Application and Significance of Web Usage Mining in the 21st Century: A Literature Review

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Abstract—**Web mining is an exciting discipline in the domain of data mining as well as in classification/clustering. Identifying the usage patterns of users is very important in utilizing the vast information available in the World Wide Web. Web usage mining entails identifying usage pattern and has many practical applications. It focuses on techniques that have the potential to predict user behaviour while the user interacts with the Web. The aim of this paper is to provide a general view on web usage mining and its importance for designers and those interested in e-commerce and website personalization. The paper explains in detail the process of web usage mining and the different techniques used for pattern discovery. Also, it illustrates the different applications and tools used for web usage mining. Finally, it explains some current issues and challenges such as privacy and scalability, which are important issues in web usage mining..**

***Index Terms*—Privacy, usage mining, web mining, web personalization.**

I. Introduction

The Internet is a vast resource of information of different types: text, images, audio and video. The Web is doubling in size every six to ten months [1]. With this growing amount of information and with the development of communication technology, the Internet has become the main resource of information and knowledge. This has led to an urgent need to improve the techniques and tools that match this increasing amount of information in order to accomplish user needs and deliver satisfaction. Web mining is an application of data mining that uses various algorithms and techniques to extract useful information from web documents or patterns from user access.

Web mining is classified into three types based on the data to be mined. Content mining is the process of extracting useful information from web documents. Structure mining is the process of discovering structural information from the Web. The structure of the Web can be represented as a network where the web pages are nodes and the hyperlinks that connect two related pages are edges between any two nodes. The third type is usage mining, which is the process of extracting user access pattern from server logs [2].

This paper focuses on web usage mining due to the importance of the information it extracts in supporting website design and the decisions taken by production and marketing companies.

The structure of the papers is as follows: Section I illustrates web usage mining, describes its importance, and explains its processes in detail. Section III discusses different pattern discovery techniques. Section IV illustrates different applications for web usage mining. In Section V, a list of tools according to major applications is presented. Section VI discusses the privacy issue vis-à-vis web usage mining, and then Section VII discusses some related open issues and trends in web usage mining. Finally, we close the paper with our conclusion.

II. Web Usage Mining

During user interaction with web pages, usage mining exploits web data sources to discover hidden information about user behaviour on the Web. The sources of data can be referred to in [3], [4].

- Server access logs, agent logs, refer logs, cookies
- User profiles
- User ratings
- Click streams
- Database transactions on websites
- Page content and site structure

A. Web Usage Mining Process

Web usage mining consists of the basic data mining phases, which are: data collection, data preprocessing, pattern discovery and pattern analysis. In the following, we explain each phase in detail from the web usage mining perspective [5]-[7]. Fig. 1 explains the basic web usage mining phases.

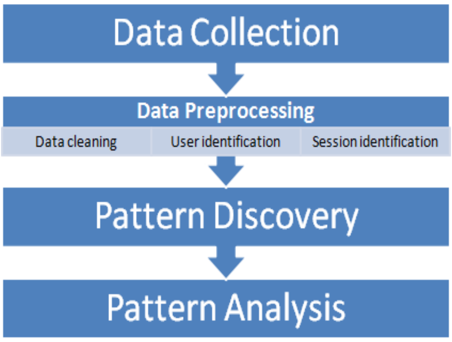

Fig. 1. Basic web usage mining phases.

1) Data collection

The first step is to collect relevant data from the different sources. There are three main sources for data inusage mining: server side data, client side data and intermediary data. The following clarifies each type:

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a) Server data

Server data are data that are collected from web servers; it includes log files, cookies and explicit user input.

i) Server log files

Servers contain different types of logs, which are considered to be the main date resource for web usage mining. The most popular logs are:

- Common Log Format (CLF): created to keep track of requests that occur on a website in chronological order. It contains the IP address of the client, hostname, username, time stamp, file name and file size. CLF has the following elements:
- Remote host: the IP address or domain name of the client
- Base URL: the URL of the user request
- Date: the date and time of the request
- Method: the method used by the client, such as GET, HEAD or POST
- File: the file requested by the client
- Protocol: the protocol used
- Code: the status code of the three requests; it consists of 3 digits
- Bytes: the number of bytes returned to the client
- Referrer: the URL from the referring server
- User agent: the operating system type and version

Fig. 2 illustrates the standard log file format, whereas Fig. 3 shows an example of a server log.

