

Applying Web Intelligence*

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Abstract:

This paper describes the practical application of web intelligence for visitor behavioural analysis. The objective of the paper is to show how the research in data mining carried out in the authors' laboratory has been synthesised to address the requirements of web intelligence. Initially, Web Intelligence is defined, and the data components used are explained. Then, the individual components of web intelligence are outlined. Our research goals and our previous work is described in the following sections, followed by the inter-linked goals for digital marketing using web intelligence. The main body of the paper describes the various data-mining based analytical processes employed for web intelligence, including segmentation, sequences & click streams, and visitor data. The section on closing the marketing circle describes how the output of web intelligence forms a firm foundation for personalisation activities. The final section draws conclusions on the application of web intelligence in the near future.

Key Words:

Web Intelligence, Personalization, Web Mining, Data Mining, eCRM, Visitor Profiling

Introduction

This paper outlines the application of *web intelligence* for visitor behavioural analysis, using existing data mining algorithms that have been modified, and new data mining algorithms that have been specifically created. The objective of this paper is to show how the research in data mining carried out in the authors' laboratory has been brought together to address the requirements of web intelligence.

The paper is divided into several sections. Initially, web intelligence is defined, and the data components used are

enumerated. Then, the individual components of web intelligence are outlined. Our research goals and our previous work is described in the subsequent sections, followed by the inter-linked goals for digital marketing using web intelligence.

The main body of the paper describes the various data-mining based analytical processes employed for web intelligence, including segmentation, sequences & click streams, and visitor data. The section on closing the marketing circle describes how the output of web intelligence forms a firm foundation for personalisation activities. The final section draws conclusions on the application of web intelligence in the near future.

Web Intelligence

What is Web Intelligence? Quite simply, it is the application of business intelligence software and methods to Internet data. It is defined as an infrastructural architecture containing data warehousing and data mining technologies, which draw upon a broad spectrum of components. These components are data warehousing loading and transformation tools, OLAP reporting and query tools, and data mining algorithms.

In the present competitive environment, e-commerce organisations need to win and retain high-value customers to remain competitive. One technique that can be used to achieve greater loyalty from customers in Internet based retailing is to offer services that are predicated upon closing the marketing circle. These services include personalisation, recommendation, optimisation, etc. However for these services to succeed, "a library of rich visitor profiles must be present" [1]. Web intelligence is the means by which e-commerce companies can build these rich visitor profiles, utilising all the data that is generated by visitors and buyers at Internet e-commerce sites.

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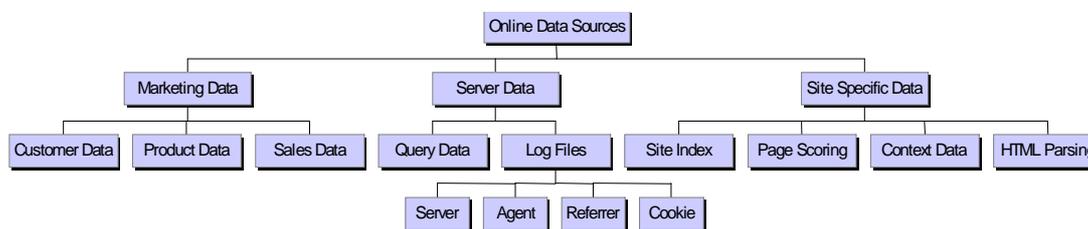


Figure 1. Data Available for Web Intelligence

Web Data

The data available in electronic commerce environments is three-fold (Figure 1) and includes server data in the form of log files, site specific web meta data representing the structure of the web site, and marketing information, which depends on the products and services provided [2,3]. Server data is generated by the interactions between the persons browsing an individual site and the web server. This data can be divided into log files and query data.

Historically, web servers recording server activity, errors and referrer information used a log file to record each event. It is now the standard that web servers use a combined log file format, called Common Logfile Format [4]. This format combines the server and error logs into one file. More recently, the Extended Logfile Format [5] has been used, which consolidates the Common format with additional information, namely the referrer (misspelled 'referer' in the original standard) and cookie information.

