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Integrating web mining and neural network for personalized e-commerce automatic service

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ABSTRACT

Electronic commerce (EC) has become a trend in the world nowadays. However, most researches neglect a fundamental issue – the user's product-specific knowledge on which the useful intelligent systems are based. This research employs the user's product-specific knowledge and mine his/her interior desire on appropriate target products as a part of personalization process to construct the overall EC strategy for businesses.

This paper illustrates a novel web usage mining approach, based on the sequence mining technique applied to user's navigation behaviour, to discover patterns in the navigation of websites. Three critical contributions are made in this paper: (1) using the footstep graph to visualize the user's click-stream data and any interesting pattern can be detected more easily and quickly; (2) illustrating a novel sequence mining approach to identify pre-designated user navigation patterns automatically and integrates back-propagation network (BPN) model smoothly; and (3) applying the empirical research to indicate that the proposed approach can predict and categorize the users' navigation behaviour with high accuracy.

1. Introduction

In recent years technological advances of the Internet and Web have continuously boosted the prosperity of e-commerce (EC). Although the business-to-business (B2B) model is the main focus in the current electronic commerce development, the business-to-consumer (B2C) model has shown immense potential in the electronic marketplace through the encouragement of on-line trading due to continuing technological advances of the Internet. In order to facilitate transactions, the problems associated with complex activities in electronic commerce must be resolved. The abundance of information available on the Internet allows consumers to communicate with sellers for a bargain. Therefore, the traditional commerce negotiation process, similar to human-based life bargaining between buyers and sellers, will also arise in the electronic market in order for both parties to reach an agreement that is satisfactory to both (Chou, Chen, & Wu, 2006).

As the Internet moves further into the mainstream of everyday life, EC is becoming an important mechanism for conducting business. EC helps merchants and consumers to reduce costs and enables customized delivery of goods and services. Among current business models, electronic auctions are emerging as one of the most successful EC technologies. This fact is causing users a serious problem of information overload when they try to retrieve information from the dynamically and continuously growing web resources. Therefore, the need from web users in identifying and using more intelligent systems or tools for conducting information gathering and information filtering from the huge size of web related sources is on the rise (Li & Zhong, 2004). Nevertheless, the taste and inclination of a person on products and services may also change or evolve with time. Thus, the 'one-to-one marketing' strategy was proposed to provide personalized service in the EC environment (Allen, Kania, & Yaeckel, 1998; Weng & Liu, 2004).

In general, there are two major approaches to provide personalized information: content-based and collaborative filtering (Aggarwal, Wolf, Wu, & Yu, 1999; Yu, 1999). In the content-based approach, it matches the content of candidate items against the user profile, which is constructed by analysing the content of items that the user has fevered in the past or user's personal information and preferences. Some recommendation systems, which are used by EC companies to suggest products and provide information to customers, operate based on this approach, such as NewsWeeder (Lang et al., 1995) and Infofinder (Krulwich et al. (1996)). Besides, Kwan, Fong, and Wong (2005) also use content-based approach to produce a view of the frequent access patterns of e-customers and

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foster the development of a marketing plan for B2C Web sites (Kwan et al., 2005). However, it is often inhibitive to estimate the preference similarities between various customers. For example, similar preferences may be defined as the preferences of customers who have similar ratings of items (Yoon & Jae, 2004).

In the collaborative filtering approach, it identifies other users that have showed similar preference to the given users and provides what they would like. Nowadays, most e-learning recommendation systems (Lee, 2001; Papanikolaoum & Grigoriadou, 2002; Rashid et al., 2002) consider learner/user preferences, interests, and browsing behaviours when analysing learner/user behaviours for personalized services. In the e-commerce environment, Chen and Cheng (2008) propose a novel collaborative filtering methodology for product recommendation when the preference of each user is expressed by multiple ranked lists of items (Chen & Cheng, 2008). Moreover, Lee, Park, and Park (2008) also built an effective collaborative filtering-based recommender system for an e-commerce environment without explicit feedback data (Lee et al., 2008). However, these systems neglect the importance of learner/user ability for implementing personalized mechanisms. Due to the drawbacks of traditional approaches, various hybrid approaches were proposed to cope with the shortcomings of content-based personalization and collaborative filtering, and to increase the accuracy of recommendation systems (Li, Zhou, & Chen, 2004; Pan & Lee, 2006), applying data mining (DM) techniques (such as texting mining, clustering technique) to collaborative filtering (Aciar, Zhang, Simoff, & Debenham, 2007), and combining collaborative filtering based on group behaviour theory in consumer psychology (Cho, Kwon, & Park, 2007) and collaborative filtering based on multi-criteria ratings approach about the preferences of a user (Adomavicius & Kwon, 2007).

However, collaborative filtering and content-based filtering perform unsatisfactorily without large amounts of usage data, which discourages users from using the system and the system's performance cannot be improved without sufficient user participation. To solve this problem, many scholars use reviews from experienced consumers that are already available on the Internet to determine the most popular product according to the given criteria. In the online world, consumers can exchange their experiences with a product in several ways (Curien, 2006; Damiani, di Vimercati, Paraboschi, Samarati, & Violante, 2002; Dellarocas, 2003; Prete, McArthur, Villars, Nathan, & Reinsel, 2003; Ramanathan, Kalogeraki, & Pruyne, 2001). Therefore, we will adopt hybrid approach to construct one novel recommender system in EC.

In this paper, we present our initial design for identifying the user's prior knowledge for specific products. Our method is based on the customer's on-line navigation behaviors by analyzing their navigation patterns through web mining and constructing artificial neural networks to predict potential customers' need in the future. The remainder of this paper is organized as follows. Section 2 describes the background and development of marketing techniques, web mining, and artificial neural network. Section 3 demonstrates and explains in detail how to construct the personalization recommendation system architecture. Implementation results are presented in Section 4. Finally, conclusions are drawn in Section 5.

2. Preliminary

In the development of the e-commerce recommendation system in collaboration with end user application some technologies are required, such as the web mining, and the artificial neural network. These will be discussed in the following sub-sections.

2.1. Marketing techniques

2.1.1. Marketing strategies

"Marketing" is an instructive business domain that serves to inform and educate target markets about the value and competitive advantage of a company and its products. "Value" is worth derived by the customer from owning and using the product. "Competitive Advantage" is a depiction that the company or its products are each doing something better than their competition in a way that could benefit the customer (Kotler, 1997).

Marketing is focused on the task of conveying related information of pertinent companies and products to specific customers, and there are a multitude of decisions (strategies) to be made within the marketing domain regarding what information to deliver, how much information to deliver, to whom to deliver, how to deliver, when to deliver, and where to deliver. Once the decisions are made, there are numerous ways (tactics) and processes that could be employed in support of the selected strategies.

The goal of marketing is to build and maintain a preference for a company and its products within the target markets. The goal of any business is to build mutually profitable and sustainable relationships with its customers. While all business domains are responsible for accomplishing this goal, the marketing domain bears a significant share of the responsibility. There is a basic fact about business that is often forgotten – the customer wants to be sold on something. That's why the customer seeks out a business in the first place. Everybody gets up-sold or cross-sold in daily life. No harm need be intended in such sales. It is simply polite to offer a customer additional options. There are two basic marketing strategies described as follows.

