart from these some of the other algorithms include Gaussian processes, Simple CART, Variants for AODE, Wrapper classifiers. Many multiple instance algorithms have been added and some meta algorithms also have been added which can be wrapped around base learning algorithms which enables performance of WEKA. Some of the meta algorithms include nested dichotomies, dagging, rotation forest etc.

**2.6.2.4 Preprocessing filters [Christian Kraetzer, 2007]**

WEKA has a large number of preprocessing filters which have increased along with number of preprocessing tools. Some of the preprocessing filters are listed as follows:

- **Add Classification**: Adds predictions of a classifier to a data set
- **Add values**: Add labels from a given set of data to attribute if they are missing
Apart from these there are other preprocessing filters including Add ID, Attribute reorder, Numeric to nominal, Partitioned multi-filter, propositional to multi-instance and vice versa, random subset, subset by expression, wavelet etc.

### 2.6.2.5 User Interfaces [Christian Kraetzer 2007]

The GUI chooser of WEKA has been modified and now provides access to various other interfaces, system information and logging information. The new GUI interface includes scatter plots, ROC curves, decision trees which are a part of visualization menu. The tools menu of WEKA supports two new GUIs which are termed as “SQL viewer” which allows user entered queries to run against a data base and results are observed. In the explorer, “Open DB” button is used to retrieve data from a data base. Another GUI is the “Bayes network editor” which helps in analyzing, building and visualizing bayesian network classifiers.

### 2.6.2.6 Extensibility

Large number of updates has been added and a number of plugin mechanisms have been added which makes it widely extensible.

### 2.6.2.7 Standards and Interoperability

WEKA 3.6 supports importing PMML models. PMML supports predictive modeling markup language. PMML is a XML based standard for expressing statistical and data mining models that has gained huge importance. WEKA 3.6 supports import of PMML regression, and neural network model types. It also supports ability to read and write data in the format used by the well known Lib-SVM and SVM-Light support vector machine implementations.
2.6.2.8 Download and Installation [Remco 2010]

WEKA can be downloaded at www.cs.waikato.ac.nz/ml/weka/. WEKA can be downloaded in various formats including a developer version. This can be downloaded along with Java software or without it if the system already has a version of Java. Since WEKA is written in Java, it is a mandatory thing to install in Java. The following steps give a detailed explanation on how to start and install WEKA [Christian, 2007]. The welcome wizard of WEKA is displayed in Figure 13.

![Figure 13 Starting WEKA](image)

Figure 13 Starting WEKA

Figure 14 shows the installation screenshot of WEKA.
14 Installing WEKA

The setup window pops up as the installation is done which appears as the one in Figure 15.

As the installation is completed, the WEKA GUI directly pops up on the desktop. If it does not, go to start menu->programs->WEKA ->WEKA 3.6 and WEKA interface is ready to use. WEKA GUI chooser is displayed in Figure 16.
2.6.2.9 Application Interfaces

WEKA provides a large option of application interfaces as stated above. The Explorer interface is responsible for data preprocessing, attribute selection and also visualization of data. The Experimenter interface consists of a set of machine learning algorithms and they are tested and evaluated in this phase. The Knowledge flow interface is responsible for designing the data mining process. Apart from these data mining can be performed through a simple command line interface using commands without a normal Graphical user interface.

2.6.2.10 WEKA Functions and Tools [Christian Kraetzer 2007]

WEKA provides a large set of functions and tools which makes it user friendly. They include preprocessing filters, attribute selection, classification and selection of data, data clustering, association discovery and visualization of data which are performed at various panels of WEKA data mining process. The preprocessing filters are responsible for various activities including adding/removing attributes, substituting attribute values, discretization etc. Attribute selection refers to selecting relevant data. Selecting data can be done by using certain search methods including best-first search, genetic search and
ranking search. After the data is found, relevant data needs to be selected based on a set of evaluation measures. Another function of WEKA includes classification of data. Classification of data refers to sorting of data based on a specific category. Data can be classified using a set of methods including decision trees, naïve bayes method, neural networks etc. The data thus classified is evaluated using certain evaluation methods including test data set or cross validation. Data clustering is yet another important function of WEKA. Clustering can be implemented using a set of algorithms including k-means, Cobweb, X-means, Farthest first etc. Clustering can be used to compare visualized clusters and original clusters. Regression is also one of the commonly used function of data mining using WEKA. The methods for regression of data include linear regression, neural networks, regression trees etc.

