

Web Page Endorsement Based on Web Usage and Dominion Erudition

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Abstract: This paper presents a new framework to recommend the web pages in the efficient manner based on web usage and Domain Knowledge of the user. Web-page recommendation plays an important role in intelligent Web systems. On web different kind of web recommendation are made available to user every day that includes Image, Video, Audio, query suggestion and web page. Recent studies have shown that conceptual and structural characteristics of a website can play an important role in the quality of recommendations provided by a recommendation system. Resources like Google Directory, Yahoo! Directory and web-content management systems attempt to organize content conceptually. Semantic Web Mining aims at combining the two fast-developing research areas Semantic Web and Web Mining. In this paper, we discuss the interplay of the Semantic Web with Web Mining, with a specific focus on usage mining. Two new models are proposed to represent the domain knowledge. The first model uses ontology to represent the domain knowledge. The second model uses one automatically generated semantic network to represent domain terms, Web-pages and the relations between them. Another new model, the conceptual prediction model, is proposed to automatically generate a semantic network of the semantic Web usage knowledge, which is the integration of domain knowledge and Web usage knowledge. The experimental results demonstrate that the proposed method produces significantly higher performance than the WUM method.

Keywords: Web usage mining, Web-page recommendation, domain ontology, semantic network, knowledge representation.

I. INTRODUCTION

This paper develops a prototype of the new semantic-enhanced Web-page recommender system (SWRS) utilizing these models to leverage recommendations produced by a community of users to deliver recommendations to an active user. Firstly, the system needs to learn users' Web usage experience which is Web logs of given websites. The Web logs are the records of users' Web browsing behaviours daily, that is Web usage data. By mining Web usage data, useful knowledge can be discovered and represented in the models, i.e. DomainOntoWP or TermNetWP, WPNavNet, and TermNavNet, which can facilitate making Web-page recommendations. Web page recommendations are becoming very popular, and are shown as links to related web page, related image, or popular pages at websites. When user sends request to web server, session is created for the user. During session when user browses a website the list of page that user visits is stored as a session data.

Web mining (WM) is the process of discovering useful knowledge from Web data. Depending on different types of Web data, appropriate mining techniques are selected. There are three main broad categories of Web mining (Kolari & Joshi 2004).

- Web content mining (WCM) is used to mine Web content, such as HTML or XML documents.
- Web structure mining (WSM) focuses on Web structure, such as hyperlinks on Web-pages.

Web usage mining (WUM) is applied to Web usage data, such as Web logs or clickstreams, from a website.

Web usage mining aims to discover some useful patterns from the Web usage data, such as, clickstreams, user transactions and users' Web access activities, which are often stored in Web server logs (Liu, Mobasher & Nasraoui 2011). A Web server log records user sessions of visiting Web-pages of a website day by day. It can be used to discover potentially useful Web usage knowledge, e.g. the navigational behaviour of Web users, (Mobasher 2007a).

Generally speaking, a Web usage mining process includes three phases: pre-processing, mining, and applying mining results (Woon, Ng & Lim 2005). After pre-processing Web log files, Web access sequences (WAS), for example, are generated and filed in a dataset (Ezeife & Liu 2009). An element of this dataset is a sequence of representing a user browsing session. In the mining phase, some sequential pattern mining techniques, such as clustering, classification, association rules, and sequential pattern discovery (Pierrakakos et al. 2003), can be applied to the WAS to extract the frequent Web access patterns (FWAP), which is useful Web usage knowledge. In the third phase, the discovered knowledge will be used in a specific application, e.g., a Web-page recommender system, in which FWAP are used for generating the recommendation rules to support on-line Web-page recommendation. The mining phase using sequential pattern mining techniques is the core phase in a WUM process

and plays a crucial role in a Web-page recommender system to support users to make better decision based on their current Web navigation history.