Up-selling is a sales technique whereby a salesman attempts to have the customer purchase more expensive items, upgrades, or other add-ons in an attempt to make a more profitable sale. Up-selling can imply selling something additional, or selling something that is more profitable or otherwise preferable for the seller instead of the original sale.

Cross-selling means the sale of additional products to a customer for more business. The term is usually related to selling an item that complements a customer's purchase. Selling a color-coordinated tie and a shirt to go along with a selected suit can be an example of cross-selling. Businesses that offer more than one product or service often use the cross-selling technique for marketing. Cross-selling is also very common with in-bound telemarketing calls. It should be done in a pleasant way and never pressed. Though it may simply sound like a temptation for impulse buying, cross-selling offers legitimate added benefits to shoppers.

Personalization, a special form of differentiation, when applied in market fragmentation can transform a standard product or service into a specialized solution for an individual (Schafer, Konstan, & Riedl, 2001). Through personalization, businesses can get to know customers' buying behaviours and accordingly develop more appropriate marketing strategies to attract each customer of a specific type and efficiently deliver the suitable information and products/services to him/her. The customer's satisfaction and loyalty can thus be enhanced, and the increase in each customer's visiting frequency can further create more transaction opportunities and benefit the Internet businesses (Lee, Liu, & Lu, 2002).

2.1.2. Product knowledge

Bettman and Park (1980) postulated that the two main aspects in consumer choice environment were product information and prior knowledge (Bettman & Park, 1980). It is obvious in the virtual environment that product information is not only readily available but also enormous. However, unlike offline shopping environment where consumers have the opportunity to engage in person-to-person interaction, the virtual environment does not allow this. Therefore, consumers need to have in order to conduct online purchase necessary skills and knowledge to search and process information effectively.

In general, consumers are assumed to have some amount of experience or information about products they are using or plan to purchase. Consumer knowledge upon any particular product or service, i.e. product knowledge, has been traditionally referred to as product familiarity or prior knowledge. Alba and Hutchinson (1987) proposed that there were two major components, familiarity and expertise, in the construction of consumer knowledge, and familiarity and expertise were defined as 'the number of product-related experiences that have been accumulated by the consumer' and 'the ability to perform product-related tasks successfully', respectively (Alba & Hutchinson, 1987). They also indicated that increased product familiarity results in increased consumer expertise, different tasks require different types of expertise, and the successful performance of any particular task requires more than one type of knowledge.

A great deal of research evidence has suggested that differences in information processing and decision-making between experienced and inexperienced consumers could be the function of knowledge in their memory (e.g., Alba et al., 1983; Jacoby, Troutman, Kuss, & Mazursky, 1986; Sen, 1998). Prior knowledge is not only related to consumers' behavioral motivation, such as the intention of searching information, but facilitates the acquisition of new information and increases search efficiency (Brucks, 1985). Specifically, research suggests that experienced consumers have better conceptual structure (schemata) of the product domain that results in early development of purchase criteria for the product selection. Inexperienced consumers, in contrast, will need to spend more time to establish these criteria. Rao and Monroe (1988) found that experts (i.e. those who have high product knowledge) and non-experts (i.e. those who have low product knowledge) are more likely to use product price for determining the quality of product, as compared to the group of consumers with intermediate product knowledge (Rao & Monroe, 1988). Therefore, it can be found that consumers with higher degree of prior knowledge will require less amount of time on information processing related activities than consumers with less prior knowledge. Since product knowledge may influence consumer's needs and behaviors, we propose that the knowledge of the customer's product knowledge level can be used to enhance the personalization strategy for EC companies.

Product knowledge is important in different ways depending on which the stakeholder is; i.e., Buyer, Seller, and Manufacturer. For the buyer's/consumer's aspect: You want to know whether it's the right product for you? Is there anything better out there that will meet you needs better, or simply are you getting better value for your money? For the manufacturer's aspect: He needs to know how many other firms manufacture the product; should he add features to it that will make it more attractive to retailers and ultimately the consumer? He needs to know in which segment he needs to compete-high end/high quality, medium or low end. For the seller aspect: He needs to know what are competitive products and how to price the one in question; who are other retailers in the vicinity selling the same product or competitive products? Will his usual customers be able to afford this product or will he draw new customers by displaying this product on his shelf.

Knowledge is power and for likewise product knowledge means more sales in EC. It is difficult to effectively sell something to a consumer if we cannot show how a particular product addresses a consumer's needs. Therefore, based on the above findings, we design a system to automatically and non-intrusively assessing consumers' product knowledge and identify their need.

2.2. Web mining

Data mining (DM) refers to extracting knowledge from a large amount of data (Han & Kamber, 2001; Huang, Chen, & Lee, 2007). Data mining by automatic or semi-automatic exploration and analysis on a large amount of data items set in a database can discover potentially significant patterns inherent in the database. Kleissner (1998) defined that data mining is a new decision support analysis process to find buried knowledge in corporate data and deliver understanding to business professionals (Bose & Mahapatra, 2001; Kleissner, 1998). Hence, with data mining analysis, decision makers can make better decisions with more information and knowledge which other tools may not be able to provide.

A particular data mining algorithm is usually an instantiation of the model preference search components. The more common model functions in the current data mining process include the classification, regression, clustering, association rules, summarization, dependency modeling, and sequence analysis (Agrawal et al., 1993; Attar Software Limited, 2002; Brin, Motwani, Ullman, & Tsur, 1997; Chen & Chen, 2006; Mitra, Pal, & Mitra, 2002; Piatetsky-Shapiro, 1991). As the Internet and Web 2.0 era coming (O'Reilly et al., 2005), a thorough understanding of how users navigate or browse through a site is important in the development of web-based applications, especially when including features such as recommendations, advertising or personalization (Mobasher, Dai, Luo, & Nakagawa, 2002). This understanding is also critical for performance evaluation and website redesign (Ting, Kimble, & Kudenko, 2004). In web-based educational technologies, such as e-learning, the identification of navigation strategies and patterns is also critical for understanding the navigation behaviours of learners to improve the website design and the service quality of e-learning quality.

Analysis of click-stream data (server-side logs) can aid our understanding of user navigation behaviours by providing detailed information on the patterns generated by users as they navigate through a website hosted on that server. However, the size and nature of Click-stream logs can make pattern detection and classification difficult and time-consuming. The most basic way to visualize the user's click-stream is using the spanning tree technique to convert a log file into the user's browsing map using tools such as Web map (Dömel et al., 1994), Naviz (Cugini et al., 1999) and History Graph (Hirsch, Meeks, & Brooks, 1997). Using such tools is easy; however this technology is not robust enough to construct a user's browsing map when the amount of click-stream data is too large or complex.

In Ting, Kimble, and Kudenko (2005) they introduced the "Footstep" graph, a visualization tool for identifying user's navigation patterns. The Footstep graph is based on a simple x–y plot where the x-axis represents time (in seconds) and the distance between points indicates the time between two nodes (pages visited). The y-axis represents the nodes on the user's navigation route and the changes in the vertical axis indicate a transition from one node to another. An example of a Footstep graph is shown in Fig. 1.

The footstep graph not only indicates the time-trends of a user's navigation history but also illustrates the relationship between each navigation node, transforming complex and unorganized click-stream data into a form more suitable for understanding and interpretation.