The incorporation of referrer information results in the output of the mining of these logfiles being much more useful and actionable in marketing terms. For example, people often locate a site using search engines. The referrer field contains the search engine name, and the search terms. Cookies are tokens generated by the web server and held by the clients. The information stored in a *cookie* helps to ameliorate the transactionless state of web server http interactions, enabling servers to track client access across their hosted web pages. The logged cookie data is customisable and can contain keys for relating the navigational data to the content of the marketing data, including transactional data. Usually the following information is contained in a cookie: User ID, source IP address, time-to-live, randomly generated unique ID and user defined information.

A fourth data source that is typically generated on electronic commerce sites is *query data* to a web server. This data is usually generated when users of the web site use search or product locator facilities on the site to search for relevant pages/products. This is often through user interaction with a product database, via the company's Internet site. The query data is normally stored in the URL. POSTed data is generally handled by server extensions, such as CGI.

The final source of data is web meta-data. This data describes the structure of the web site and is usually generated dynamically and automatically after a site update.

Web meta-data generally includes neighbour pages, leaf nodes and entry points. This information is frequently implemented as a site-specific index table, which represents a labelled directed graph. Meta-data also provides information regarding whether a page has been created statically or dynamically. It also indicates whether user interaction is required or not. In addition to the structure of a site, web meta-data can also contain information of more semantic nature, usually represented in XML [6].

Any organisation that uses the Internet to trade in services and products uses some form of information system to operate Internet retailing. Clearly, some organisations use more sophisticated systems than others do. The lowest common denominator information that is typically stored is about customers, products and transactions, each in different levels of detail. More sophisticated electronic traders also keep track of customer communication, distribution details, advertising information on their sites associated with products and / or services, demographic and other information from third-party providers.

Vernacular of Web Servers

The vernacular of web intelligence can be confusing. For our research we define a *visitor* as a user or computer that has made at least one visit to a web site. A *visit*, called a server session by the W3C [7], is defined as an interaction with a web site that results in a log of that visit being recorded in the web site's server log file. A visit can result in a number of *hits* to the web server. Typically a web page with two images would result in three hits to the web server by one visit. Collectively these hits together are called *page impressions* or *page views*. Thus one visitor's single visit to a page with two images would be recorded as a single page impression. A visitor *session* is synonymous with a visit. A *multi-session* visitor is one who revisits the web site, often clicking through several different routes in the web site, resulting in a *click stream*. For a description of click streams and *sequences*, see the section later in this paper.

Web Intelligence Components

Data Warehousing

As well as standard semantic and schematic heterogeneity resolutions across Internet data [8], online information is ideally represented in a data-warehousing environment. From a cube, which is based on the example web log snowflake schema in Figure2, it is a straightforward

procedure to create multiple materialised views using basic OLAP functionality, which can be used as input for data mining, reporting and querying tools.

Typically, the log files that are generated by web servers require substantial enrichment, consolidation and enhancement in the process of conversion from ‘one-hit-per-line’ log file representations to data warehouse incorporation. It is only after this Extract, Transform and Load (ETL) operation is complete, that the log file data can be joined with other data sources, including customer, product and transaction data, to provide a more homogeneous storage environment.

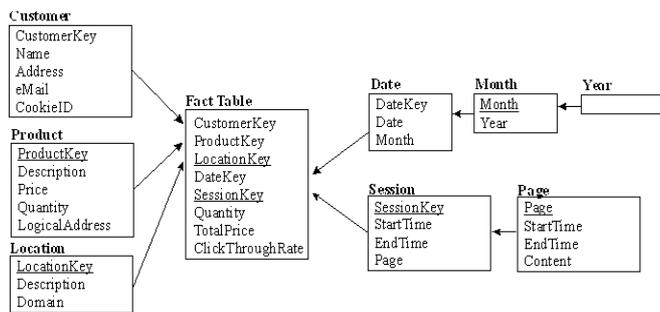


Figure 2. An Example Web Log Snowflake Schema

Web Mining

In the context of web intelligence, web mining may be defined as the application of data mining techniques to Internet data. Web mining has been sub-divided into web structure, web usage, and web content mining [9]. These are now defined and discussed in turn.