<ip_addr><base_url> - <date><method><file><protocol><code><bytes><referrer><user_agent>

Fig. 2. Standard log file format.

- *Extended Log Format*: this includes W3C, which is supported by the Apache and Netscape web servers, and W3SVC, which is supported by the Microsoft Internet Information server. They include additional information such as the referring URL, name and version of the browser, and the operating system of the host.

Log files can contain unreliable data about the usage of the site. Two main sources of unreliability are web caching and IP address misinterpretation. Web caching is a technique used to reduce web latency by saving a copy of requested pages for a certain time, either in the user's local browser or in a proxy server. If the requested page is cached, the server is unaware of any new access to the page, and therefore it is not recorded in the log file. The second source for unreliability is IP misinterpretation, which is accrued either by using an intermediate proxy server that assigns the same IP to all users, or by the same computer being used by many users. Both cases lead to misinterpretation of usage data.

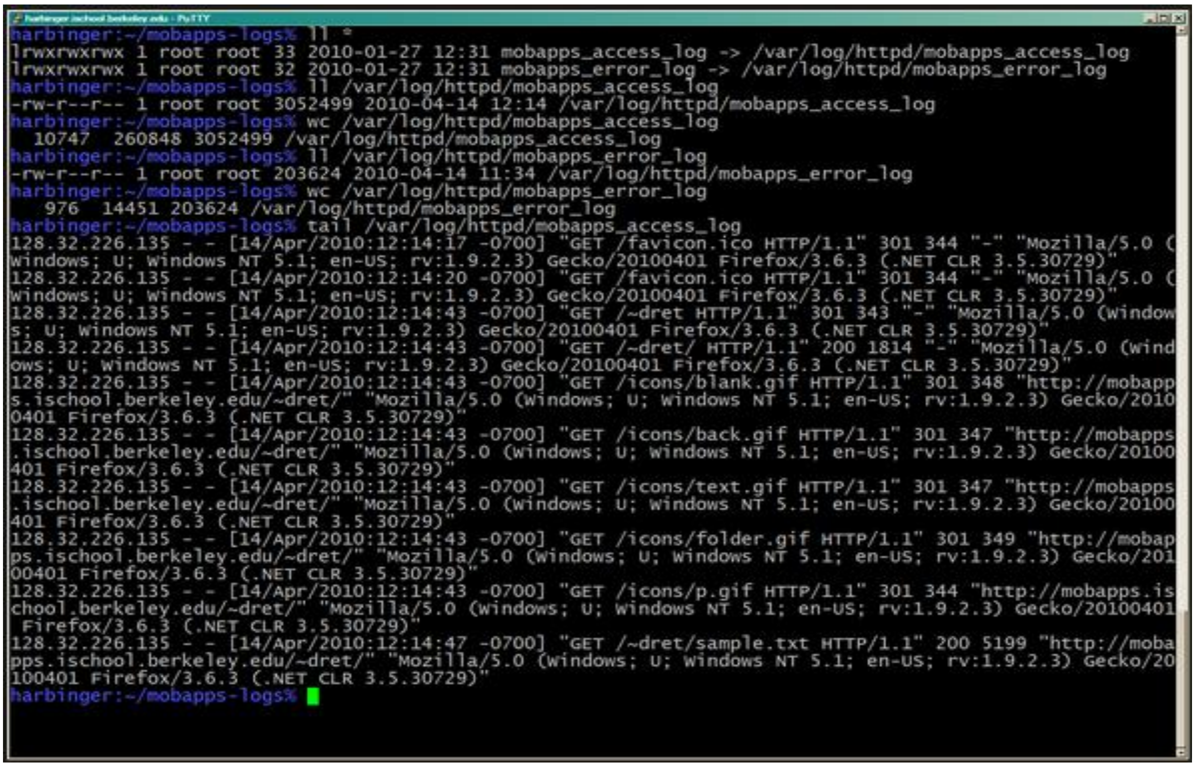

Fig. 3. Example of server log.

ii) Cookies

Cookies are strings that are sent from the web server to the client's browser. The browser saves the cookie in a text file and resends it to the server each time the user visits the site. This way, the server stores information about all visitors, the pages visited, any products purchased, etc. in the cookie log within the client's machine.