Footstep graphs were produced to demonstrate how this visualization technique could help analyse user's navigation behaviour. From this research, we found certain frequently occurring patterns that were illustrative of user navigation behaviour. These patterns were named "Stairs" (including "Upstairs" and "Downstairs"), "Mountain" and "Fingers".

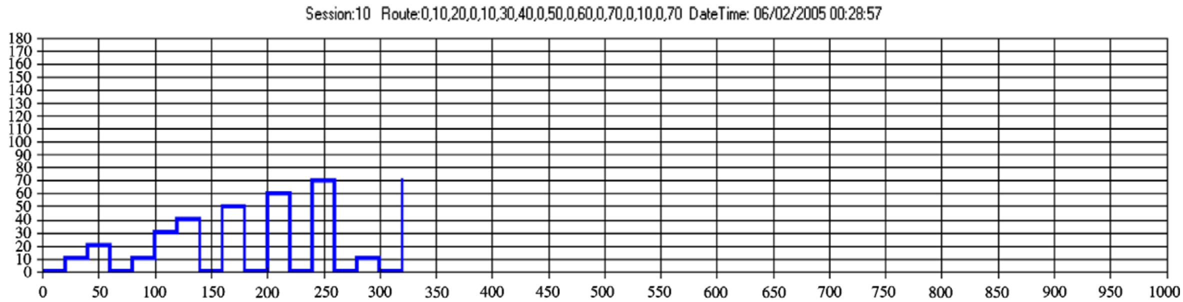


Fig. 1. A sample footstep graph.

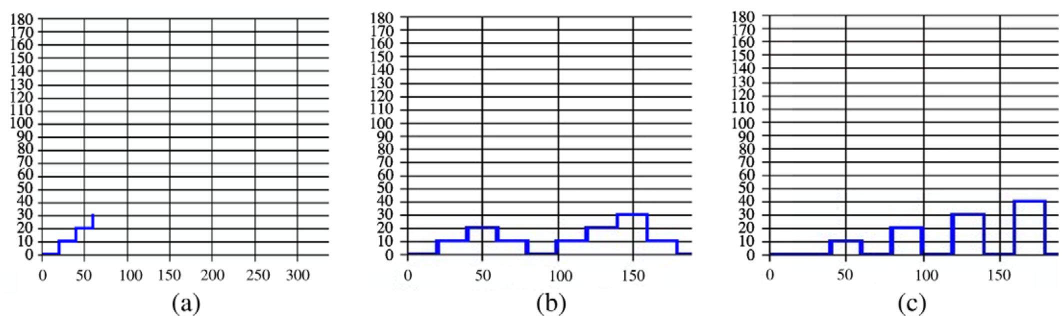


Fig. 2. (a) An example of a *Stairs* pattern. (b) An example of a *Mountain* pattern. (c) An example of a *Fingers* pattern.

(1) Stairs patterns
The Upstairs pattern is created when the user moves forward through previously unvisited pages in the website to and the Downstairs pattern is produced when the user moves back through pages they have visited before. An example of a Stairs pattern is shown in Fig. 2a. These patterns are similar to Canter's "Path" pattern, which indicates that the user is exploring the website (Canter, Rivers, & Storrs, 1985).

(2) Mountain pattern
The Mountain pattern, where a Downstairs pattern is immediately followed by an Upstairs one, is found when the user moves through several pages in order to reach or return from a specific page. An example of a Mountain pattern is shown in Fig. 2b. This pattern is equivalent to Canter's "Loop" pattern, which indicates that the user is searching the site for a specific target.

(3) Fingers pattern
The Fingers pattern is found when the user moves directly from one page within the site to another and then directly returns to the original page. An example of a Fingers pattern is shown in Fig. 2c. This pattern is equivalent to Canter's "Spike" pattern and indicates that the user may have fallen into a navigation loop.
Our aim here is to investigate the users' need, thus, even the web usage mining algorithm is very efficient, and it is of little practical use if the patterns it discovers are difficult to explain. In the case of users' navigation patterns, we believe that end user is the person with most knowledge about the way the website should be browsed and product should be brought, consequently, we have based our technique on the expected navigation route as defined by the users' navigation patterns.

2.3. Artificial neural network

A back-propagation network (BPN) is a neural network that uses a supervised learning method and feed-forward architecture. A BPN is one of the most frequently utilized neural network techniques for classification and prediction (Wu, Yang, & Liang, 2006) and is considered an advanced multiple regression analysis that can accommodate complex and non-linear data relationships (Jost, 1993). It was first described by Werbos et al. (1974), and further developed by Ronald, Rumelhart, and Hinton (1986). The details for the back-propagation learning algorithm can be found in Medsker and Liebowitz (1994).

Fig. 3 shows the $l-m-n$ (l denotes input neurons, m denotes hidden neurons, and n denotes output neurons) architecture of a BPN model (Panda, Chakraborty, & Pal, 2007). The input layer can be considered the model stimuli and the output layer the input stimuli outcome. The hidden layer determines the mapping relationships between input and output layers, whereas the relationships between neurons are stored as weights of the connecting links. The input signals are modified by the interconnection weight, known as weight factor w_{ji}, which represents the interconnection of the ith node of the first layer to the jth node of the second layer. The sum of the modified signals (total activation) is then modified by a sigmoid transfer function (f). Similarly, the output signals of the hidden layer are modified by interconnection weight w_{kj} of the kth node of the output layer to the jth node of the hidden layer. The sum of the modified signals is then modified by sigmoid transfer (f) function and the output is collected at the output layer.

Let $I_p = (I_{p1}, I_{p2}, \ldots, I_{pl})$, $p = 1, 2, \ldots, N$ be the pth pattern among N input patterns. Where w_{ji} and w_{kj} are connection weights between the ith input neuron to the jth hidden neuron, and the jth hidden neuron to the kth output neuron, respectively (Panda et al., 2007).

Output from a neuron in the input layer is

$$O_{pi} = I_{pi}, \quad i = 1, 2, \ldots, l \tag{1}$$

Output from a neuron in the hidden layer is

$$O_{pj} = f(NET_{pj}) = f\left(\sum_{i=0}^{l} w_{ji} o_{pi}\right), \quad j = 1, 2, \ldots, m \tag{2}$$

Output from a neuron in the output layer is

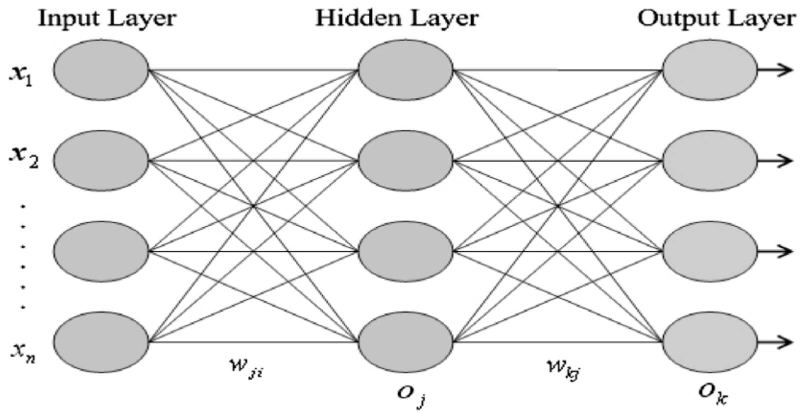


Fig. 3. Back-propagation network architecture.

$$O_{pk} = f(NET_{pk}) = f\left(\sum_{j=0}^{m} w_{kj} o_{pj}\right), \quad k = 1, 2, \ldots, n \tag{3}$$

where $f()$ is the sigmoid transfer function given by $f(x) = 1/(1 + e^{-x})$.