Web Structure Mining

Web structure mining is the application of data mining techniques to web site structures. In many cases this may be the entire web, and research in intelligent search engines and intelligent agents is described in many articles, e.g., [10]. In our research, we define web structure mining as the mining of Internet data - *together* with data about the structure of the site. This may be thought of as enriching the efficacy of the data mining process with domain knowledge. Therefore knowledge such as concept hierarchies, which correspond to areas of the ‘site specific data’ branch of the taxonomy of web data available for web intelligence in Figure 1, can be added to the source data that the mining algorithms use. The application of domain knowledge is further discussed in the analytical process section.

Web Usage Mining

Web usage mining is the application of data mining to Internet web server log file data, which is described in the earlier section on web data. Web usage mining forms the core of our research in web mining for web intelligence, and log files provide the foundation data for visitor analysis. This type of analysis of the visitors to a web site

can be subdivided into technographic and psychographic analysis [11].

Technographic analysis focuses on what is known about the visitor’s technical platform, i.e., operating system, browser, plug-ins, user language, cookie information. On its own, this information is not a rich source of discriminatory data for visitor profiling. However, when joined with the homogenous data sets available after ETL to data warehousing, it plays a significant contribution.

Psychographic analysis is the analysis of what we know about the behavioural patterns of web site visitors. This includes the routes taken by visitors through a site, the time spent on each page, route differences based on differing entry points to site, aggregated route behaviour, general click stream behaviour, etc. This is the information of most use to web marketers, and is equivalent to marketing intelligence about where shoppers enter the store, where shoppers go in the store, where they leave the store, what they look at but don’t buy, what they buy and how quickly, etc.

Web Content Mining

Web content mining is the application of data, as well as text mining algorithms and techniques to the web page content (semi-structured data). At its most rudimentary form, this entails the extraction of text between HTML tags for headings and titles, or the extraction of the HTML Meta tag content. However, as no rigidly enforced standards exist for the content of these tags, it is only by the use of advanced text mining techniques, which utilise context that meaningful content may be used. Even so, there is no guarantee that the content is correct. Our research is based upon XML and RDF-based [12] data schemas that help to ensure correctness and proper context.

Research & Technology Goals

The NIKEL laboratory at the University of Ulster has long carried out data mining research [13-15]. Our interest and research in the application of data mining techniques to Internet data has been on-going since 1996 [16,17]. This paper represents the synthesis of our research in this area, and our progress to transform this research in the highly technical area of web mining into web intelligence software for Internet marketing.

Our research goal in the fundamental data and web mining technology area are now almost complete. We have developed web intelligence-optimised technology for segmentation, sequence & click stream detection [18], visualisation, and visitor activity analysis. Our technology goals have been to take the research developed in the laboratory and combine it into a software product. This goal is now complete, and the Easyminer product is marketed through a spinout company, MINEit Software [19].

Digital Marketing Goals

As web sites develop into a mature medium for customer interaction, organisations are realising the gap between the information they require to support electronic *customer relationship management* (eCRM) and the information provided by the current suite of software aimed at analysing *web server* activity, called log analysis tools. While organisations want to know how to increase profit per checkout, increase retention of customers, increase browser to buyer conversion rates and reduce clicks-to-close rates, log analysis tools provide information such as frequency of page accesses to individual pages on the web site and counts of top-level domains.

Organisations have typically invested a lot of money into developing their web sites and web strategy. Now they are seeking to assess the return they are receiving on their investment. Most sites use hits and page views as measures of success of the web site. According to a recent report by Forrester, however, using hits and page views as a measure of site success is comparable to evaluating a musical performance by its volume [1]. Clearly the answer to this problem lies elsewhere.

The technique used for measuring the success of a web site clearly depends on what the goal of setting up the web site is in the first place. A web site is commonly used for:

- Selling products and services;
- Providing product/ company information;
- Providing customer support online to reduce customer service costs.

Using page hits as a metric does not provide a measure of success for any of these goals. Just as churn rates, retention rates and revenues are used to measure the health of a business that is not on-line, these traditional marketing metrics should be used to monitor web success.

In addition to measuring the success of their web sites and the effectiveness of banner ads, organisations also see the web as a medium for one-to-one marketing and providing personalised services. However, to achieve this they need to glean as much information about the customer from the interaction of the customer with the web site.

