Big Data Analytics in E-Commerce for Gaining the E-business Competitive Advantage

Ansam Khraisat
School of Science, Engineering and Information Technology
Ballarat, Australia
a.khraisat@federation.edu.au

Ammar Alazab
School of Information Technology and Engineering
Melbourne Institute of Technology
Melbourne, Australia
aalazab@mit.edu.au

Savitri Bevinakoppa
School of Information Technology and Engineering
Melbourne Institute of Technology
Melbourne, Australia
sbevinakoppa@mit.edu.au

Hania Alhamad
School of Science
Royal Melbourne Institute of Technology.
Melbourne, Australia
hanshiari@gmail.com

Abstract—E - commerce has resulted in organisations putting huge assets in online systems to stretch out business forms on to the World Wide Web. Traditional techniques for estimating Web use miss the mark regarding the wealth of information required for the powerful assessment of such methodologies. Many organizations are interested in analyzing and evaluating the web data for their websites because websites are a very important platform to carry out their business. However, website evaluations face many challenges in using analytics, especially with the huge amount of data that the websites are collecting from various sources. This calls for methods to examine, understand and visualize the huge amounts of stored data collected from the websites. In this paper, a framework is developed for identifying user's behaviours on websites. Firstly, the attributes are extracted from different websites using Google Analytics and other API tools. Secondly, data mining techniques such as clustering, classification and information gain are applied to build this framework. The obtained results of the study can be used to evaluate the website and provide some guidelines for the webmaster team to increase user engagement with a website and understand the influence of user behaviour in purchases. In addition, this framework is able to identify which behaviour features influence user purchasing decisions. Our proposed framework for identifying user's behaviours on websites is tested on a large dataset that contains a variety of individual users from different websites.

Keywords— Web Data mining, E-Business websites, Web structure mining, Web analytic, E-commerce websites

I. Introduction

Business has revolutionised business and changed the shape of competition over the Internet. However, some companies are struggling to satisfy the customers' demand through e-commerce websites and lead generation websites. Lead generation is a specialised service to obtain information for the purposes of expanding a business, increasing sales revenues and looking for new clients. Lead generation websites are created to encourage and motivate customers. In marketing, lead generation is the beginning of buyer interest or query into service or product of a business.

The internet is being used more and more in E-business and digital consumers have increased dramatically. Figure 1 presents a prediction of the number of digital buyers worldwide up to 2019, based on realistic statistics from 2014 to 2015 [1]. In 2019, over 2 billion individuals global are estimated to purchase items and facilities online, up from 1.46 billion universal digital consumers in 2015.

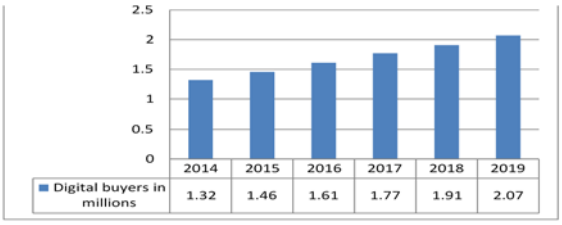

Figure 1 Number of digital purchasers global from 2014 to 2019

Many online businesses rely on free web analytic tools such as Google Analytics, Woopra, Clicky, Site Catalyst, Webtrends and other API tools to understand their web marketing campaigns and strategic business decisions. Unfortunately, these tools do not provide enough information to evaluate the websites and understand customers' behaviours. Therefore, extra analysis with data mining involvement needs to be done to help the decision makers gain a better understanding of the business insight.

Customer profiles can be created by analysing how customers found a business website, which websites they visited and left from, how long they stayed on the website and which pages they browsed. Customers visit websites and leave behind valuable information about their behaviour. A customer behaviour study's purpose is to enhance business performance through an analysis of past and present customers and target prospective customers and their behaviour. However, the companies are working very hard to keep their competitive standing to achieve good revenue [2]. To achieve this, web mining is applied to enhance company revenue by extracting useful information from the customer surfing pattern on the site such as the length of page view. In addition, data mining can also be providing information to improve the website structure, availability of information in the website and to simplify access. The result from this, allow visitors to navigate the website easily and intuitively, thus transforming a visitor into a buyer.

It is argued the capability and flexibility to increase the conversion rate can be boosted by optimising the website and applying data mining techniques based on users' interaction patterns on the website. Data mining can also help to achieve website goals such as e-commerce goals and lead generation goals. In this research, users' interactions within the websites

are captured. Next, data mining techniques are applied to this big data to understand which attributes could influence user decisions. This can also help to understand the influence of user behaviour in purchases on the website. This is vital to identify the opportunities supplied by the market, to anticipate the decisions of the competitors, as well as to learn from their mistakes and achievements. For example, collecting and analysing data produced by customers of e-commerce websites is vital to understand, model and predict human behaviour.

The rest of this work is organized as follows. Related work of the evaluation websites is presented in Section 2. The proposed maximizing competitive advantage on e-business Websites based on data mining techniques is expounded in Section 3. The results are discussed in Section 4. Conclusions are presented in Section 4.

II. Literature Review

This section discuss literature approaches that the previous researchers used for mining usage patterns from web data. Also describe the overview of a general web mining process and highlight recent research carried out in mining different types of frequent patterns.

A. Website development and evaluation theory approaches

The evaluation of websites has been a common subject of academic studies. Tan et al. (2009) proposed that websites can be evaluated from many different perspectives and site effectiveness assessment depends on the viewpoint of the evaluator [3]. The authors propose that the effectiveness of a website can be evaluated from different perspectives: function-related, user-related, or investor-related. Function-related models study the architectural web design and quality of websites. User-related focuses on user factors like website usability and consumer satisfaction. Investor–related models focus on the websites' operational performance and evaluate how well the website supports the general business objectives of the company.

Based on the investigation of previous research, there are three popular approaches to the evaluation and development of websites: IS-approach, marketing-approach, and combined both approaches [4]. The IS-approach focuses on technical factors, for example, ease of use, graphic design, content quality and the website navigation structure. IS-approach linked with user-related model and function-related model for good website design and user-friendly interface proposed by Tan et al [3].

The marketing mix concept was created by Neil Borden, the president of the American Marketing Association in 1953 [5]. This term is still used today to make critical decisions that lead to the execution of a marketing plan. Several approaches that are used have evolved with the increasing technology use. The marketing mix is an important tool to understand what can be offered and how to plan for a successful product offering. It is executed through the four P's of marketing: Price, Product, Promotion, and Place. Marketing-approach concentrates on the commercial side and examines web visitors as potential customers.