In summary, making recommendations is the main application of WUM in recommender systems as WUM can obtain the actual user behaviour rather than the behaviour expected from the Web design. And pattern discovery methods play an important role in mining user behaviour sequences. Ontology may include individuals (instances), classes, attributes, relations, restrictions, rules, and axioms. Based on these components, we can build an object-oriented model for an application domain and use this model for sharing and reusing domain information on the Web. Such an ontology model allows human- and machine-understandable content and human-machine interaction.

This paper presents a different method to provide better Web-page endorsement based on Web usage and domain erudition, which is supported by three new knowledge representation models and a set of Web-page recommendation strategies. The first model is an ontology-based model that represents the domain knowledge of a website. The construction of this model is semi-automated so that the development efforts from developers can be reduced. The second model is a semantic network that represents domain knowledge, whose construction can be fully automated. This model can be easily incorporated into a Web-page recommendation process because of this fully automated feature. The third model is a conceptual prediction model, which is a navigation network of domain terms based on the frequently viewed Web-pages and represents the integrated Web usage and domain knowledge for supporting Web-page prediction. The construction of this model can be fully automated. The recommendation strategies make use of the domain knowledge and the prediction model through two of the three models to predict the next pages with probabilities for a given Web user based on his or her current Web-page navigation state. To a great extent, this new method has automated the knowledge base construction and alleviated the new-page problem as mentioned above. This method yields better performance compared with the existing Web usage based Web-page recommendation systems.

II. RELATED WORK

Web Mining techniques arose as a tool for helping managers and web masters in the enhancements task. However, many tools provide not very useful results to perform off-line web site enhancements. A big problem is how the people in charge of a Web site modifies the site based on a web mining tools' results. The issue of analyzing huge amount of subjective information, hundreds of features, and mil-lions of user sessions; to extract useful information to enhance a web site is not straightforward. Moreover, most tools or processes use terms as features, making even harder to see a good solution in a reasonable time. Therefore, the development of new methods which may lead to good results in relatively short processing times is quite important.

This papers' idea is the development of a new methodology to perform better Web Usage Mining (WUM), based on the introduction of concepts into the mining process. This type of web mining allows for the collection of Web access information for Web pages. This usage data provides the paths leading to accessed Web pages. This information is often gathered automatically into access logs. It recommends only accessed pages for the users.

This way we can take advantage of the organizations' business knowledge and use it in the mining task. This process is called concept-based web usage mining. A strong difficulty occurs to evaluate the proposed technique. Usually papers in data mining field doesn't provide any means of comparison with other techniques. In these case, the problem of evaluation is bigger since we need to evaluate a mining process. Based on [1] we developed an evaluation schema to be applied in a real web site.

On the other hand, by mapping Web-pages to domain concepts in a particular semantic model, the recommender system can reason what Web-pages are about, and then make more accurate Web-page recommendations [3, 8]. Alternatively, since Web access sequences can be converted into sequences of ontology instances, Web-page recommendation can be made by ontology reasoning [2, 9]. In these studies, the Web usage mining algorithms find the frequent navigation paths in terms of ontology instances rather than normal Web-page sequences. Generally, ontology has helped to organize knowledge bases systematically and allows systems to operate effectively.