2.6.2.11 Advantages and Drawbacks of WEKA

WEKA is open source free software which makes it available to all the common people. It is widely extensible and lots of features have been added since its discovery. WEKA can be integrated into other java packages. WEKA supports a wide variety of graphical user interfaces which makes it simple and flexible. WEKA can be used to build various phases of data mining process or it can also be used to run individual experiments. Though WEKA is a widely used tool it suffers from certain limitations one of which include poor documentation. Systems are updated constantly which might at times be confusing and the user might need to learn the process repeatedly.

2.6.2.12 Data Formats in WEKA [RemcoR.Bouckaert 2010]

The data formats for WEKA can be of various formats. The files can be ARFF (Attribute relation file format) [RemcoR.Bouckaert 2010], Comma Separated value
format (CSV), decision induction algorithm acceptable format etc. Apart from these data can be read from URL or a SQL database.

2.6.2.13 Data retrieval from CSV file

Data can be imported from a CSV file. A step by step procedure is illustrated below for a clear overview. Open WEKA and WEKA GUI chooser opens on the desktop. It has several applications one of which is the explorer. WEKA Explorer shows up which looks similar to what is shown in Figure 17.

![WEKA Explorer](image)

**Figure 17 WEKA Explorer**

The explorer has various open file, open DB, open URL, generate as options. If the user needs to import a CSV file, he needs to click on open file and select the required CSV file. The following example shows the preprocessed data for CSV file which consists of various presidents of USA, presidency period, Wikipedia entry, took office, left office, party, portrait, thumbnail, home state. An example of visualizing data when President field is selected. After preprocessing, the data is organized which can be seen in figure 18.
Data which is retrieved can also be classified based on a set of options. A choose option exists which allows the user to select from a large set of options. A set of test options also are applied so as to classify data. For example, a cross validation field exist which can enable the user to enter the number of folds he wants the data to be which is displayed in figure 19.

Once the data is classified, select the choose option in the classify tab to choose from various classifiers out of which include bayes, rules, trees etc. If the user wants to draw a decision tree J-48 he can choose the option in trees. In the result tab which is at
the bottom, right click on the result and select visualize tree. Thus the decision tree can be obtained.

Figure 20 Example of Decision tree

Figure 20 represents a decision tree for the CSV file which holds information about USA presidents.
3. DESIGN

The objective is building a data mining system which consists of collecting the data initially, pre-processing the data, clustering of data, and regression analysis of data and association rule mining of data. The flow of data is represented using figure 21.

START->PREPROCESSING->ASSOCIATE RULE MINING->CLASSIFICATION->CLUSTERING->REGRESSION->VISUALIZATION

Figure 21. Flow of Data Mining Methodology in WEKA

In this project, initially data is loaded into WEKA explorer using pre-processing technique, data is classified based on the attribute selection, and data is then divided into clusters based on the types of grouping that the user selects. The output obtained after clustering gives the accuracy of data when data is clustered which can be used for future predictions. Finally regression analysis describes how regression can be applied and results can be visualized.
4. IMPLEMENTATION

The project is implemented in 4 modules. Each module represents various stages of data mining process. Each module represents each task of data mining methodology. The four stages of data mining process include association, classification, clustering and regression. Initially source data is imported using either the command line interface or the explorer option in WEKA.

The data taken into consideration in this project is the bank data which consists of the following fields which has the attributes stated in table1.

<table>
<thead>
<tr>
<th>Field</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Id</td>
<td>a unique identification number</td>
</tr>
<tr>
<td>Age</td>
<td>age of customer in years (numeric)</td>
</tr>
<tr>
<td>Sex</td>
<td>MALE / FEMALE</td>
</tr>
<tr>
<td>Region</td>
<td>inner_city/rural/suburban/town</td>
</tr>
<tr>
<td>Income</td>
<td>income of customer (numeric)</td>
</tr>
<tr>
<td>Married</td>
<td>is the customer married (YES/NO)</td>
</tr>
<tr>
<td>Children</td>
<td>number of children (numeric)</td>
</tr>
<tr>
<td>Car</td>
<td>does the customer own a car (YES/NO)</td>
</tr>
<tr>
<td>save_acct</td>
<td>does the customer have a saving account (YES/NO)</td>
</tr>
<tr>
<td>current_acct</td>
<td>does the customer have a current account (YES/NO)</td>
</tr>
<tr>
<td>Mortgage</td>
<td>does the customer have a mortgage (YES/NO)</td>
</tr>
<tr>
<td>Pep</td>
<td>did the customer buy a PEP (Personal Equity Plan) after the last mailing</td>
</tr>
</tbody>
</table>
The following is a step by step procedure to demonstrate Association in data mining. [Remco, 2010]

- For demonstrating initially change the number of attributes. The source file can be in one of the forms which is either .arff or .csv. Initially the data is loaded into WEKA using “Open file” in the Explorer of WEKA GUI interface.