As an alternative option the 4S web-marketing mix framework allows the web marketer to solve the strategic and operational and efficient way[6] .The 4s framework save considerable time in designing and completing the online project, 4S web-marketing mix model created from the 4Ps (product, price, place, and promotion) marketing mix by [5]. The dimensions scope of web-marketing mix by are includes strategy and objectives, site (contains website browsing experience), synergy (includes integration with other marketing channels), and system (contains the technological aspects of a website) [6].

IS approach has been used by Palmer (2002) for website design elements study, the study suggests five website design elements which are related to website usability. The elements contain navigation structure, site content, interactivity, responsiveness and loading time of a website [7]. The marketing-approach is linked with the investor-related view obtained by Tan et al. (2009) as the combined-approach, combining both IS and marketing elements [3].Website developers need to be careful about all these design elements and find suitable metrics to evaluate the performance of the elements. The investor-related view and marketing-approach are applied in the study of the decision-making

process of online customers by Soonsawas The study examined the relationship between the customer decision processes and website components [8]. The objective is to gain knowledge of how to turn site visitors into conversions Tan et al. (2009) states that the IS achievement model of [9] has been frequently used as a theoretical background for website evaluation researches [3].

Others says the website success model is the extension of the original IS success model. The models contain three elements (subjective model, information quality model, and system quality model), which are related to two different website success measurements (individual impacts and website satisfaction) [10]. Other popular theoretical frameworks include the Technology Acceptance Model (TAM) and the human-computer interaction (HCI) field by [11]. These theoretical backgrounds are linked more with the IS-approach of website improvement. The marketing-approach studies draws more from the field of e-marketing than information system science.

No matter which approach or perspective is applied to website development and evaluation, it is very necessary for the website developer and for the company to objectively measure the website to achieve their business goals.

Web analytics such as webmaster tools can be used to measure user-related, function-related and investor-related factors. Web analytics can provide metrics that have a strong usability focus, such as the average time on page and the number of page views. Also it is possible to create metrics with a technical focus like the page loading time. Conversion rates play an important part of web analytics[12]. Conversions have a strong commercial focus and can be used to measure the success of marketing efforts and operational performance.

1) *E-Business analysis*

Business analysis is used to analyse the data into useful information to understand the organisation's strengths and weaknesses. These applications are capable of handling big data and allow organisations to collect, store, access and analyse the data.

The companies are working very hard to obtain, implement, and process information systems of all the business activity to increase the productivity, improve the competitiveness, and reduce costs. However, the companies are dealing with big data from different sources and several data types such as text, images, video, and sound. Business Intelligence is used to discover and analyse these data in order to improve businesses knowledge, which helps in business decisions for improving the customer relationships. It is implemented in digital and online marketing intelligence. This is can be done through working on marketing-oriented business by using data mining techniques.

Business analysis is used in several areas such as customer profiling, customer support, market research, market segmentation, product profitability and statistical analysis. Business intelligence consists of several activities such as data mining, online analytical processing, querying and reporting. Business analysis can be applied to several business purposes as shown in Table 1.

Purposes	Description	Applications
Measurement	Performance metrics and benchmarking about business goals progress	Business process management
Analytics	Transform the row data into meaningful information to perform business knowledge discovery	Data mining, process mining, statistical analysis, predictive analytics, predictive modelling, business process modelling and data lineage

Reporting/enterprise reporting	Provide the business management reporting to serve the strategic.	Data visualisation, executive information systems and OLAP(online analytical processing)
Collaboration/collaboration platform	Gets inside and outside the business	Data sharing and electronic data interchange.
Knowledge management	Help the company with business insights and experiences	Learning management and regulatory compliance and data mining

Table 1 Business analysis purposes

The Internet has revolutionised business areas such as marketing. Nowadays, Internet is the channel of customer relationships and sales. Proper marketing is the key for any business success. This can't be done without understanding what is going on in the website so the best way to achieve this goal is by analysing a user's behaviours in their website by applying a proper analysis.

Measuring the performance of websites is becoming a strategic issue and critical for e-marketing. Hundreds of thousands of e-commerce web owners worldwide use a web analysis programme such as Google Analytics[12]. This analysis programme provides basic and simple statistics about the website such as number of visitors, the average number of page views per visitor, average session duration, most requested pages, domain classes and website traffic [12]. However, understanding users' behaviour gives the companies the ability to satisfy and meet the customers' requirements based on user behaviour analysis. For example, the information gained from website activity helps to understand the users' behaviour such as the number of website visitors on the website, which products the customers have purchased, what categories they prefer, if they have registered as a member or not, and so on.

Different web analysis tools are used in business analysis. One of the web analysis tools is Google Analytics [13], which is a free service provided by Google that reports website traffic, tracks the website, monitors website visitors' activities in real time, finds the exit page path, provides the geographical traffic, and understands the keywords queries of the visitors who use the website. This is just an example of the possible data gathered through Google Analytic which can also provide us many other data available in web analytics. Google Analytics provides basic analytical tools used for search engine optimization (SEO) and marketing. It is useful for small and medium-sized retail websites. Some researchers have studied the Google Analytics operating and they have evaluated it as a useful web analytics tool [14, 15]. Plaza used Google Analytics data in combination with time series methodology for evaluating the performance of tourism websites [16]. Carroll et al. (2014) found the data visualisations created from Google Analytics assists readers to understand the information from complex data sets [17].

Although thousands of e-commerce web owners relay on web analysis programmes Chen et al. (2012) studied the availability of a huge amount of information and found that visualising this information can overwhelm users and this may cause a misuse of this information and leave most of the data unused [18].

Web-Enabled Electronic Business (e-business) is creating a huge amount of data such as customer information, purchases, users' browsing patterns, and so on. E-commerce provides the business world with various services such as delivery of information, goods, services, payments and workflow electronically and automatically [19]. The aim of e-commerce websites is to decrease the service costs while improving the quality of goods and increasing services delivery and usage of online services. E-commerce is quickly reshaping the market domain transactions [20]. Different data

mining techniques can be applied in several businesses objective as shown in Table 2 .