A new breed of software tools are now being developed to provide organisations with the opportunity to discover knowledge from the data collected from customer web interaction. These tools, otherwise known as web intelligence tools, allow them to achieve their goals of personalised services and one-to-one marketing. The following section describes the analytical processes used in the application of our web intelligence software called Easyminer.

The Analytical Processes

Segmentation

A starting point for traditional marketing is the segmentation of the customer base into smaller, more manageable groups of customers that have similar interests with respect to their interaction with the business. In the context of a traditional retailer and in the absence of more customer data, this generally implies customers who buy similar products. In the case of an e-retailer, the web logs provide a large source of additional information about customers at no additional cost. E-retailers are not limited to analysing sales data. They can also discover similarities between customers based on their navigational behaviour, that is, products they may have browsed but not necessarily bought.

Segmentation based on a small number of attributes can be employed manually or through using a database query language. However, segmentation based on navigation behaviour is dependent upon a large number of attributes (the number of pages on the web site). Easyminer provides a variant of the k-means algorithm that has been adapted for use in web mining. Currently, two kinds of clustering may be undertaken: session clustering based on pages visited and the average time spent on the pages. The user specifies the number of segments that are expected to be present within the log file data and the minimum number of sessions needed for a cluster to be assumed to be valid.

Segments are described in terms of the likelihood of a web page being visited during the sessions that belong to the segment.

Once the segments have been discovered, the sessions belonging to a segment can be extracted into a new log data table and can be analysed further using segmentation or characterised using various summaries. Further investigation of the sessions within the cluster may be carried out using drill-down facilities that result in more detailed graphs as shown in Figure 3. One of the challenges faced in segmentation of web log data is the high dimensionality of the data. Concept hierarchies defined on the documents can be used to reduce the dimensionality of the data. XML documents provide easy access to well defined domain knowledge as set by the Dublin core [20].

Sequences & Click Streams

Navigation of a web site is temporal in nature. Therefore, one of the basic forms of knowledge that needs to be discovered from data collected in web logs is navigational sequence knowledge. This describes the most commonly tread pathways through the web site, where a pathway is defined based on a threshold value of sessions that follow the pathway, referred to as support. Easyminer uses the Midas sequence discovery algorithm [21] to discover these sequences.

Two types of sequences may be found using Easyminer: *open sequences* and *click streams*. A sequence is a list of web page accesses ordered by the time of access within a session or across sessions for a particular customer. An open sequence is not necessarily a contiguous navigation of the web site. This means that an open sequence of the form <index.html, orderform.html> does not imply that there is a direct link between the index.html page and the orderform.html page that was navigated by customers that support this sequence. Customers supporting this sequence may have taken distinct paths from index.html to orderform.html, however, none of the individual paths navigated by the customer have the required support value to be considered as interesting within their own right. A click stream is a special type of sequence where the pages accessed have contiguous navigation. Thus a click stream of the form <index.html, orderform.html> does imply that a direct link exists between the index.html and orderform.html page and that the customers navigated this link during a particular session.

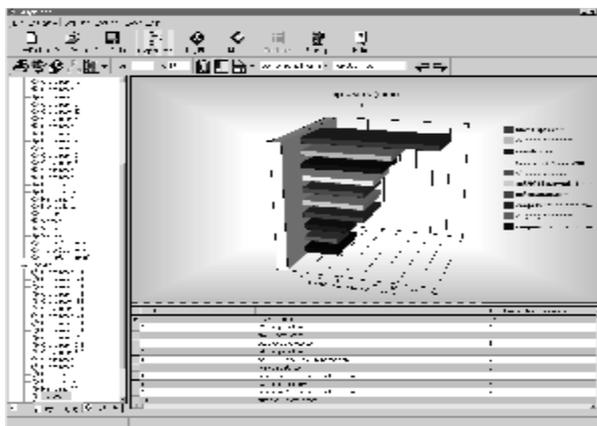


Figure 3. More detailed view of segment characteristics, using drill-down

Three kinds of domain knowledge can be used within the discovery of sequences. These are navigational templates, network topologies and concept hierarchies. *Navigational templates* are used to tailor the sequences discovered from the log file to the users needs. Using these templates, goal-driven navigation pattern discovery is possible through the specification of start, end, as well as middle pages for sequences that are of interest to the user. A typical start locator is the home page, a customer support page, or a URL providing information about a special marketing campaign. A typical end page is a purchase page or a page for requesting more information. The second type of taxonomical domain knowledge is that of *network topologies*, which is useful when the topology of web site or a sub-network of a large site is of interest to the user for the discovery of sequences. This domain knowledge is used to include or exclude parts of a web site from analysis.