![Figure 22 Preprocessing window](image)

- The left panel of the window shows the attributes and when the user clicks on any of them, the statistics are displayed on the right side of the explorer.
- The top panel of the explorer shows the values or the basic information of the attributes selected.
• Let us consider an example for children as attributes.

• The attribute children tab which is initially “numeric” should be changed to attribute “children” \{0,1,2,3\} which conveys that the data is verified for 4 attributes since WEKA needs a set of specific inputs.

• The id attribute is removed. This can be done by clicking on filter panel and then click choose button. A window pops up with available filters. Scroll down and select unsupervised in attributes and then click remove.

• The invert selection button is set to false and click OK. The filter box shows Remove –R1.

• Association is one important methodology in data mining. This can be performed on categorical data. For association rule mining, discretization can be performed on numeric or continuous attributes.

• In this sample set, ”age”, ”income” and “children” are three continuous attributes. For example consider the “children” attribute, and edit the key word “numeric” values to “children” as 0,1,2,3.

• Now click on the filter icon and select choose. Choose to find unsupervised and now select the attribute as discretize

• Click “Discretize –B 10 –M -0.1 –R first-last”. Change attribute indices to 1,4 and bins to 3 and then click OK and then click apply

• Save the data to bank-data-final. arff.

• Change data such as ‘\(-\inf -34.333333)\’ to 0_34.
• Click “Associate” tab which is used for association. Use apriori algorithm to associate the data of bank. The attributes in the associate tab may be of various formats.[Sean Peisert 2008], [Shi Na 2010]

Lift: \( \frac{P(L,R)}{P(L)P(\bar{R})} \)

Leverage: \( P(L,R) - P(L)P(\bar{R}) \)

Conviction: \( \frac{P(L)P(!R)}{P(L,!R)} \)

• Apriori algorithm is the default algorithm that is to be used in association rule mining [Sean Peisert 2008].

• The resulting rules are sorted based on various metrics such as confidence, leverage and lift [Sean Peisert 2008].

![Figure 23 Dialog Window for apriori](image)

• In priori dialog, set “lowerboundMinSupport” to 0.1, set “upperBoundMinSupport” to 1, set “metricType” to lift, set “minMetric” to 1.5, set “numRules” to 100 [Shi Na, 2010] and finally click “start”.

58
CLASSIFICATION [Davis, 2010]

The following is a step by step procedure to demonstrate classification in WEKA GUI explorer.

• Initially the data is imported into WEKA using open file tab in the explorer preprocessing window.

• The left panel of the window shows the attributes and when the user clicks on any of them, the statistics are displayed on the right side of the explorer.

• The top panel of the explorer shows the values or the basic information of the attributes selected.

• Consider an example for children as attributes.

• The attribute children tab which is initially numeric should be changed to attribute children \{0,1,2,3\} which conveys the data is verified for 4 attributes.
• The id attribute is removed. This can be done by clicking on filter panel and then click choose button. A window pops up with available filters. Scroll down and select unsupervised in attributes and then click remove.

• The invert selection button is set to false and “OK” is selected. The filter box shows Remove –R1

• Association is one important methodology in data mining. This can be performed on categorical data. For association rule mining, discretization can be performed on numeric or continuous attributes.

• In this sample set, ”age”, ”income” and “children” are three continuous attributes. For example consider the “children” attribute, and edit the key word “numeric” values to “children” as 0,1,2,3.

• Now click on the filter icon and select choose. Choose to find unsupervised and now select the attribute as discretize.

• Click “Discretize –B 10 –M -0.1 –R first-last”. Change attribute indices to 1,4 and bins to 3 and then click OK and then click apply.

• Save the data to bank-data-final. arff.

• To verify for the correctness of data, classification allows the data to be tested using a test data set apart from the training data set.

• In this project bank-orig.arff is used to train the model while bank-test.arff is used to test the model

• Go to classify tab in the explorer and click “choose” button to see the filter conditions
14. For data to be classified, click on filter dialog box and choose binary attributes, numeric attributes and binary class and now the number of available algorithms are decreased.