Techniques	Business Objective	Use	Example
Association	The main idea is to consider every URL requested by a user in a visit as basket data (item) and to discover relationships with a minimum support level between them. Improving the usability and comfort for the customer of the website.	Help web designers to restructure their website. Helps personalise the delivery of web content and improve web design, customer satisfaction and user navigation through pre-fetching and caching [21].	Used in an e-commerce website of Extra virgin olive oil sale [22].
Cluster of users' trends	Clustering of users trends to establish groups of users exhibiting similar browsing patterns. Such knowledge is especially useful for inferring user demographics in order to perform market segmentation in e-commerce applications or provide personalised web content to the users.	Internet search engines. Understand the behaviour of ecological consumers and their intention to purchase.	Determining the factors influencing consumer behaviour towards organic food [23].
Cluster of page	Clustering of pages will discover groups of pages having related content, semantic analysis systems, crawlers and search engines query and keyword extraction. [24].	Assisted to identify website issues in order to improve the website structure.	Provide high quality recommendations method for E-commerce website [25]. *B.*

Statistical Analysis	Statistical information such as the most frequently accessed pages, average view time of a page or average length of a path through site.	Improving the system performance , enhancing the security of the system, facilitating the site modification task, and providing support for marketing decisions.	analyse the impact of ecommerce on hotel performance [26].
Classification	Mapping a data item into one of several predefined classes.	Developing a profile of users belonging to a particular class or category.	Use website success factors to predict e-commerce companies success [27].
Sequential Patterns	Web marketers can predict future visit patterns.	Helpful in placing advertisements aimed at certain user groups. Predicting future business activities. Design and implement a WUM model to improve the Website from the users' viewpoint [21].	Uses the web traffic volume data of a destination marketing organisation to predict hotel demand [28].
Dependency Modelling	Used to develop a model which can state the dependence between the various variables [29]. Build a model representing the different stages a visitor undergoes while shopping in an online store based on the actions chosen.	Analysing the behaviour of users but is potentially useful for predicting future web resource consumption , information may help develop strategies to increase the sales of products.	Influence of online shopping information dependency and innovativeness of Internet shopping adoption [30].

Table 2 Business Techniques and Objective

In prior research, there are several data mining techniques applied in the e-business area such as classification, cluster, predictive modelling, and association rules. Fayyad et al. (1996a) provides an overview for intelligent data analysis necessary to extract useful knowledge from the data, which is called Knowledge Discovery in Databases (KDD). In marketing, the main application is database marketing systems, which analyse customer databases to identify diverse customer groups and predict their behaviour [31].

Kim et al. (2003) present a personalised recommendation procedure by which we can get additional recommendation effectiveness when using Internet shopping sites. The suggested procedure is based on web usage mining, product taxonomy, association rule mining, and decision tree induction [32]. Hu et al. (2004) propose a methodology to extract information from customer questionnaires and set personalised

recommendations in websites based on extraction [33]. Zhang et al. (2007) presents an associative classification-based recommendation system to support online customer decision-making when facing a huge amount of choices [34]. They discussed various personalisation techniques like content-based recommendations, regulation-based recommendations and cooperation recommendations [35].

Yuantao and Sigin (2008) used the principles of data mining to cluster customer segments by using k-means algorithm and data from web logs of various e-commerce websites [36]. Yu and Ying (2009) described various data mining procedures useful for e-commerce. They discussed website optimisation and their benefits in close detail such as enhanced website design that not only helps customers but increases revenue, residence time of customers on websites and improves the competitive rank of enterprises, etc. [37].

Thorleuchter et al. (2010) introduced a web mining approach for automatically identifying new product ideas extracted from web logs [38]. Liu and Wang explained about customer behaviour for website structure improvement. They also discussed two research directions, General Access Pattern Tracking and Personal Usage Records Tracking. On the basis of General Access Patterns Tracking, website ranking can be improved [39]. Zhang proposed that data mining in website-commerce websites is a popular research area [40]. In 2012, Thorleuchter et al. studied the issue of predicting new customers as profitable or not based on information about existing customers in a business-to-business environment. In their research, they showed how latent semantic concepts from textual information of existing customers' websites can be applied to reveal features of websites of companies that will turn into profitable customers. Hence, the use of predictive analytics will assist in identifying new potential achievement targets. In addition, they showed that a regression model based on these concepts is effective in the profitability prediction of different customers [41].

Zuo and Hua defined various data mining techniques which have been used to define customer behaviour and feedback for website structure optimisation [42]. Rajaraman et al. (2012) applied data mining to massive commerce data to discovering the problems of finding frequent item sets and clustering, identify recommendation systems and web advertising applications problems [43].

Poggi et al. (2013) compared web clicks, and then presented a methodology to classify and transform URLs into events, and evaluated the traditional process of mining algorithms to extract business models from web log data [44].

Ferrara et al. (2014) provide a comprehensive overview for Web Data Extraction literatures as the web data is the key to perform the Business and the Competitive Intelligence Systems. By using simple classification framework to extract data from web pages [45].

Alzue et al. (2014) used DWM systems to improve the measurement, analysis and modelling for a tourism website as a platform for competitive intelligence to improve the online marketing strategies [46]. Verma et al. (2015) used semantic web mining and neural computing to improve the page ranking and help the website designers to optimise the website structure [47].

There are several data mining techniques that could be used in e-business such as classification, cluster, predictive modelling, and association rules. Unfortunately, all the previous research focused on e-commerce websites. In this research I will use clustering, classification and information gained from e-commerce websites .

Conversely, the websites which are suffering from low conversion may need some diagnostics to understand which user behaviours are responsible for these poor conversions. A framework will be used to identifying the customer's behaviours on e-commerce websites that provides an objective basis for e-business websites.

The purpose of this research is to apply a set of descriptive data mining techniques to gain knowledge that will help to the webmaster team to improve the design of the website. We extracted the features from e-commerce websites by using webmaster tools. Data mining techniques will be applied such as classification, cluster and information gained. The results from this can help companies to discover the patterns of customers for conversion. However, previous progress into developing a comprehensive theory of e-business has failed to identify a range of factors which are responsible for low conversions. This project is the first to identify them by using data mining.

C. Data Mining

Data mining, which is also called knowledge discovery in databases, is the process of extracting knowledge from large quantities of data. Data mining models consist of a set of rules, equations, or complex ‘‘transfer functions’’ that can be used to identify useful data patterns, understand, and predict behaviour [48].

Several algorithms and techniques such as classification, clustering, regression, artificial intelligence, neural networks, association rules, decision trees, genetic algorithm, nearest neighbour method , are used for discover the knowledge from databases. They can be grouped into three main classes according to their goal as shown in Figure 2.I will explain classification in order to distinguish between buyer and non-buyer, and clustering to identify visitor groups with common behaviours and information gain to rank which website elements may responsible about low conversion. Full details of the proposed data mining process are given in chapter 3.