Network topology domain knowledge within Easyminer, is specified through a site map that is constructed from the log file being analysed (see Figure 4). Sub-networks can be

selected using point and click. In general, a network can be represented as a set of navigational patterns. The reason for distinguishing these two types of domain knowledge is that navigational templates are goal dependent and may change with each execution of *Midas*. A network, on the other hand, is based on the structure of the web site and is less likely to change with the same frequency.

Finally, concept hierarchies may also be specified and employed to reduce the granularity of the discovered sequences in a similar way as their use within segmentation.

Two methods for visualising sequences exist within Easyminer. The first method uses the site map and overlays the sequences so that the user can see the sequences within the context of the web site, as well as the logfiles which they have been discovered from. The alternative method is to use a sequence tree view.

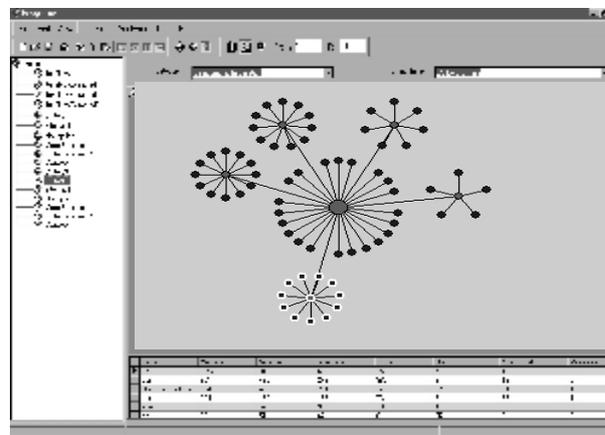


Figure 4. Site Map constructed from log files

Visitor Data

In tandem with the powerful analytical tools available in web intelligence, visitor data can provide valuable marketing knowledge on the interactions between browsers and an e-commerce site. Typically, conventional log analysis tools are based upon analysis of web server activity. However, Easyminer provides additional capabilities to these tools. Firstly, the visitor information in Easyminer can be customised using profiles, whereby visitors may be identified as individual IP or domain addresses, or profiles can be constructed that describe sets of visitor activity. For example visitors from UK domain at weekends only, or all visitors from academic institutions (ac.uk, edu.cn, edu, etc.). Using these profiles, visitor groupings can be examined. The second additional capability in Easyminer is the ability to 'drill-down' into graphs and charts on visitor activity. In marketing terms, this facilitates examination of visitor activity from both a macro- and micro perspective.

Visitor activity analysis in the form of loyalty (frequency returning), page interest (time spent on page sequences),

and deviation from designated profile groups is also provided.

Closing the Marketing Circle

Generating models with predictive capabilities is an important objective of our implementation. One use of such predictive models – click streams, segments, etc – is to provide a workbench for marketing analysts. Another more powerful application is to assist in *closing the marketing circle*. That is, to generate model output from our software that is in a form which is also machine readable, by the web servers that host e-commerce sites upon which the analyses and model building have been based. In this situation, the e-commerce sites can produce real-time, dynamically generated pages tailored to individual or group profiles.

The tailoring made possible by predictive models hosted on web servers is very different from the two other types of tailoring popular in e-commerce sites. The first of these is ‘check-box’ tailoring, where a visitor customises a personal page, for example, to specify the region for the weather forecast, which news feeds are wanted, etc. The second form of tailoring is sometimes called collaborative filtering, where a visitor specifies a profile by form filling. The profile is then matched against ‘like-minded’ visitors, and individualised content is fed back to the visitor, based upon the collective preferences of these like minds.