15. Choose the 10 fold cross validation in the classification tab and click on start. This starts the process.
The confusion matrix displayed in the above window shows the details of the cross validation.

For classified data to be displayed using trees, go to choose and click on trees. The result is displayed on the bottom right of the window.
• The algorithm used here is J48 tree algorithm.

• Right click on the result that is obtained and select “visualize tree”

![Decision Tree Image]

**Figure 29 Decision tree**

• To test the data, test data function is used.

• The classification tab has various test options including use training set, supplied test set, cross validation and percentage split.

• Click on the “supplied test set” and set the test instances. For this purpose a window pops up and the user can select the test file.
Figure 30 Test instances in WEKA

- The results are displayed in the dialog box which can be demonstrated in figure 30.

Figure 31 Test instances

CLUSTERING [Remco, 2010], [Shi, 2010]

Clustering is yet another important step of data mining. Clustering in WEKA is performed using K-means algorithm. The following is a step by step procedure to demonstrate clustering.

- Initially load the data and save it in arff format or csv format.
- Change the attribute “children” to attribute “{0,1,2,3} which means it is for attributes from 0-3
- Repeat steps 8-11 of classification.
- The new data is now save to bank_cluster.arff
- Now go to cluster tag in the Explorer and click “choose”.

64
Choose the simple K-Means algorithm in the list of algorithms and the display would be as follows:[Shi, 2010]

- The user can change the attributes by clicking on the tab which opens up.
• Change the number of clusters’”numclusters”’ to 6 and we can change seed to 10 to 100 or whatever and click on Start

• The following window shows up which displays the instances after attributes are changed

Figure 35 Result data set in Clustering

• Cluster Instances are displayed on the screen of explorer
• The result is displayed on the bottom of the screen which says simple K means and right click on the tab where many options are displayed. One of them is visualize cluster assignments and the following window shows up.

![Figure 36 Visualization Window in clustering of WEKA](image)

Figure 36 demonstrates the process of Clustering in data mining Regression [Remco, 2010]

• Initially load data or import data into WEKA and then change the attributes as mentioned above. Remove the id attribute.

• Go to filters in weka, then choose unsupervised and then choose attribute and finally discretize Change the attribute indices to 1,4 and the bins to 3 and click OK

• Discretize the attributes as in classification

• Now the result is obtained in the result box which is at the bottom of the explorer screen
- Click on tree J.48 and various options are observed and right click on the result. Choose “virtualize tree” to observe the tree. We can also get the “classification_margincurve” and “classification_threshold curve” as shown in figure 37 and 38.

![Image of Weka Classifier Visualizer: Threshold Curve](image)

**Figure 37** Visualization threshold curve in Regression

Apart from these visualization margin curve can also be observed.
After understanding and analyzing data mining methodology using WEKA, the main aim of the project is to retrieve data from a storage device and measure its performance in comparison to that of existing forensic tools including FTK and pro-discover. Thus testing is done on a set of .csv files which are stored in a thumb drive and the results are tabulated. For performing testing, initially metrics for both data mining tool and forensic tools needs to be analyzed.

Performance metrics include absolute speed, time, accuracy, completeness and reliability.

The evaluated results after data mining process are as follows:

- The preprocess panel displays the results of newly assigned attribute values and new labels after changing the attribute values. The data set can be visualized in the right bottom of the window.
In the classify tab, the correctly specified instances are fifty one percent approximately while incorrectly specified instances are forty nine percent. This conveys that the data mining process is accurate to a certain extent since correctly specified instances are more than the incorrectly specified instances. Thus classify is used to test accuracy of the model.

The data is then organized into clusters. To observe clustering results “view clustering results” is used. The results are displayed using various colors of clusters. Each color represents a cluster which represents the amount of relevant data in that particular cluster.

**Testing with WEKA:**

- **Testing with thumb drive (small data set)**

  Consider a test case with a set of sample data which consists of data regarding presidents of USA. The data is initially present in the thumb drive which is in csv format. The data is now loaded into WEKA using WEKA Command line interface since WEKA explorer accepts data in Attribute Related File Format (.arff). The command used to load data is as follows

  ```
  java weka.core.converters.CSVLoader bank-data.csv > bank-data.arff.
  ```

  The csv file containing details of “Details of Presidents of USA” is loaded into the WEKA explorer and then it is run through WEKA.