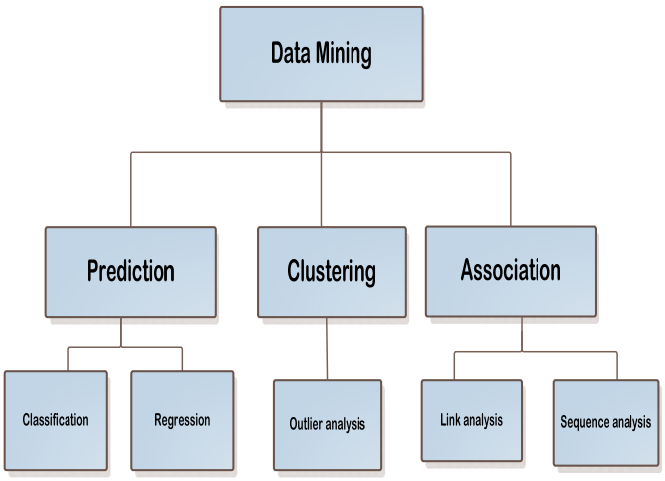

Figure 2 Data Mining Models

a) Classification

A classification technique is a systematic approach for building classification models from an input data set. Classification is the task of mapping a data item into one of a number of predefined classes [49]. For example, classifying electronic mail as spam or non-spam based upon the message header, sender, and content. Classifying an application as a malicious application or benign application upon the behaviour of these applications or classifying if a tumour is cancerous or benign.

Classification can present a suitable support for decision making. For example, suppose a car company would like to promote a new car model product to the customer. Instead of bulk mailing the advertising catalogue to everybody, the company may be able to decrease the operation cost by aiming only at a specific type of customer. More specifically, it may categorise each customer as a prospective buyer or non-buyer based on their personal information such as salary, occupation, lifestyle, and credit ratings. Analysis of online behavior may also assist in categorising each customer as a prospective buyer or non-buyer based on their profile information such as time on site, page views, bounces, and transactions.

In the Web domain, classification is applied to build a profile of users belonging to a certain class.

This needs to extract the attributes that best define the properties of a given class. Classification can be achieved by applying supervised machine learning algorithms such as decision tree classifiers, naive Bayesian classifiers, k-nearest neighbour classifiers and Support Vector Machines.

Classification is the task of learning a target function (f) that represents each attribute set (x) into one of the pre-defined class labels (y). the target function is also known as a classification model. A classification model is suitable for classification between objects of different classes or it could be applied to predict the class label of unknown instances. Classification models are most suitable for predicting or designating data sets with binary or nominal target attributes. Figure 3 shows a general approach for applying classification techniques

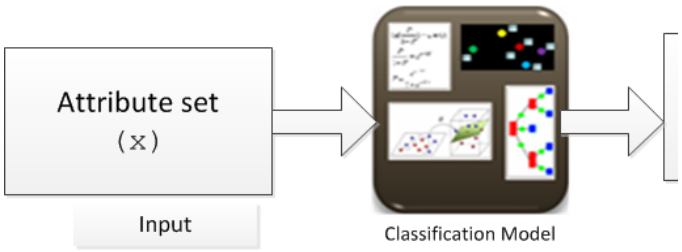

Figure 3 Classification as the task

There are many classification methods such as decision tree classifiers, rule-based classifiers, neural networks, support vector machines, naïve Bayes classifiers and nearest-neighbour classifiers. Each technique employs a learning algorithm to identify a model that produces outputs consistent with the class labels of the input data. However, a suitable classification approach should not only appropriate the input data well, it should also predict accurately the class labels of records it has not ever seen before. Creating a classification models with reliable generalisation ability is an important task of the learning algorithm. The work in this thesis will use a decision tree algorithm to classify each of the collected data records obtained from the feature phase as a buyer or non-buyer.

Decision Tree

Decision Trees are considered one of the most popular classification techniques. The decision tree is made up of nodes that shape a rooted tree, meaning it is a directed tree with a node called a "root" that has no incoming edges [50]. All other nodes have exactly one incoming edge. A node with outgoing edges is called an internal or test node. In decision analysis, a decision tree can be utilised to visually and simply act for decisions. In data mining, a decision tree represents data but not decisions; rather the outcome of the decision tree can be used as an input source for decision making. Each leaf is given to one class indicating the best suitable target value. In addition, the leaf may contain a possibility vector showing the possibility of the target feature having a specific value. Instances are categorised by routing them from the root of the tree down to a leaf, according to the outcome of the tests along the path. There are many different decision trees algorithms including : ID3 [51] C4.5 [52], CART [53].

b) Clustering

Clustering is a technique to group together a set of items having similar features that helps to distinguish them from other items. Cluster analysis has been applied in different research to identify groups of individuals, who are common in some aspect. Figure 4 explains the result for three clusters each cluster represent a group in such a way have the similar objects.

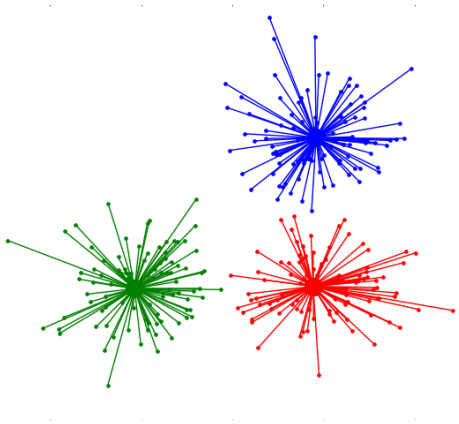

Figure 4 Example for Three Clusters

In the web usage area, there are two types of clusters frequently used: usage clusters and page clusters [54]. Clustering of users aims to create groups of users having similar browsing patterns. Such knowledge is especially useful for inferring user demographics in order to perform market segmentation in e-commerce applications or provide personalised web content to the users. On the other hand, clustering of pages will discover groups of pages that have related content. This information is useful for Internet search engines and web assistance providers. In both applications, permanent or dynamic HTML pages can be created that suggest related hyperlinks to the user according to the user's query or past history of information needs. Clustering techniques can be used to recognise the natural groupings of customers and find an answer founded on observed data patterns. Providing the data mining models are properly built; they can discover groups with diverse profiles and features and guide to a lot of segmentation patterns with business insight and vision [55]. These segments are essential in order to give precedence to customer handling and marketing interventions according to the significance of each customer.

K-means:

Many different clustering algorithms exist, but one of the most commonly used is K-means clustering proposes to separate observations into k clusters in which each observation is in the right lace to the cluster with the nearest mean, operating as a prototype of the cluster [56]. It is a distance-based clustering technique and it does not need to compute the distances between all combines of records. The amount of clusters to be designed is prearranged and determined by the user in advance. Typically an amount of several solutions should be tested before accepting the most appropriate. It is best for handling continuous clustering fields [55].

c) *Big Data*

Nowadays, a huge amount of data is being collected and stored from web data, e-commerce, bank and social network. Big data is the term use for large-volume and complex data, that it becomes difficult to process it using typically database management systems or data processing applications. The challenges consist of the areas of collection, storage, search, sharing, transfer, analysis, and visualization of this data [57].