BPN has been applied to various areas, such as investigating bankruptcy and credit predictions (Tsai & Wu, 2008), improving laser micro-weld process (Lin & Chou, 2008), predicting stock trend in Korea and Taiwan market (Huang, Yang, & Chuang, 2008), and exploring customers' behavior prediction in choosing hospital (Lee, Shih, & Chung, 2008). Based on the above literatures, many researches employed the BPN techniques for many applications. However, few of them used it to carry out empirical investigations of customers' behavior prediction related topics. Therefore, in this study we will use the BPN technique to forecast customers' behavior in the e-commerce domain.

3. Research methodology

The proposed system architecture in this paper is shown as Fig. 4. The rationale of this proposed approach is that if users have similar navigation patterns, then they may have similar interests for some products. For enhancing the personalization strategy with an ultimate goal of attracting/retaining customers and enforcing the competitiveness for EC businesses, we built an interior desire system (IDS) to assess potential customer's product knowledge levels and their needs, and then promote appropriate products to them. Thus, the approach follows three phases to identify users' behavioural pattern.

In the first phase – "Data Modelling", the goal is to record users' navigation paths from the website and translate the raw data into data warehouse. It is the essential stage to execute the web mining or neuron computing algorithm. If we can collect and translate more navigation records, the more meaningful rules we can get. In the next phase – "Content-based Modelling", the goal is to provide some initial users' information about their browsing behaviours to assist the IDS system. We will use web mining algorithm to discover users' navigation patterns and their potential behaviours in the website. In the final phase, the "Collaborative Filtering Modelling" will make recommendations about the preferences of a user on the basis of the other users' collective taste information. We will apply BPN techniques to classify users into groups with similar behavioural patterns. The goal is to find out the potential types for the online customers. Then, the business administrators can make correct marketing strategies to each customer based on his/her type. In the other way, the IDS presented in this research will recommend potential products or service for each user. We also hope this approach will improve the competitive ability and earning profit for each online company.

1. Phase I – Data Modelling
   - Step 1. Navigation recording
     The database approaches to web mining have generally focused on techniques for integrating and organizing the heterogeneous and semi-structured data on the web into more structured and high-level collections of resources, such as in relational databases, and using standard database querying mechanisms and data mining techniques to access and analyse this information.
     Several researchers have proposed a multilevel database approach to organize web-based information. The main idea behind these proposals is that the lowest level of the database contains primitive semi-structured information stored in various web repositories, such as hypertext documents. At the higher level(s) meta-data or generalizations are extracted from lower levels and organized in structured collections such as relational or object-oriented databases. Besides, there have been many web-base query systems and languages developed recently that attempt to utilize standard database query languages such as SQL, structural information about web documents, and even natural language processing for accommodating the types of queries that are used in WWW searches.
     In this paper, when a user enters and starts a session on a website, IDS would invoke its navigation recorder to start recording his/her browsing behaviour and navigation path into a database. Immediately after the navigation path is recorded, IDS would employ its built-in web mining techniques to match the path to pre-identified seeking, buying or abandoning patterns.
   - Step 2. Data preparing and pre-processing
     This step is the basic data operations include removing noise if appropriate, collecting the necessary information to model or account for noise, deciding on strategies for handling missing data fields, and accounting for time-sequence information and known changes.
     "Data Cleaning" is to clean a server log to eliminate irrelevant items are of importance for any type of web log analysis, not just data mining. The discovered associations or reported statistics are only useful if the data represented in the server log gives an accurate picture of the user accesses of the web site. Elimination of irrelevant items can be reasonably accomplished by checking the suffix of the URL name. For instance,

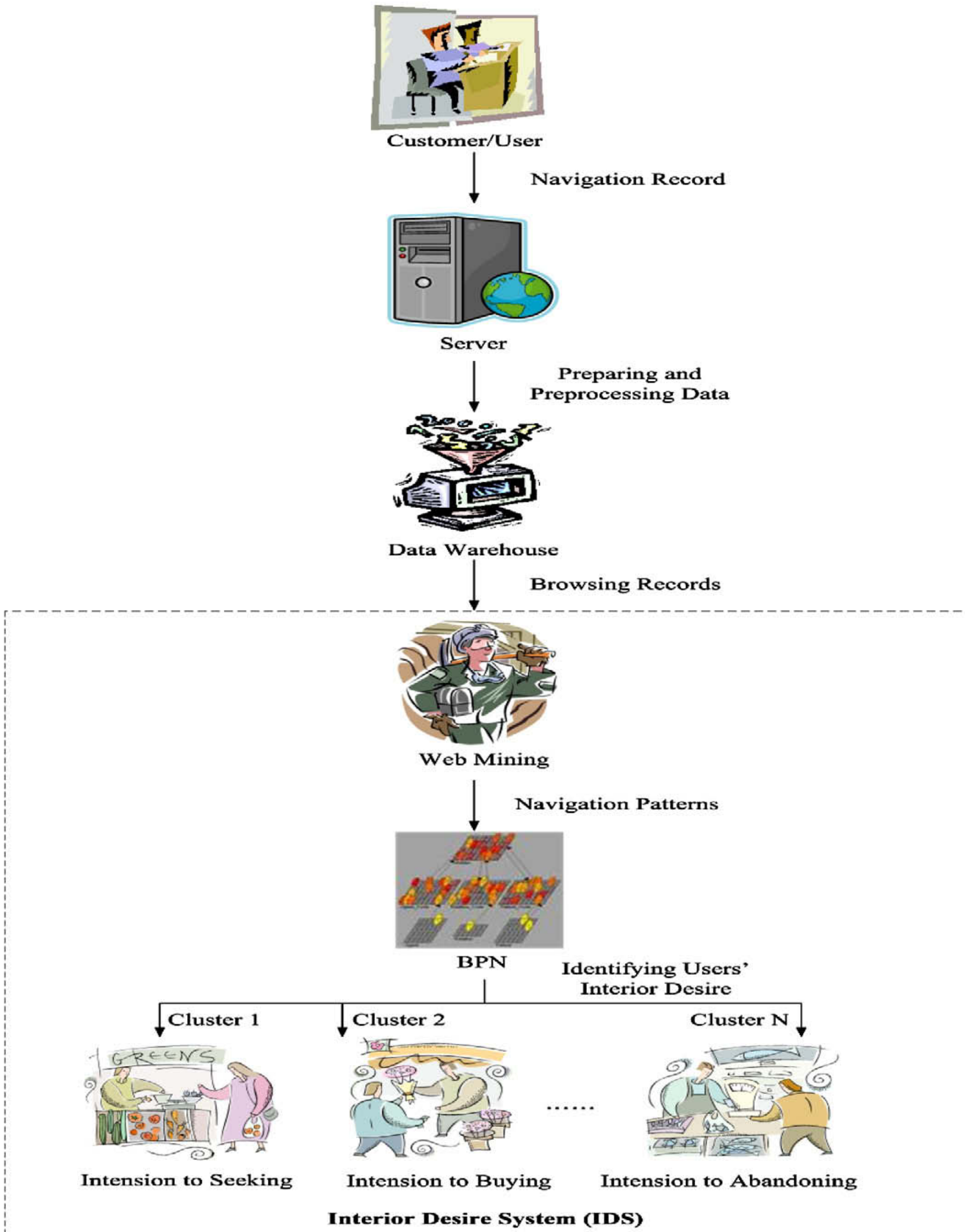


Fig. 4. The research architecture.

all log entries with filename suffixes such as, gif, jpeg, GIF, JPEG, jpg, JPG, and map can be removed. Another problem associated with proxy servers is that of user identification. Use of a machine name to uniquely identify users can result in several users being erroneously grouped together as one user. In this paper, we involve cookies using a combination of IP address, machine name, browser agent, and temporal information to identify users.