The most important type of web page tailoring is personalisation, which can operate even while the visitor remains anonymous. If the visitor is identified with a cookie, or as a returning customer, then more targeted tailoring can take place. Personalisation is the provision to the individual of individually tailored products or services or indeed information relating to products or service. Using the output of our predictive models, an e-commerce site can personalise content to the user, based upon the degree of membership that the visitor has to particular profiles. This can be a tailored banner ad, personalised prices for identified valuable returning customers, etc. An “improvement of the site based on interactions with all visitors” [22] is another objective that can be addressed using the predictive model’s output.

Technology Requirements to Close the Circle

In order for an e-commerce web server to utilise the marketing knowledge (the output of the models), the knowledge must be made available to the server in a machine-readable form, and the web server must be able to act upon the knowledge. These two problems are *representation* and *deployment*.

The most suitable vehicle for the representation of marketing knowledge output from our software is based upon XML. An XML-based representation offers flexibility in the sense that it can be used by a web server, and also be transformed into a form easily understood by people. The Predictive Modelling Mark-up Language (PMML) [23] is a subset of XML, which is being developed by a consortium of data mining vendors, under the aegis of the Data Mining

Group. Currently, PMML has representative Document Type Definitions (DTD) for regression and decision trees. Our current research is adding PMML resources for web intelligence applications, including sequences and click streams. Figure 5 illustrates the current operation of the tool with a schematic architecture, showing the positioning of the PMML component.

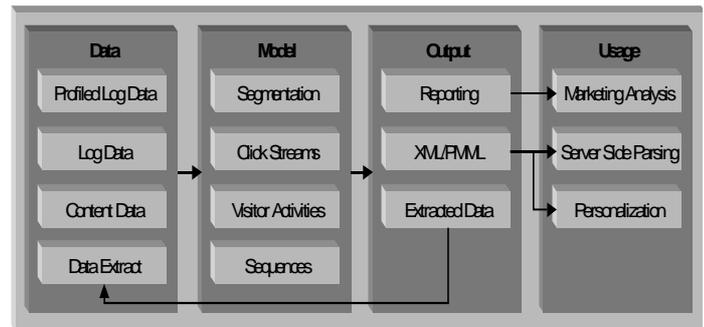


Figure 5. Easyminer Architecture Schematic

The deployment of the marketing knowledge by the web server is heavily dependent upon the system architecture in place. All of the following impact upon deployment:

- Server type: Netscape, Apache, IIS, etc
- Dynamic content from back-end databases or static pages
- Secure access for visitors (SHTTP)
- (Reverse/Forward) Proxy server set-up
- Front-end packet sniffing
- Load-balancing architecture

What is required to close the marketing circle - in technical terms - is the capture of the click request from a visitor *before* the content/action that has been requested is served back to that visitor. It is only by performing this capture operation that the web server can decide 1) the appropriate PMML model, 2) the correct action to perform, 3) the content to source, 4) the dynamic construction of the page (e.g., banner ads, recommendations, personalisation, etc).

The capture operation can occur as a packet sniffing operation before the visitor request ‘hits’ the web server. However, most secure e-commerce sites make this a complicated operation, and the work-around (proxies, etc.) can add considerably to the server workload. This results in reduced performance of the web server, and ultimately visitor disenchantment. One method that ameliorates this problem is to pass-through the visitor request to the back-end content database (aka reverse proxy configuration), and process all the steps outlined above on either the content database server, or a third personalisation server. In this way, the web server architecture is unstressed, and optimisation of the personalisation server can tune-up the resulting system.

Conclusions & Future Work

This paper has described the application of some key research findings in a software tool called Easyminer. While Easyminer employs a number of data mining techniques to provide the user with useful web intelligence, it hides the complexity of these algorithms from the users who would typically be marketers, not data miners.

Easyminer provides the means to discover the knowledge required to achieve goals such as one-to-one marketing and personalisation of web services. It also provides a way to measure the success of on-line business and assess the return on investment for web strategies.

The research underlying this software tool is on going. The technology required to close the circle with marketing automation components such as marketing knowledge representation and execution is well-advanced, and shows promising early results. Future research areas will concentrate on expanding the capabilities of the software to manage digital market interactions through other digital 'touch-points', including WAP 'phones, PDAs, and digital interactive TV. In addition, work will concentrate on expanding web intelligence into multi-channel marketing analysis, encompassing call centres and digital devices.

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