In e-business area, big data refers to the huge quantities of transaction, click-stream, voice, and video data in the e-commerce landscape. In general, e-business websites have characteristics with both structured and unstructured data [58]. Structured data belongs to kinds of data with a high level of organization, such as information in a relational database such as age, gender, date of birth, address, and preferences. Whereas unstructured data refers to information that either does not have a pre-defined data model or is not organized in a pre-defined manner. Unstructured information is normally text-heavy, but may hold data such as dates, numbers, and facts as well.

Big data can be explained in terms of five Vs: volume, velocity, variety, veracity, and value [59]. The ‘volume’ refers to the quantities of big data, which is increasing exponentially. The ‘velocity’ is the speed of data collection, processing and analyzing in the real time. The ‘variety’ refers to the different types of data collected in big data environment. The ‘veracity’ represents the reliability of data sources. the ‘value’ represents the transactional, strategic and informational

benefits of big data. Figure 5 shows the main characterization of Big Data.

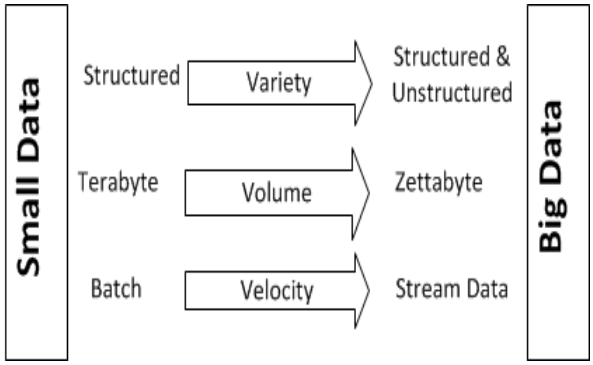

Figure 5 Main characterization of Big Data

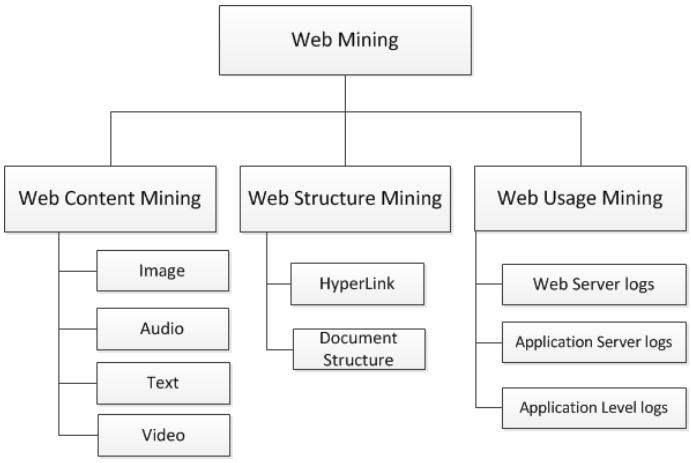

Figure 6 Web mining classification

D. Web Mining

Web usage mining is a systematic way of using data mining techniques to find usage patterns from web data, including web documents, hyperlinks between documents and usage logs of websites [60]. Web mining can help to understand customer behaviour and evaluate the performance of a website.

Web mining can be classified into three different varieties as shown in Figure 6. These are: web usage mining, web content mining and web structure mining [61].

Web mining consists of three phases [62]:

- Discovering resources
- Choosing information and pre-processing
- Extracting knowledge and analyzing patterns.

As shown in Figure 6, the data obtained through different sources can be classified into three main groups, namely: web usage data, web content data and web structure data. Table 3 shows web mining techniques, objective, collection source and examples of their applications.

		Objective	Collection source	Applications
Web mining techniques	Web Content	Index:extraction knowledge from Web page contents	Text pages	• Text Mining • Opinion Mining • Website Improvement
	Web Structure	Map:discover useful knowledge from the hyperlinks structure	Hyperlinks	• Web Page Rating • Web Clustering • Web Classification

	Web Usage Mining	Behaviour:discover user access patterns	User accessing, Logs	• Navigational Patterns • Session and Visitor Analysis • Business Intelligent System

Table 3 Web mining techniques, objective, collection source and example of their applications.

a) Web Usage Mining

Web usage mining is the application of data mining techniques to discover patterns from the websites [60]. The log data is collected automatically by the web and application servers act for the fine-grained navigational behaviour of visitors , It is considered the main source of data in web usage mining [63]. The operational database(s) for the site may include additional user profile information. The data may include demographic information about registered users, user ratings on various objects such as products or movies, past purchases or visit histories of users, as well as other explicit or implicit representations of users' interests.

However, web usage mining aims to find an interesting knowledge from the web data gained from the interactions of the users with the web. Web usage mining uses data mining techniques to analyse search or other activity logs to find interesting patterns. The purpose of web usage mining is to recognise the behaviour of Internet users through the process of data mining techniques. Knowledge gained from web usage mining can be applied to improve web design, present a personalised service and facilitate more effective browsing. One of the main applications of web usage mining is to create customer profiles. Web usage mining has become essential for operational web site management. For example, the quality of services could be improved by applying web usage mining as companies can recognise the needs of their customers and therefore take necessary action to respond to their needs. In addition, companies can identify, attract and keep customers [64].

Web usage mining is used to discover usage patterns from web data, in order to recognise and improve the needs of websites such as personalised services, adaptive web sites, customer profiling and creating attractive web sites. This is can be done by applying data mining techniques to discover user's pattern. These patterns are used to understand the core features of the users' behaviours in order to improve the website structure and establish personal or dynamic recommendations about content of the web [65]. For example, applying data mining techniques on web access logs can help to identify the user behaviour and the web structure. From the business perspective, knowledge gained from the web usage patterns could be used to usefully manage activities related to e-business as showed in Figure 7.

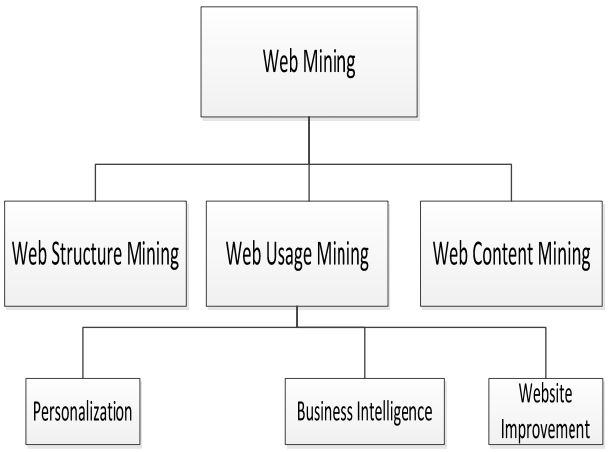

Figure 7 Web Usage Mining in E-Business

The usage patterns extracted from web data can be used in a different range of web applications such as web personalisation, analysing page sequences, website improvement, site modification, and business intelligence discovery usage characterisation.