"Transaction Identification" is one necessary task before any mining. It is done on web usage data, sequences of page references must be grouped into logical units representing web transactions or user sessions. A user session is all of the page references made by a user during a single visit to a site. In this paper, we use navigation-content approach, where each transaction consists of a single content reference and all of the navigation references in the traversal path leading to the content reference. These transactions can be used to mine for path traversal patterns.

2. Phase II – Content-based modeling
   - Step 3. Data warehousing

     After above steps, we can collect the target dataset including users' click-streams and navigation paths. The user's click-stream is logged directly in a log file using a client-side logging agent. The client-side logging agent records all requests directly without caching so that no data is missed and the user is asked to "think aloud" while they browse the site so that their experience of the site can be captured. Thus, the complete pattern of the user's requests in the client-side log file can be linked to a record of the user's thoughts and behaviour while they browsed the site.

- Step 4. Web mining
  In this paper, we integrate path analysis and sequential patterns analysis. There are many different types of graphs that can be formed for performing path analysis, since a graph represents some relation defined on web pages. The most obvious is a graph representing the physical layout of a web site, with web pages as nodes and hypertext links between pages as directed edges. Other graphs could be formed based on the types of web pages with edges representing similarity between pages, or creating edges that give the number of users that go from one page to another.
  In the sequential patterns analysis, is to find inter-transaction patterns such that the presence of a set of items is followed by another item in the time-stamp ordered transaction set. In web server transaction logs, a visit by a client is recorded over a period of time. The time stamp associated with a transaction in this case will be a time interval which is determined and attached to the transaction during the data cleaning or transaction identification processes. The discovery of sequential patterns in web server access logs allows web-based organizations to predict user visit patterns and helps in targeting advertising aimed at groups of users based on these patterns. In this step, several interesting patterns and footstep graph will be discovered. Finally, several interesting patterns and footstep graph will be discovered in this approach.

3. Phase III – Collaborative filtering modeling

- Step 5. BPN implementation
  Discovering classification rules allows one to develop a profile of items belonging to a particular group according to their common attributes. This profile can then be used to classify new data items that are added to the database. In web mining, classification techniques allow one to develop a profile for clients who access particular server files based on demographic information available on those clients, or based on their access patterns.
  Afterward BPN method is employed to facilitate this clustering, according to above navigation path. Our goal is used to classify users into groups with similar behavioural patterns. The extracted users' behavioural patterns are used to forecast users' behaviours such as their potential interesting products or buying intension.
- Step 6. Interior desire investigation
  Since one of the principal goals of the web is to act as a world-wide distributed information resource, a number of efforts are underway to develop techniques that will make it more useful in this regard. The term web mining has been used to refer to different kinds of techniques that encompass a broad range of issues. However, while meaningful and attractive, this very broadness has caused web mining to mean different things to different people, and there is a need to develop a common vocabulary for all these efforts.
  Towards this goal, in this paper we proposed a definition of web mining, and developed a recommender system of the various ongoing efforts related to it. Then we presented a brief survey of the research in DM and BPN area. Next, we concentrated on the aspect of web mining which focuses on issues related to understanding the behaviour of web users. Then, we provided a general architecture of a system – IDS to do web usage mining and BPN techniques. Finally, the IDS can identify the behavioural patterns and recommend potential products for users.

4. Experiment results and performance evaluation

4.1. Data description

A case study is used to illustrate the methodology. The subject is a very successful EC website was sold soaps and skin care products in UK. A sample web page of our experiment EC website is shown in Fig. 5, in which the information recorded by the navigation

Fig. 5. A sample web page of our experiment website selling handmade soap.

recorder. Data on the background of customers in the EC website had been collected from Dec. 1, 2004 to Dec. 31, 2005. Some historical data were processed in advance prior to extracting the buying records of these customers.

4.2. Web mining

4.2.1. Clickstream data pre-processing

Click-stream data pre-processing is a necessary step for any web usage mining technology. A standard data pre-processing process has been well-developed in current web usage mining research (Cooley, Mobasher, & Srivastava, 1999). In general, it should include the following steps: data filtering, data cleaning, user identification, session identification, 'bot' detection and data formatting. Some click-stream data, however, may be lost due to the caching problem of the browser when a user uses the back button to do the backward navigation. It is therefore necessary to restore the lost click-stream data in the data pre-processing step before performing any web usage mining technique, in order to get more accurate results.

4.2.2. Users' navigation route transformation

In order to discover a user's navigation pattern, the navigation route must first be transformed to a number-based sequence so that the order of the sequence can be measured. For example, a user's navigation route (pre-processed click-stream data) is shown in Table 1.

After its transformation, a number-based sequence emerges as shown in Table 2. In this case, the sequence starts from 0 and the increasing order of the sequence is 10. The transformation algorithm will search each node in the user's navigation route and assign each one a sequence number. In addition, the algorithm will also check whether each node has occurred before in the user's navigation route. If so, the algorithm will assign the same sequence number to the same nodes (e.g., the node No. 3/index.asp has already occurred in the user's navigation route and has a sequence number '0', so the sequence number for the node No. 3 is also '0'). After the user's navigation route has been transformed to a number-based sequence, the order of the sequence can be used to detect the basic navigation elements in order to develop the user's navigation pattern.

Table 1
A sample user navigation route.

No.	Date and time	Accessed URL
1	24/12/2005, 12:14:24	/index.asp
2	24/12/2005, 12:15:38	/contact.asp
3	24/12/2005, 12:16:40	/index.asp
4	24/12/2005, 12:17:34	/about.asp
5	24/12/2005, 12:18:48	/index.asp
6	24/12/2005, 12:19:22	/oursoap.asp
7	24/12/2005, 12:19:45	/index.asp
8	24/12/2005, 12:20:10	/news.asp
9	24/12/2005, 12:20:35	/index.asp

Table 2
A number-based sequence and time duration after the navigation route transformation.

Number-based sequence	Time duration	Accessed URL
0	0	/index.asp
10	74	/contact.asp
0	62	/index.asp
20	54	/about.asp
0	74	/index.asp
30	34	/oursoap.asp
0	23	/index.asp
40	25	/news.asp
0	25	/index.asp

4.2.3. Users' navigation route segmentation

In sequential mining, the focus is always on the segmentation or transformation method of the sequence (Aggarwal et al., 1999) as a good sequence segmentation method can help the sequential mining algorithm to generate better analysis results (Zhou, Hui, & Fong, 2004).