The main advantage of cookies is their small size. However, cookies, like log files, may contain unreliable user information if the same user is using different devices, or when different users use the same device. Also, users may disable the browser option for accepting cookies due to privacy or security concerns.

iii) Explicit user input

The third source of server data is the user data supplied directly by the user when accessing the site, such as the data collected by registration forms. However, this type of data is often inaccurate and incomplete.

b) Client data

The second source for data in web usage mining is client data, which are collected from the host that accesses the website. Client data are accessed through sending remote agents implemented in Java or JavaScript and are then embedded in web pages; they are used to collect information from the client such as user navigation history. Client data is more reliable than server data because they avoid caching and IP misinterpretation problems. However, this data needs cooperation on the part of users who often restrict the operation of Java and JavaScript programs for security reasons.

c) Intermediate data

The last source of data is intermediate data, which can be collected from proxy servers or packet sniffers.

i) Proxy server

A proxy server is a software system that acts as an intermediary between the client and other servers, i.e., between the host and the Internet. Proxy servers use access logs to store web page requests and responses from servers. However, the problem of caching and IP misinterpretation also exists in proxy server data.

ii) Packet sniffers

A packet sniffer is a program or hardware that monitors network traffic. This means that TCP/IP packets are directed to the web server and the data are extracted from them. Packet sniffers include detailed timestamp information that is not present in log files, such as request time and response time. The problem with the data collected is that they are not logged and may be lost for a variety of reasons.

2) Data preprocessing

The next step after having collected huge quantities of various data types is data preprocessing. Data should be consistent and integrated in order for them to be used in pattern discovery. Data preparing includes data cleansing, user identification, session identification and path completion.

a) Data cleansing

The discovered patterns are only useful and valuable if the data collected offer an accurate picture of user access patterns on the website. The server and proxy server collect all user interactions, and therefore the data collected by them could be noisy and in need of having irrelevant or redundant items removed. While client data are usually clean, explicit user input data may need to be verified, corrected and normalized.

In web usage mining, the aim is to collect user access patterns. Therefore, any unnecessary items should be removed; for example, videos, audio files, graphics and the format information, meaning files that have particular suffixes (JPEF,GIF, etc.), which are usually downloaded without user consent. Error status entry and bots as well as spider requests are also removed. These irrelevant data can make up to 50% of the actual data size [8]. So, cleansing this high percentage is very important to increase the efficiency of the usage-mining model.

b) User identification

User identification is to identify who accesses the website and which pages are accessed. Many approaches have been proposed to automate user identification, and the most well known are [6]:

- Assign each user to a unique IP in the log file.(check) This method is not accurate with user proxy servers or if different users use the same host machine.
- Cookies are also useful for identifying users but they are also inaccurate because users may disable or delete them.
- Use special Internet services such as inetd or fingered services, which provide user information about the client. This method may also be disabled for security reasons.
- Analyze the web server log file to look for different operating system types and versions, different browsers, even if the IP is the same. This method has the problem of computational effort. Also, it may fail if the user opens more than one browser windows or opens different browsers.
- Combine the access log referrer entries with the topology of the site. This means that if there is more than one access to the same page from the same IP but without a direct hyperlink between the pages, then it assumes that a new user has accessed the page.
- Include a unique ID generated by the web server in the URL instead of using the cookie file. The user is asked to create bookmarks for one of the delivered web pages. This method is semi-automatic because users must bookmark the page and use this bookmark to access the site.

c) Session identification

Session identification, which encodes the navigational behaviour of the users, is very important in usage mining. A user session is a series of web pages that the user visits in a single website access. Various methods have been proposed to identify user sessions. These methods are divided into time-based and context-based [6]:

- Time-based methods: these have been used in most of models, and they have different approaches:
- A set of pages is considered as single user session if the pages are requested within a specific time period (default 30 min.). This method is not reliable because the exact actions of the specific user are not known.
- Using Java agents that send the client's time to the server each time a new page is loaded. However, this method is affected by browser type and network traffic. Also, JavaScript can be disabled by users.
- Context-based methods: in this method, user sessions are processed to provide useful entities using transactions; a transaction is a subset of pages that occur within a user session. Different approaches are used:
- The pages of the site are divided into three types: navigational pages, which contain hyperlinks to other web pages, content pages, which contain the actual information, and user interest and hyper pages, which combine both types. However, this classification is very strict and it depends on user need; what is a content session for the user may be a navigational session for others.
- Examine the time spent on the page; if it is greater than a specific time, then it contains useful information and therefore is a content page (otherwise, it is a navigational page).

- The last page the user visits is always a content page.
- A transaction is defined as a set of pages visited by the user from the first page until the first backward reference occurs. The next session starts with the next forward reference. This method has a problem in that the caching of web pages prevents backward references being recorded in the log file.

d) Path completion

There are many reasons for incomplete paths; for example, clicking the back button, local and agent caches, and proxy servers. These will result in missing important accesses in the access log file, and therefore the user access path will be incomplete. So, the missing pages should be added using different techniques [9].

After these steps, the collected user information is ready for applying different methods to discover useful patterns in usage mining.

3) Pattern discovery

In this stage, pre-treated information is analyzed to extract valuable patterns. Statistical methods and machine learning are used to mine patterns. The better known approaches used are: path analysis, association rules, clustering, classification, sequential patterns and order model discovery. Section 3 will explain each approach in detail.

4) Pattern analysis

After usage patterns are discovered, techniques and tools are needed to make these patterns understandable for analysts and to maximize the benefits from these patterns. Techniques include database querying, graphics and visualization, statistics and usability analysis. The most used techniques are:

- Visualization: this is a very successful method to help in understanding user behaviour. Several tools have been developed to apply this method; for example, WebKIV, which is a tool that provides structural visualization for small and large web structures, web navigation, which is for individuals and aggregate user navigation patterns, and result comparison [10].
- On-Line Analytical Processing (OLAP) tools enable users to analyze multi-dimensional data from multiple viewpoints.

III. Techniques for Pattern Discovery

The pattern discovery stage is the application of various data mining techniques to discover useful patterns. The most common techniques used for data mining are: clustering, classification, association mining and sequential pattern discovery [6].

A. Clustering

The most common techniques used for pattern discovery are clustering methods. Clustering is a way to divide a dataset into groups that differ from each other but whose elements are similar. There are two types of cluster to be discovered: page cluster, which aims to find pages of similar content, and usage cluster, which aims to define a group of users who have similar browsing patterns [11]. This knowledge is useful for exploring user demographics to perform market segmentation in e-commerce applications or to provide personalized web content to users. The information from page cluster is useful in search engine and web assistance [12]. Clustering can be divided to three types: partitioning, hierarchical and model-based methods.

1) Partitioning methods

This is where the data are divided into k groups (clusters). Various algorithms that can be applied for different purposes [6], [13]:

1) Algorithms that are used to cluster user sessions:

- Leader algorithm
- Expectation-Maximization (EM)
- Fuzzy clustering
- Graph partitioning
- Self-Organizing Maps (SOM)
- Ant-based
- k-means with genetic algorithm

2) Algorithms that are used to index page synthesis:

- Page Gather

2) Hierarchical methods

This is where the data is decomposed to create a hierarchical structure of clusters. It uses the Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) algorithm for clustering user sessions.