Data type	Description	Data Examples
Web Server Data	The user logs are collected via HTTP.	IP address, page reference and access time.
Application Server Data	Contains data generated by web application server. This application server hosts business layer	Users transactions and encryption data
Application Level Data	Data are collected from an application.	Trace messages, Debug messages, Information messages, Warning messages, Error messages.

Table 4 Web usage mining sources

Web server data, application data server, and application level data can very easily collect data about web usage, as shown in Table 4. There are various resources for web usage mining as shown in Table 4, such as web access logs, cookies, data tags, login information, client or server side scripts, packet sniffing. However, web access logs are the major sources for web usage mining. They are recorded in standardised text file format used by web servers when generating server log files [64]. Because the format is standardised, the files can be readily analysed by a variety of web analysis software packages. Web server logs store data about every visit to the website hosted on a server. For example, when a web user visited a web page, valuable information can be stored on web server data such as the Internet Protocol (IP) address of the request, the error code, and the number of bytes sent to the user, and the type of browser used. Logs file can also be stored by web server, which shows the page from which a web user makes the next request. Client-applications, such as web user's browsers can also be utilised to store a user's actions.

Customer's behaviour and useful information can be discovered by application data mining and performing analysis on websites. This knowledge has numerous applications, such as personalisation and collaboration in web-based systems, marketing, website design, website evaluation, and decision support. Web logs usually consist of usage data for more than one user. Web usage mining can help identify users who have accessed similar web pages. The patterns that emerge can be applied in collaborative web searching and collaborative filtering.

However, the main objective of web usage mining is to find interesting information about customers' patterns. One of the main difficulties confronted by web usage mining applications is that web server log data are unidentified, creating a challenge to recognise users and user sessions from the user transaction. Techniques like web cookies and user registration have been applied in some applications, but each technique has its weaknesses. In pattern discovery, data mining techniques, such as association rule mining, classification and clustering, can be used. For example, Munk et al. (2010) applied clustering on web log data to recognise users who have browsed similar web pages.

Authors	Propose Model
Perkowitz and Etzioni (2000)	They proposed the idea of optimising the structure of web sites based on co-occurrence patterns of pages within usage data for the site [66].
Schechter et al (1998)	They developed techniques for using path profiles of users to predict future HTTP requests, which can be used for network and proxy caching [67] .
Castellano et al (2013)	Have applied data mining techniques to extract usage patterns from web logs, for the

	purpose of deriving marketing intelligence [68].
Eirinaki and Vazirgiannis (2003)	Have proposed clustering of user sessions to predict future user behaviour [69] .
Yadav (2012)	Clustering the buyer's behaviour on ecommerce site depending on their age [29]
Carmona et al.(2012a)	Applied data mining techniques used in an e-commerce website of extra virgin olive oil to provide some guidelines for improving its usability and user satisfaction [70].
Verma (2015)	Used semantic web mining and e-neural computing to improve the page ranking and help the website designers to optimise the website structure [47] .

Table 5 Different approaches applying web usage mining in websites.

Table 5 shows the web usage mining has been used to evaluate the websites which helped to optimise the website structure and improve user satisfaction.

III. METHODOLOGY

In this research, several features related mainly with the user behaviours in purchasing are analyzed and then rank those features to understand which user behaviours feature maximize conversion in order to discover new knowledge and extract a new business insight. This will help to increase the conversion rate and help the business to grow. Also, classify and predict the buyers and non-buyers. In order to do this, the following approach will be used: this approach contains 7 stages starting from understanding the business requirements to ranking the features. A high-level overview of the methodology is presented in Figure 2.

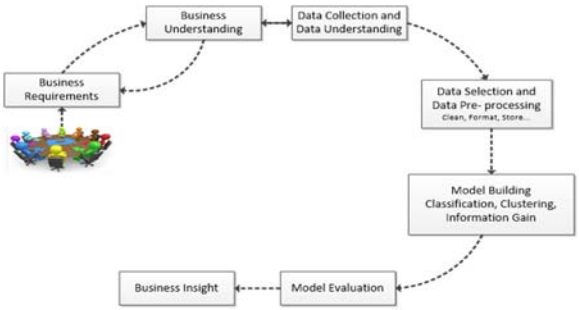

Figure 2 Ranking algorithm approach

A. *Business Requirements and Business Understanding*

This primary stage focuses on understanding the business objectives and business requirements for this research from a business view. A business object is analysing the websites that are suffering from low conversion rates to understand which user's behaviours are responsible for this poor conversion. Next, our research goal is to increase the conversion rates for the websites. The business goal translated into a data mining objective and development of a project plan. The business purpose is very important for the model building. For example, understanding how sales revenue is related to website evaluation to optimise the website structure. Therefore, the business objective should be interpreted as a data mining objective.

B. *Data Collection and Data Understanding*

The data understanding stage begins with a preliminary data collection of necessary information, proceeds with events in order to get aware with the data and to find first insights into the data. This data lets companies bring into line their websites' aims with their business objectives for the purpose of recognising areas for enhancement, promoting popular parts of the site and eventually increasing revenue.

Data requirements are considered, understanding the meaning of each feature and what the purpose is for this feature as well as what knowledge we can discover from this feature. In addition, understanding how web analytics tools collect data, process data and generate reports. For example, engagement, which holds a visitor's attention, presents how long a visitor can stay on a specific website. However, if a visitor only stays any page and quits then analytics tools sets them in the zero to 10 seconds classification.

The data will be collected using webmaster tools such as Google Search Console API and Google Analytics [71]. The data is collected from different websites, Web analytics such as webmaster tools are a free service that gives statistics and essential analytical tools for search engine optimization (SEO) and marketing purposes. This service is provided by Google. Google Analytics is currently the most commonly used web analytics service on the Internet. Developers can integrate the data from web analytics tools into existing products or create standalone applications that can be built on several processes that have been applied in a data set in order to import the visitor's data. Table 6 shows the List of the user's behaviour features.