In this research, the segmentation method is easier than other sequential mining methods. For example, a user's navigation route $R = \{0 \rightarrow 10 \rightarrow 20 \rightarrow 30 \rightarrow 40 \rightarrow 50\}$ (the arrow symbol in R means from one node to another node) will be divided to $R' = \{0, 10, 20, 30, 40, 50\}$, and a segmented route will never look like $R'_2 = \{0, 10, 20 \rightarrow 30, 40 \rightarrow 50\}$, because the continuous nodes are not allowed in users' navigation route after segmentation. The segmented users' navigation route can then be used for the pattern detection step.

4.2.4. Users' navigation pattern detection and definition

In this research, we extract user's navigation routes based on two types of basic navigational elements. "Static" elements consist of the *Same*, *Up*, and *Down* elements; "Dynamic" elements combine selected "Static" elements into *Peak* and *Trough* elements.

(1) Static elements
The segmented user navigation route is transformed to basic level-1 elements by comparing the relation between every two nodes. These elements are known as "*Same*", "*Up*" and "*Down*".
A *Same* element occurs when the user continuously browses the same web pages by either refreshing a page, opening the same page in a different window/tab or other similar activity. If there are two nodes in the user's navigation route $\{n_i, n_{i+1}\}$ and $n_i = n_{i+1}$ (e.g. {1,1}) then the relationship between these two pages will be assigned the level-1 element *Same*. An *Up* element occurs when the user has moved through the website by using forward navigation behaviour, i.e. moving from one web page to another web page they have not yet visited during the session. For example, if there are two nodes $\{n_i, n_{i+1}\}$ in a user's navigation route and $n_i < n_{i+1}$ (e.g. {1,2}), then the relationship between these two pages will be assigned the level-1 element *Up*. A*Down* element occurs when the user has moved through a website by using backward navigation to one they have visited before, causing the order of the sequence to be lower. If there are two users' navigation nodes $\{n_i, n_{i+1}\}$ in a user's navigation route and $n_i > n_{i+1}$ (e.g. {2, 1}), then the relationship between these two pages will be assigned the level-1 element *Down*.
After transformation of a segmented user navigation route to a level-1 based navigation route, the route should only consisted of the level-1 elements *Up*, *Down* or *Same*. For example, for a navigation route $R = \{0, 10, 20, 30, 30, 20, 10, 0\}$ the user's level-1 based navigation route would be $R' = \{Up, Up, Up, Same, Down, Down, Down\}$.

(2) Dynamic elements
The dynamic elements are based on measuring the relationship between each contiguous element of the user navigation route to discover changes in navigational directions or turning points. These level-2 elements, *Peak* and *Trough*, are be used to define these turning points.
A *Peak* occurs when the navigation direction shifts from a forward to a backwards direction. For example if there are

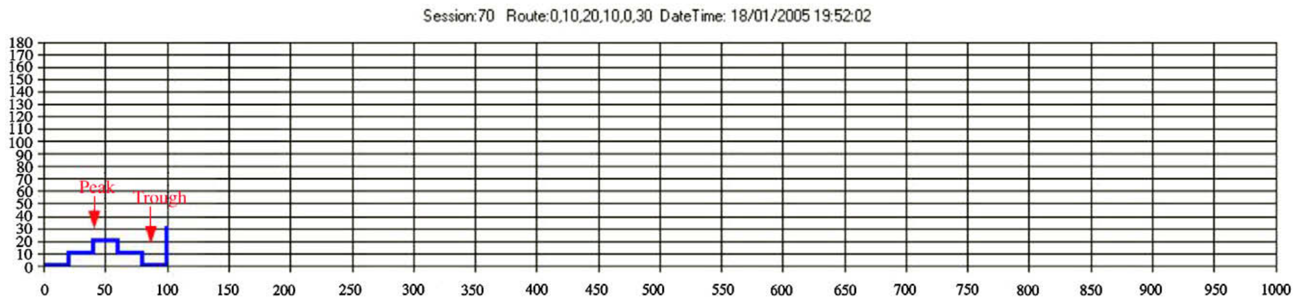


Fig. 6. An example of the *Peak* and the *Trough* elements.

two nodes $\{n_i, n_{i+1}\}$ in a navigation route, and $n_i = Up$ and $n_{i+1} = Down$ (e.g., {*Up*, *Down*}) then the relationship between these two nodes will be assigned the dynamic element *Peak*. A *Trough* occurs when the navigation direction shifts from backwards to forwards. For example if there are two nodes $\{n_i, n_{i+1}\}$ in a navigation route, and $n_i = Down$ and $n_{i+1} = Up$ (e.g., {*Down, Up*}) then the relationship between these two nodes will be assigned the dynamic element *Trough*. Fig. 6 presents an example of both *Peak* and *Trough* elements in a Footstep graph.

After a user's navigation route has been converted to the basic navigation elements, the route should consist of the elements *Same, Up*, and *Down* and the elements *Peak* and *Trough*. For example a static navigation route of R={Same, Up, Down, Up, Down}, becomes the dynamic based route of R'={Same, Peak, Trough, Peak, Down} which in turn becomes the navigation route used for subsequent pattern detection.

4.2.5. Web mining example

After the pattern rules were defined, the web mining method was used to process and analyze the Clickstream data from the website. We used the standard data pre-processing approach, including a pattern restore method (Li & Zhong, 2004), to pre-process the raw Clickstream data. Then the pre-processed Clickstream data was transformed to number-based sequence and each navigation route (session) in the Clickstream data was segmented. A sample of the results of this processing is shown in Table 3.

The segmented navigation routes were then transformed to dynamic-based navigation routes by using static and dynamic based navigation route transformation algorithms. Table 4 shows the resulting static based user's navigation routes and Table 5 the dynamic based user's navigation routes.

Finally, the user navigation patterns were automatically identified and categories according to the pre-defined pattern rules and pattern detection algorithm in Table 6.

4.3. BPN model training and performance evaluation

While the IDS system can assess the user's product knowledge level and achieve the goal of dynamic and personalized recommendation and marketing in a real-time on-line web environment, a predefined and well trained BPN model is needed in this proposed system. BPN model training process is highly important, since it affects the accuracy of the knowledge assessment, i.e. the quality and applicability of IDS. This model training process is required for every new product category and for every new website structure, and it is divided into four steps: collecting training data, mining web navigation paths, extracting buying, seeking, and abandoning patterns, and training the BPN networks. The first step is to collect and record navigation patterns, by identifying and inviting buying, seeking, and abandoning users to participate in our research and ask them to browse through the designated website. Afterwards, the users' navigation paths will be analysed using applicable web usage mining algorithms to extract those more significant and meaningful navigation patterns, which would be further categorized into buying, seeking, and abandoning patterns. Finally, these patterns derived from previous three steps will be used to create training datasets. For training the BPN model of IDS, there are each 60 buying, seeking, and abandoning users identified through our selection process to browse through soaps and skin

Table 3
Segmented navigation routes after transformation.

Session number	Number-based sequence
1	0, 1, 3, 5
2	0, 4, 3, 2, 1
3	0, 1, 3, 1, 4
4	0, 0, 3, 0, 5, 0, 6, 7, 9, 5, 7, 9
5	0, 2, 0, 1, 2, 3, 0

Table 4
User's navigation routes in static elements.