3) Model-based methods

These find the best fit between a given dataset and a mathematical model. There are different algorithms for clustering user sessions [6]:

- Autoclass
- Self-Organizing
- COBWEB
- ITERATE

B. Classification

Classification is a technique used to define data set into different classes [14]. In web usage mining, it is may be used to develop a profile of users belonging to a specific class [12]. For example, classification in log files may give useful rules like: 40% of users who order online from x website are aged 20-30 and live in the Middle East. There are various algorithms that can be applied for different purposes [6]-[13]:

- Algorithms for extraction rules that represent user interests:
  HCV
  CDL4
- Algorithms for predicting an interesting page:
  RIPPER
  C4.5
  Naïve Bayesian
- Algorithms for classification of sessions according to a concept:
  Rough Set Theory

C. Association Rules Mining

In web usage mining, association rules refer to set of pages that have been accessed together with a minimum support value; this can help in organizing web space efficiently; for example, 80% of users who visited page x also visited page y. So, the designer should put a direct link between the two pages [15]. The application for association mining in usage mining is normally focused on the prediction of the next most interesting page for the user [6]. There are various algorithms for association mining [13]:

- Maximal forward references
- Markov Chains
- Improved AprioriAll
- Fpgrowth and Prefixspan
- Custom-built Apriori algorithm

D. Sequential Pattern Mining

Sequential pattern mining tries to identify relationships between occurrences of sequential events in order to determine whether there exists any specific order to those occurrences [13]. This information can be used to predict the next visit for the user, and this assists in placing advertising for a specific group. We can discover sequential patterns by using two methods: deterministic methods, which record the navigational behaviour of the user, and stochastic, methods which use the sequence of web pages that are visited in order to predict subsequent visits [16]. For a deterministic approach, there are several algorithms, such as [6]:

- Spiliopoulou: used to extract sequence rules
- Paliouras: used to cluster navigational patterns
- CAPRI: used to discover temporally ordered navigational patterns

Also, the stochastic approach has a number of algorithms, such as [6]:

- Borges: used to extract navigation patterns from user sessions
- Markov models: used for next-link prediction.

IV. Applications for Web Mining

The main goal of web usage mining is to study user navigation and their use of web resources. There are various applications for web usage mining in different areas, and such applications are:

- Personalization of web content

The web usage mining technique can be applied to personalize websites, depending on user profile and behaviour. Personalization is important in creating a deeper relationship, to build acceptable marketing strategies, and to automate the promotion of products for potential customers. Also, web usage mining aims to obtain information that supports website design to allow easier and faster access on the part of customers [17].

- System improvement

The results produced by web usage mining can be used to improve the performance of web servers and web-based applications. By understanding the behaviour of web traffic, polices and strategies can be produced for web caching, network transmission, load balancing and data distribution [8].

- Security

Web usage mining can provide patterns that are useful in intrusion, attempted break-ins, fraud, etc. [12].

- Site design support

Usability is one of most important issues in the design and implementation of websites. The results of web usage mining give designers information about user behaviours that help in decisions about any redesign of the content and structure of the website. Moreover, some tools automatically change the structure of the site based on usage patterns discovered [12].

- Enhance e-learning environment

Usage mining tools can be used to track the activities happening within the course's website, and then extract patterns and behaviours that need to be changed, improved or adapted to the course contents. For example, designers can identify the links that are always visited, links never visited, and the cluster of users that visit specific links [18].

- Business Intelligence

The primary goal of business intelligence is to help people make good decisions to improve company performance and to maintain competitive advantage in the marketplace, i.e., it helps companies to make the best decisions quickly and easily. Web usage mining is the appropriate technique for extracting information and building a useful and knowledgeable database about customer behaviours. Also, it is very important in determining effective marketing strategies, i.e., those that increase sales and place the company's products on a higher level [5].

V. Tools for Web Usage Mining

Many different tools are used to perform analysis on collected data, and most of them are based on statistical analysis techniques. The number of commercial tools increased again last year and most of them are included in the Customer Relationship Management (CRM) software, which has solutions for e-commerce [8]. The majority of the tools are traffic analyzers; their function is limited to producing reports on website traffic such as: number of visits and page view time, user statics (such as user geographical regions), operating systems and web browser, and diagnostic statistics (such as "page not found"). Few tools analyze user sessions and specific statistics about individual users [19]. We can categorize the tools based on the applications that use them, as shown in Table I [8], [12], [19], [20].