Feature name	Description

Browser	This feature contains the browser which is used by the user when visiting. Such as Internet Explorer, Firefox, Chrome, Safari or a mobile browser.
City	The cities of users, derived from IP addresses or geographical IDs.
Source	This feature describes the source used by the user to access the website. Direct (D): Access performed directly to the website address. Engine (E): Access performed through a search engine.
OS	The operating system is low-level software that handles computer hardware and software assets and delivers basic public functions for computer programs.
User ID	A logical entity to identify the user on a website or within any generic IT environment. It is used to distinguish between the users who access the website.
Sessions	A session is a time of action by an individual web browser from the arrival point to departure point.
View Duration	The duration of user sessions represented in total seconds.
Page View	The total number of page views on the website.
Transaction	The overall of browsers who buy services or goods.
Transaction Revenue	The total sale revenue provided in the transaction excluding shipping and tax (total income cash or credit for goods, services or assets).
Transaction Quantity	The total number of items purchased. For example, two items have been purchased.
Website ID	A logical entity to identify the website within any generic IT environment. It is used to distinguish between the websites.

Table 6 List of the user's behaviour features

C. Data Selection and Data Pre-Processing

This stage is about the process of retrieving data from the websites by using webmaster tools, the websites provide a huge amount of data but unfortunately, this data is usually unstructured and requires a long process. There is a need to develop the APIs which extract the relevant data from the various third-party tools (such as Google AdWords and Google Analytics) and present this in meaningful ways to business owners and marketers, meaning current and future predicted website issues can be addressed.

Since E-business websites are high-volume, high-velocity and high-variety information. Therefore, the effective and innovative forms of information processing are necessary to assist enhance insight, decision making. Figure 3 shows the process that I have used to transfer the raw data which is extracted from webmaster tools in order to prepare it for the data mining stage. Tasks involve table, record and feature selection, in addition to conversion and cleaning of data for building the model.

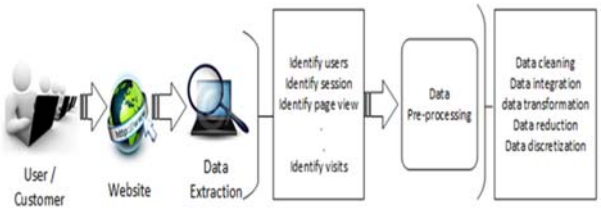

Figure 3 Data Pre-processing stage

Since the data has different issues such as redundancy and unstructured data, opacity and incomplete, pre-processing this data is essential in order to solve these issues and become ready for applying data mining techniques. For these purposes, the database management system, specifically MYSQL, has been used to manipulate the data in order to clean the data then applying data mining techniques. Row data has converted to popular Comma Separated Values (CSV) format.

This stage includes the acquisition, integration, and formatting of the data corresponding to the data mining requirements. The consolidated data have to be ''clean'' and correctly converted according to the requirements of the specific data mining techniques that would be applied. After the data is converted into an understandable format data mining techniques can be applied. This process is critical to the successful extraction of the website visitor pattern. It is a process that involves several tasks and which cannot be totally automated. The process requires pre-processing of the primary data, combining information from various websites, and converting the combined machine learning techniques. This is mainly significant in websites because of a series of mouse clicks made by a customer while accessing the e-commerce websites and its association with other related data collected from several sources. Usage data preparation brings a sum of difficulties, which requires the use of a range of algorithms and database management techniques for pre-processing tasks. However, inadequate pre-processing of data usually results in inaccurate and unreliable data mining results.

The final set of attributes consists of User_ID, Sessions, ViewDuration, Pageviews, Transactions, Browser, Operating System, City, transaction revenue and ItemQuantity, Website_ID.

D. Model Building

In this stage, modeling techniques are selected. In particular, the building and evaluation of alternative modeling algorithms, dividing of the dataset into training and testing subgroups for assessment purposes. The handled data are then applied for model training. Analysts should select the suitable modeling methods for the specific business purpose. In advance, the training of the models and especially in the case of predictive modeling, the modeling dataset should be divided so that the model's performance is assessed on an isolated dataset. A specific mathematical algorithm is applied to the pre-processing data in order to extract website issues. This also involves ingesting and wrangling of a wide variety of relevant data sources to profile, monitor and measure website performance to predict future performance issues, using a combination of supervised and unsupervised learning approaches.

E. Model Evaluation

The conversion rate is the percentage of customers who browse a commercial website and make a purchase. It is very

important to know when the customer who comes to the website and "convert" to the buyer because the conversion rate can be calculated. Next, Conversion rate can be used to predict future success or use it to determine that something isn't working. In addition, conversion rates are actually useful to website owners, who can use website traffic data to figure out what other marketing processes should be used to raise product sales. Moreover, we can track the online user behaviour previous to buying and finding interesting information about the buyer and non-buyer such as demographic analysis of who purchases, and the browser platform that users are mainly using. This information is vital to increase leads and revenue for any website.

The created models will then be evaluated not only in terms of technical perspective but also, more significantly, in terms of the business success conditions set out in the business understanding phase. In this stage the best model is chosen that represents the websites evaluation issues and how well the chosen model will work. A specific table layout will use that allows visualization of the performance of an algorithm called Confusion Matrix. The table reports the number of false positives, false negatives, true positives, and true negatives and provides analysis details that correct guesses (accuracy).

Our model is evaluated based on the following standard performance measures:

True positive (TP): Number of correctly predicted as a visitor conversion.

True negative (TN): Number of correctly predicted as a non-visitor conversion.

False positive (FP): Number of wrongly predicted a visitor conversion, when a detector predicted buyer person is a not a buyer.

False negative (FN): Number of wrongly predicted as non-visitor conversion, when a detector fails to identify the non-visitor conversion.

Recall is the percentage of correct positives that are truly predicted by the classifier.

F-measure is defined as the harmonic mean of recall and precision according to the following equation:

Table 7 shows the confusion matrix for a two-class classifier. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class.

	Predicted buyer	Predicted non-buyer
Actual buyer	True positive (TP)	False positive (FP)
Actual non-buyer	False negative (FN)	True negative (TN)

Table 7 Confusion Matrix

Table 8 shows a sample data set used for classifying customers into buyers or non-buyers.

Users	new users	Sessions	Session	Page	bounces	Browser	OS	City	Class
2	2	2	522	13	0	Firefox	Windows	Brisbane	No
0	0	1	2476	5	0	Explorer	Windows	Brisbane	Yes
37	37	37	51	40	34	Chrome	Windows	Wollongong	No
1	1	2	11	3	1	Chrome	Macintosh	Auckland	Yes
21	21	25	7452	159	5	Chrome	Windows	Auckland	NO
1	1	1	33	3	0	Firefox	Windows	Auckland	No
99	99	109	12752	311	50	Explorer	Windows	Auckland	Yes
2	2	2	779	16	0	Safari	Macintosh	Auckland	No
1	1	1	0	1	1	Firefox	Windows	Tauranga	No

Table 8 sample data set used for classifying

The decisions are typically straightforward attribute tests, employing one feature at a time to distinguish the data. New data can be categorized by sets of criteria defined at the nodes down. J.R. Quinlan (1993) has popularised the decision tree approach. The latest public domain implementation of Quinlan's model is C4.5 [72]. We used 10-fold cross-validation. The data was divided arbitrarily into 10 parts in which the class was characterized in approximately the same proportions as in the full dataset. Each part was held out in turn and the learning scheme trained on the remaining nine-tenths; then its error rate was calculated on the holdout set. The learning procedure has performed a total of 10 times on different training sets, and finally, the 10 error rates were averaged to yield an overall error estimate.