  The results of the data mining process for “Presidents of USA” data are tabulated in Table 2.

  **TABLE 2: Results for Presidents of USA Data Set**
<table>
<thead>
<tr>
<th>Data Mining step</th>
<th>Time taken to complete the model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loading and Preprocessing of data</td>
<td>4.2 min</td>
</tr>
<tr>
<td>Association rule mining</td>
<td>2.66 min</td>
</tr>
<tr>
<td>Classification and results using cross-validation</td>
<td>3.27 min</td>
</tr>
<tr>
<td>Clustering with supplied test data</td>
<td>3.78 min</td>
</tr>
<tr>
<td>Regression analysis</td>
<td>2.76 min</td>
</tr>
<tr>
<td>TOTAL TIME TAKEN</td>
<td>16.73 min</td>
</tr>
</tbody>
</table>

The time taken may vary based on various constraints like internet speed, system performance etc. The process for using WEKA is similar to the one which used bank employee’s data set as a sample.

TESTING USING FTK

For testing with FTK, install FTK and run it. Add evidence when prompted to and the user can observe various options in FTK. The following describes a step by step procedure to demonstrate using of FTK.
Figure 39. Installation of FTK

- Figure 39 demonstrates the installation procedure of Forensic tool kit

Figure 40  Case log options

- Figure 40 refers to various case log options which refer to the set of events that occur during the course of the case.
Figure 41. Processes to be performed in FTK

- Figure 41 refers to the processes that are performed while retrieving data using FTK

Figure 42. Refine case in FTK

- Figure 42 represents only necessary data to be filtered instead of useless data
Figure 43 FTK processing files from the given evidence

- Figure 43 demonstrates the file processing after evidence using FTK. Figure 43 specifies the time taken to retrieve the “USA Presidents set” from the thumb drive after scanning it.

Figure 44 FTK in retrieval of data

- Figure 44 represents a sample data result which consists of the data set regarding details of ”Presidents of USA” in another file named worksheets. Worksheets file can be seen on the right side of the screen.
Figure 45 Retrieving of data using FTK

- Figure 45 represents data retrieval if no data exists in FTK, in other words if data set is not found.

Figure 46 Data saved after FTK processing

When data is taken as evidence, and FTK retrieval is performed on it, data which is retrieved is finally saved in the same drive itself. The total time taken to scan and retrieve files from a thumb drive was just 5 min which was very much less than that of
WEKA. But this is not always true. When a large data set, in case a hard drive is considered for testing, the results are not the same.

- **Testing with Hard Drive:**

  Consider a hard drive of around 1 Terabyte data in it. It takes around 6 hours for FTK to scan and retrieve data from a hard drive. Figure 47 gives a view of the time elapsed while retrieving data from hard drive using FTK.

  ![Figure 47 Time Elapsed when Retrieving Data from Hard Drive](image)

  But when the data retrieval with WEKA has been performed, it takes around one to two hours for the entire process including loading of data to WEKA, preprocessing of data, classification of data based on the requirements, clustering, association rule mining and finally regression analysis of required data. Thus the results prove that for smaller data sets FTK is advantageous while for larger data sets data mining would be a better option.
6. CONCLUSION AND FUTURE WORK

This project gives an overview of how data mining can be used as an alternative to FTK when large capacity storage devices are considered. Thus it can be used as a source of forensic investigation in future. In this project, data mining has been performed on two data sets which include a bank employee data set and the data set containing data of Presidents of USA. The bank employee data set has been used to demonstrate WEKA data mining process in a step by step methodology while the data set containing data of Presidents of USA has been used for testing. A new data mining tool can be created which uses a combination of WEKA and data mining in organization of data which can be useful for future forensic investigators. Two important forensic tools namely Rapid Miner and WEKA are studied and then the project demonstrates the implementation of data mining process using a data mining tool WEKA, which is used to retrieve data from two storage devices namely thumb drive and a hard drive. The results are compared with those of retrieving data using well known forensic tools such as FTK. Though data mining in retrieving data is advantageous, it has its own disadvantages. This is because not much research is being done in this area. Apart from that data mining is useful and appropriate only when huge data sets are involved in large storage devices. Thus it would be a future research area to minimize cost and time when smaller data sets are involved using data mining. Thus if this is implemented successfully, it reduces cost and time.
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APPENDIX (Enclosed in CD)

- Data File of Bank Employees
- Data File of USA Presidents