TABLE I: Tools for Web Usage Mining Classified by Major Applications

Application	Tools
Personalization	WUM – SiteHelper – WebPersonalizerWebSIFT – SETA –Tellim – Oracle9iAS Netmind – Litezia – Web Watcher Krishnapuram – Analog – Accure G2 – Accure Insight 5 – Pilot HitList – SEWeP
System improvement	Rexford – Schechter – AggarwallSpeedTracerWebLogMiner – NetTracker
Business intelligence	SurfAid – Tuzilin – Burchner – SAS Intellivisor ECOMMINER – InterShop – Logisma Business Wbstore
Site design support	Etzioni – Perkowitz – iJADEMiner

VI. Current Issues and Challenges in Web Usage Mining

There are a number of issues related to web usage mining that affect the utilization of the mined information. Recently, privacy has been defined as one of the problems of data collection in the Web, especially data that are related to query or transaction users or to social networks that have valuable personal information. Web usage mining tools integrate data from different resources: web logs, cookies or explicit user entries, which increase the problem of privacy violation. Many researchers are conscious of this privacy issue and are trying to find some solutions to control the privacy problem in web mining [21]. One of the main proposals to deal with the privacy issue is the Privacy Preferences (P3P) standard, which enables websites to state their privacy practices in a standard format. However, P3P does not solve the problem completely, as it does not answer the issue of which data mining technique should be used over user data [8]. In [6] the authors suggest some directives that can applied on the websites to protect user privacy:

- Support of P3P
- Clear disclosure of data and methods to facilitate user understanding of system assumptions about them.
- Provide a number of anonymization methods to help users protect their anonymity.

Moreover, one of the most common problems that face pattern discovery methods is dealing with the huge volumes of data available on the Web, and so the scalability of pattern discovery methods is now a critical issue. Scalability means the rate of memory and time needed for the task, according to the parameters that affect the performance of the algorithms, such as number of users or pages. Another problem is the lack of studies that compare the performance of the different tools, and the reason is the difficulty of finding suitable evaluation criteria. The authors in [6] propose a multi-level evaluation approach that facilitates the comparison between the performance of the different tools:

- System evaluation: this uses the standard software engineering criteria: memory need, speed, time, scalability and interoperability.
- Modeling performance: this evaluates the web usage mining; machine learning criteria can be used: accuracy, recall and precision.
- Usability: these studies the usability features in the tool.

The lack of comparison between existing tools also causes difficulty in finding or choosing the appropriate tool for analyzing data and producing useful knowledge. There are several commercial analysis tools but most of them have limitations in speed, are expensive, inflexible, difficult to maintain, or give limited results [19]. Moreover, most of the tools work independently and the results cannot be transferred or used in other tools, which means that most tools do not support interoperability. Most of the tools provide only statistical information without useful knowledge for managers. Also, the visualization of the results should be organized, easy to understand and supported by visual graphs to facilitate knowledge extraction.

VII. Conclusion

The enormous growth of the Internet has given rise to many websites that maintain large amounts of user information. The information explosion on the World Wide Web has increased the importance of web usage mining in both commercial and education areas. Web usage mining is the area of data mining that deals with the discovery and analysis of usage patterns from web logs in order to improve web-based applications. Studying web users of interest can provide valuable information for web designers, to quickly respond to their individual needs and for the efficient organization of the website. Also, organizations need to understand their customers' behaviour, preferences and future needs.

From this review, it is clear that web usage mining is of great importance in many areas, especially in e-commerce applications and website designing. The proper application and use of web usage mining techniques and tools will greatly affect companies' success by helping them to produce productive information that is appropriate to the future of their business functions and goals, by analyzing the usage information from their websites. Also, it helps web developers in improving websites and increasing site usability and accessibility.

This paper has analyzed the importance of web usage mining, the process of usage mining in detail and the techniques used in pattern discovery. Also, it has described the various applications for web usage mining and the tools that can be used. Finally, it discussed the problem of privacy in web usage mining and detailed some directives that could be applied to protect user privacy; the paper concluded with some open research issues and challenges.

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