We classified the users based on the browses and the city and we have found the users from Brisbane using Firefox didn't buy but the users from the same city using Internet Explorer were most likely to buy.

All the users from Wollongong using Windows Chrome didn't buy. The users from Whangarei using Windows

Chrome also didn't buy. The users from Auckland using Windows Chrome didn't buy but the users from the same city using Macintosh Chrome Internet Explorer were most likely to buy. From the same city, those using Firefox didn't buy but those who used Internet Explorer were most likely to buy. Also, those who used Safari Macintosh didn't buy. The users from Tauranga using Firefox didn't buy.

We can predict that all Internet Explorer users are more likely to buy and Google Chrome users will not buy. Therefore, it seems the websites don't work well with this browser or are slow to download, etc.

Table 9 shows the confusion matrix tree C4.5 decision tree classification using five features, 18,149 of the actual buyers' test set were detected as buyers. For precision, 0.97% was detected correctly.

Non-buyer	Buyer	Classified as
95587	1259	Non-buyer
1166	18149	Buyer

Table 9 Confusion matrix using decision tree classification by using 6 features

The detailed analysis of accuracy by J48 classification using six features is shown in Table 10. This has the advantage of generally improving system performance by removing inappropriate and unnecessary attributes.

TP Rate	FP Rate	Accuracy	Class
0.987	0.06	0.976	No
0.94	0.013	0.976	Yes
0.979	0.052	0.976	Avg

Table 10 Details accuracy by J48 classification using six features

1) Importance Attributes

The task of feature selection in this stage is to increase a performance condition such as accuracy and reduce the cost associated with producing the features. The reason for this is that most of the features may be redundant and inconsistent and affect the efficiency when data mining techniques are applied. A filtering approach will be used for this stage of feature selection because of the huge computational costs for the datasets. More precisely, information gain will be used as a feature selection to determine the ranking of input attributes and ranking the importance score for each attribute. The overall entropy (I) of a given dataset (S) is defined as [73]:

$$I(S) = -\sum_{i=1}^{c} p_i \log_2 p_i$$

Where C means the entire amount of groups and pi the fraction of cases that fit class i. The decrease in entropy or the information gain is calculated for the individual feature in line with $IG(S, A) = I(S) - \sum_{v \varepsilon A} \frac{|S_{A,v}|}{|S|} I\left(S_v\right)$ where v a value of is A and $S_{A,v}$ the set of instances where A value has v. Figure 8 shows the results of ranking website elements by using Information Gain

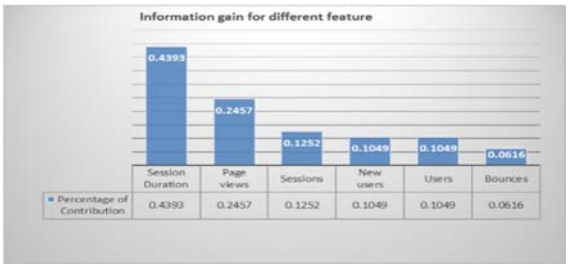

Figure 9 Ranking the website elements by using Information Gain

2) Identify visitor groups with common behaviour

Attributes	Cluster 1	Cluster 2
Users	1.5532	9.4361
Sessions	2.1869	14.5127
Session Duration	425.3737	5068.7619
Page views	8.9064	83.1075
Bounces	0.918	4.3056
Transaction	0	1.9139
Class	Non-buyer	Buyer

Table 11 Cluster Results

Table 11 shows the cluster results by applying the K-means algorithm. Each cluster shows us a type of behaviour in commercial website customers and from the cluster results.

F. Discussion

From the cluster results, we can begin to draw some conclusions. We have found that cluster 1, which means the users who did not buy, have a low number of sessions. This means the user looked at one page only. Therefore, the users are not interested to buy from this website so they leave straightaway. In the cluster 2 scenario, this means the users who actually buy, have a high number of sessions. This means the users are interested in buying and. they have more sessions on the websites. In other words, the web users didn't look at another page on the website within the next 30 minutes (that's how long a default session lasts).

For the attributes session duration, non-buyers have less session duration than the buyers, which is making sense as the buyer engaged more within the website or trying to find what they are looking to buy, while the non-buyers are not engaged with the website or they struggled to understand the website navigation scheme or to find meaningful content. For the page view attribute, the buyers have higher numbers of page views than the non-buyers; this is indicating the level of interaction and harmony between the users and website content. For the bounce attribute, although the website owners are trying to find methods to avoid or reduce the high bounces since they consider a high bounce rate is not a desirable outcome, in our case the buyers have high bounces with high conversion rates, which is a good indicator that the goal of the website has been achieved. In other words, the high bounce is not always a bad sign. Therefore, there is a strong relationship between bounce and purchase conversation rate. On the other hand, the non-buyers have a low bounce rate which may indicate that people

who come to the website are not interested in buying. The bounce rate of a website can be explained in correspondence with the buying conversion rate, perhaps the customer has not yet decided to pay and is comparing the price in this website with other websites before purchasing.

The cluster attributes in this experiment are the same as the website issues and we can understand the session duration more importantly in terms of conversion than the bounces, so this also gives some guidance when I rank the issues.

IV. Conclusion

The Internet has become the world's main knowledge source. Extracting data from the web professionally is becoming gradually significant for various reasons. In this paper, the framework is proposed to understand user's behaviour on e-business websites. Data is extracted from several websites and converted to an understandable format. Then various data mining techniques are applied to this data. Our main finding is that the high bounces it is not always a bad indication as we found that buyers have higher bounce rates than the non-buyers. In addition, the users who have longer session duration, more page views and high bounces are a more likely purchase, while the users who have less number of sessions, shorter session duration, less number of page view and low bounces are less likely purchase. In addition, we have found the most important feature influencing the costumers' decision to purchase is the session duration and the least important feature is the bounces. Therefore, the webmaster team must concentrate on finding ways to keep users more engaged in the website in order to gain more conversion visitors.

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