Session number	Number-based sequence
1	Up, up, up
2	Up, down, down, down
3	Up, up, down, up
4	Same, up, down, up, down, up, up, up, down, up, up, down
5	Up, down, up, up, up, down

Table 5
Users' navigation routes in dynamic elements.

Session number	Number-based sequence
1	Up, up
2	Peak, down, down
3	Up, peak, trough
4	Same, peak, trough, peak, trough, peak, trough, up, up, peak, trough, up, peak, down
5	Peak, trough, up, up, peak

Table 6
User's navigation patterns identified.

Session number	Patterns
1	Upstairs
2	Downstairs
3	Mountain
4	Finger, Finger, Finger, Mountain, Mountain
5	Finger, Mountain

care products from target website. In this training approach, we actually rely on the concept of subjective knowledge, i.e. all selected buying users consider themselves to possess enough knowledge about soaps and skin care products. For the selection of seeking users, we also use the similar subjective knowledge approach, i.e. the selected seeking users are those who do not know the soaps and skin care products knowledge or information very much.

The shopping website is equipped with a navigation recorder for tracking each customer's navigation path and extracting his/her navigation patterns, and the navigation patterns extracted from all 629,821 browsing records are derived and stored by IDS as the experiment dataset. The patterns in the dataset will be used to construct inputs to the BPN model of IDS for either training the BPN model or predicting the customer's purchasing intension on soaps and skin care products. Thirteen thousand and six hundred users were selected for training and evaluating the performance of the trained BPN model. One widely used evaluation strategy is based on *k*-fold cross validation. For 10-fold cross validation as an example, the chosen dataset is divided into 10 non-overlapping subsets. The system is trained by 9 subsets as the training data and tested by the other subset as the testing data. As a result, there are ten different results of the system based on the 10 different testing subsets. Then, average classification accuracy and error rates can be computed. To assess the performance of pattern classification systems, the confusion matrix (Kohavi & Foster, 1998) is usually used. Table 7 shows an example of a confusion matrix for evaluating binary pattern classification systems. Where *a* is the number of correct predictions that an instance is negative; *b* is the number of incorrect predictions that an instance is positive; *c* is the number of incorrect predictions that an instance is negative; *d* is the correct predictions that an instance is positive.

Regarding Table 7, the rate of average classification accuracy can be defined:

$$\text{Average classification accuracy} = \frac{A+B}{A+B+C+D}$$

Besides, other measures can be obtained, such as the Types I and II errors, precision and recall, and F-measure.

- Type I error (false positive rate): $\frac{C}{A+C}$
- Type II error (false negative rate): $\frac{D}{B+D}$
- Precision for the Negative Class = $\frac{A}{A+C}$; Precision for the Positive Class = $\frac{B}{B+D}$
- Recall for the Negative Class = $\frac{A}{A+D}$; Recall for the Positive Class = $\frac{B}{B+C}$
- F-measure = $\frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}}$

Type I error means that the error of rejecting a null hypothesis when it is the true state of nature. In other words, this is the error of accepting an alternative hypothesis when an observation is due to chance. Type II error means that the error of not rejecting a null hypothesis when the alternative hypothesis is the true state of nature. In other words, this is the error of failing to accept an alternative hypothesis when one does not have adequate power. These evaluation measures can be used to further examine how reliable the pattern classification system is. For the example of customers' buying decision prediction in EC, it is very important for administrators to understand the classification error rates, especially for the Type I error. The Type I error occurs when the system classifies the buying group (positive) into the seeking or abandoning group (negative). This error can cause a very high profit loss and decrease the customer relationship management (CRM) for the EC websites. On the other hand, the Type II error occurs when the system classifies seeking or abandoning group (negative) into the buying group (positive), which may make the EC websites lose really customers and ignore their need.

Table 7
Confusion matrix.

Actual/predicted	Negative	Positive
Negative	*A* (correct)	*C* (incorrect)
Positive	*D* (incorrect)	*B* (correct)

In this paper, the classifier is constructed based on 5-fold cross validation which is BPN. For BPN, we set up four different learning epochs (50, 100, 200, and 300) and five different numbers of the hidden layer nodes (8, 12, 16, 24, and 32) in order to obtain the 'best' BPN classifier for comparisons. The classification result shows that BPN with 100 learning epochs and 8 nodes in the hidden layer performs the best. In our goal, the BPN model could be used to determine whether the customer' intension for buying, seeking or abandoning. Table 8 presents the result of assessing the IDS systems respectively based on the proposed evaluation methodology. Note that the prediction performance of using the training and total data are shown here because one may interested in examining these performances. However, we will focus on the performance of using testing data.

4.4. Interesting patterns to recommendation

Several interesting patterns were identified using experiment and footstep graph described in the previous section. In this section, we will describe those patterns and relate them to the tester's experience when the patterns occurred.

4.4.1. Interesting patterns to buying

The *Upstairs* pattern is found when the user only moves forward in the website to accomplish the task. When the task is completed using this pattern, it usually means that is was "successful", that is, from the tester's real experience, they feel that they have moved smoothly through the website.

However, not all of *Upstairs* patterns are successful. There are two exceptions that indicate some problem for the user when they browse the website. The first is when there are too many stairs in the *Upstairs*pattern. More stairs mean the user needs to complete more steps to finish the task. Therefore, the structure of the website is too complex for the task. The second problem is when the time between two nodes is too long.

As discussed in Section 4, there are two possible indications that the *Upstairs*pattern is an unsuccessful pattern. If there are too many stairs, the website should try to reduce the steps necessary to accomplish the task (Fig. 7a). Suggestions that can be provided to the website designer are along the lines of: "Add more related links to help a user reach the final page and thus reduce the user's browsing steps".

Table 8
Average accuracy and Typee I and II errors.

Average accuracy	Training data		Testing data		Total data	
BPN	0.92145		0.91628		0.91164	
Types I and II errors	Type I	Type II	Type I	Type II	Type I	Type II
BPN	0.09266	0.08212	0.10146	0.08060	0.10648	0.14862

If the user's browsing time in some stairs of the footstep graph is too long, the website should aim to reduce the user's browsing time (Fig. 7b). Here a suitable suggestion might be "Highlight the link leading to the next page", "Make the web content simpler and clearer" or "Improve the speed of the search function".

4.4.2. Interesting patterns to seeking

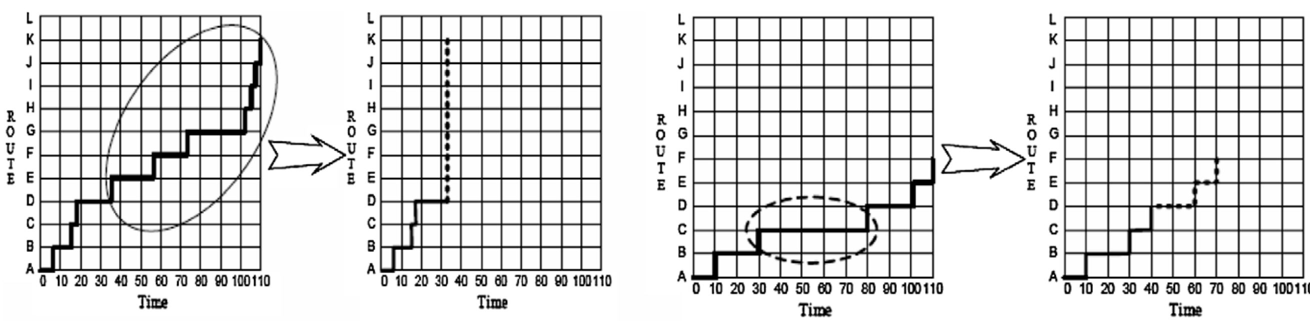
The *Mountain* pattern happens when a *Downstairs* pattern immediately follows an *Upstairs* pattern. Fig. 8 is an example of a Mountain pattern in footstep graph. In most situations, the *Mountain* pattern is an unsuccessful pattern. The reason is the user spends a lot of time browsing but they end up returning to the original web page without finishing the task. When a *Mountain* pattern occurs, there are three ways to smooth it. First, it can be added one direct link to the earlier visited page. After deploying this tip in the website, a user has no necessary to use page-by-page method to return earlier visited pages (*Downstairs* pattern 1 in Fig. 8).

Second, it can be solved when providing a recommendation or suggestion to the user when a mistake happens. For example, the website can generate a suggestion such as "Did you mean: Bill Gates" when a user makes a spelling mistake. Then, the user can find the desired page with a few additional steps (modification 2 in Fig. 8).

Finally, it should be made the *Mountain* smaller (modification 3 in Fig. 8). The website can offer some recommendation or warning such as, "You will go to the checkout following this path" If it is not the user's goal, they will realize the mistake at an earlier stage.

4.4.3. Interesting patterns to abandoning

A *Fingers* pattern in a footstep graph indicates that a user has fallen into a browsing loop. There are two possible reasons for this.



(a) Reduce the Step (b) Reduce the Browsing Time

Fig. 7. Smoothing the *Upstairs* pattern.

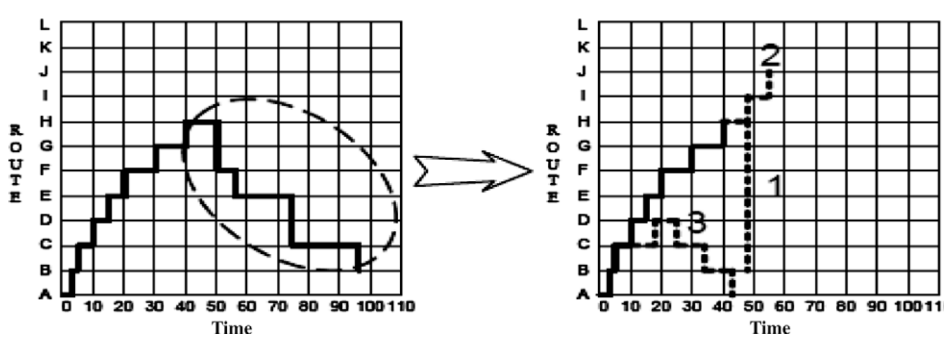


Fig. 8. Smoothing the *Mountain* pattern.

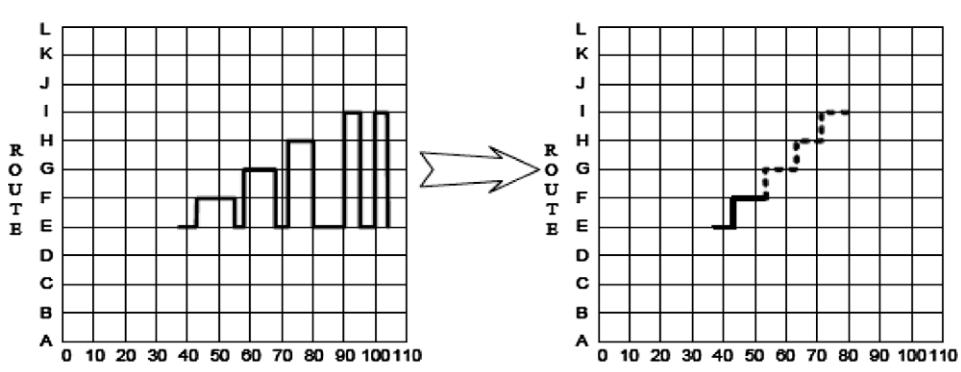


Fig. 9. Smoothing the *Fingers* pattern.

The first is that the user is confused about where he should go, possibly because of an ambiguous statement on the website. The second is that too many mistakes have occurred and the user needs to go back to a page they visited earlier to restart. When this kind of pattern happens, it usually represents unsuccessful browsing. The more fingers in the *Fingers* pattern, the more the pattern is unsuccessful. The slimmer the finger is, the faster the loop repeats itself.

When a *Mountain* pattern occurs, the user needs to back up to an earlier visited page to find the link to the page they want to go. In this situation, it is possible to turn the *Fingers* pattern into a successful *Upstairs* pattern show in Fig. 9. Providing the relevant links in the respective pages can realize this.

However, in most cases the *Fingers* pattern happens because the user falls into a loop, and cannot successfully complete his task. The user has lost his way and he cannot find the information he needs to recover. Therefore, when this kind of pattern happens, the website designer needs to review their website design thoroughly to try to find the source of the problem, and improve the navigation help provided by the website. Some missing link should be added to the web page that is the focus point of the loop. However, normally it is not known exactly which link is missing, since the user's real goal can not necessarily be extracted from the footstep graph.

5. Conclusion and discussion

This research aimed at the user's prior knowledge and needs for specific products, in order to find a better prediction and recommendation method. Our method is based on the customer's on-line navigation behaviors by analyzing their navigation patterns through web mining and constructing artificial neural networks to predict potential customers' need in the future. This research picked a very successful EC website that sold soaps and skin care products in UK. We adopted the necessary dataset from Dec. 1, 2004 to Dec. 31, 2005, to carry out a computational intelligent analysis, with each generated variable applied to web mining and BPN methods in order to predict the users' intention of buying, seeking and abandoning.

After the experiments, we summarized three critical contributions. First, the footstep graph is used to visualize the user's click-stream data. Consequently any interesting pattern can be discovered more easily and quickly in this way than by using other visualization tools. Moreover, through linking it to the user's experience, the user's behavior or intention can also be identified. Therefore, we can classify some of the patterns in our experiment and outlined some appropriate recommendation to enhance the users' buying willingness.

Second, this paper presents a novel sequence mining approach to identify pre-identified user navigation patterns automatically. We also describe the concepts of static and dynamic elements of user's navigation behavior, which constitute a vital part of the sequence mining method. Therefore, we can apply the user's navigation behavior records to train the BPN model. BPN model training process is highly important, since it affects the accuracy of the IDS system.

Third, the research identifies and categorizes the user's navigation patterns automatically and efficiently. It is an important tool not only for web usage mining analysis but also for HCI research on user's navigation behavior. Besides, we apply empirical study to indicate that the proposed approach can generate appropriate prediction accurately of users' navigation behavior based on the individual user requirements, and help them browse more effectively in a web-based environment.

For future research, additional artificial intelligence techniques, such as other neural network models, classification mining, genetic algorithms, and other soft computing techniques could be applied. Certainly, researchers could also expand the system utilities to deal with more e-commerce datasets. Besides, the IDS system is also a useful tool in the area of e-learning, in which the navigation strategies and patterns of learners need to be identified very efficiently.

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