III. PROPOSED METHODOLOGY AND DISCUSSION

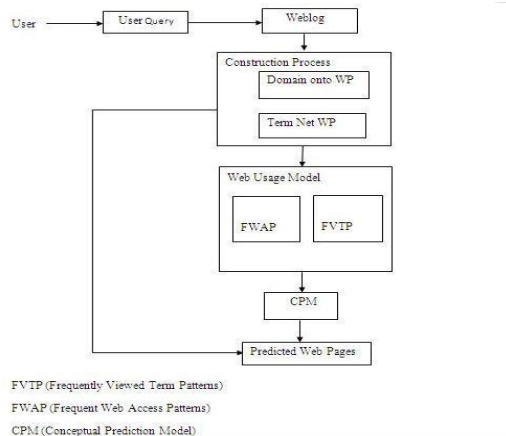
A. Domain Ontology Model

Domain ontology can be obtained by manual or automatic construction approaches. Depending on the domain of interest in the system, we can reuse some existing ontologies or build a new ontology, and then integrate it with Web mining. Web logs in a Web personalization system. Ontology is a knowledge representation technology whose implementation can be machine-understandable using the ontology language, such as OWL. Ontology defines the concepts and their associations in an application domain. In the context of Web-page recommendation, it is necessary to have an ontology that expresses the meaning of Web-pages for better understanding Web usage patterns and discovering frequently viewed domain terms for supporting more effective Web-page recommendations.

The Web usage knowledge can be discovered from Web usage data through unsupervised learning processes, such as sequential pattern mining techniques, but without the semantics of Web-pages, the discovered knowledge are limited in supporting Web-page recommendation, such as no alleviation to the "new page" problem. Domain ontology is really useful to enhance a Web-page recommendation process by adding semantics to Web-pages, but how to build effective domain ontology for Web-page recommendations is always a

big challenge. The study presented in this chapter builds domain ontology of Web-pages of a website that can be used to interpret the semantics of Web-pages. This chapter proposes a domain ontology model that represents the domain concepts, Web-pages, and the relations among them for a given website to support semantic-enhanced Web-page recommendation and also presents a novel method to build such domain ontology for a website.

In the context of Web-page recommendation, we build the domain ontology of Web-pages of a given website based on the visited Web-pages to represent the domain concepts (general domain terms), the relationships between the concepts with constraints, the instances of concepts (specific domain terms), Web-pages, and the links between Web-pages and specific domain terms.



Definition 3.1 (Domain ontology model of Web-pages - DomainOntoWP) A domain ontology structure of a website is defined as a four-tuples: $O_{man} := \langle C, D, P_{MAN}, A \rangle$, where C represents terms extracted from the Web-page titles within the given website, D represents the Web-pages of the website, P_{MAN} represents properties defined in the ontology, and A represents axioms, such as, an instantiation axiom assigning an instance to a class, an assertion axiom assigning two instances by means of a property, a domain axiom for a property and a class, and a range axiom for a property and a class. In details, C , D , and P_{MAN} are further divided into sets:

$C = C \cup T_{man}$ comprises a set of general domain terms (concepts) C , and a set of specific domain terms (instances of the concepts) T_{man} , $D = \text{SemPage} \cup D$ comprises class SemPage which represents Web-page instances, and a set of Web-pages D , $P_{MAN} = R_{man} \cup A_{man}$ comprises a set R_{man} of the relations between terms (R_c) and the relations between terms and Web-pages (R_p), and a set of attributes A_{man} defined in the ontology. In particular, R_c will be specified depending on the application domain. $R_p = \text{hasPage} \cup \text{isAbout}$, where the 'hasPage' relation states that a domain term may have some Web-pages, and the 'isAbout' relation is

the inverse of the 'hasPage' relation. That means each domain concept class has the 'hasPage' object property referring to class SemPage , and class SemPage has the 'isAbout' object property referring to the domain concept classes.

Step 1: Collect the terms

In order to collect the terms, we will: (i) collect the Web log file from the Web server of the website for a period of time (at least seven days), (ii) run a pre-processing unit to analyse the Web log file and produce a list of URLs of Web-pages that were accessed by users, (iii) run a software agent to crawl all the Web-pages in the URL list to extract the titles, and (iv) apply an algorithm to extract terms from the retrieved titles.

Using the MS Web dataset, we obtain the Web-page titles and paths. A sample dataset is shown in Table I.

TABLE I
A SAMPLE MS WEB DATASET

Page	Title	Path
d_1	MS Word	/msword
d_2	MS Word Support	/mswordsupport
d_3	MS Access	/msaccess
d_4	MS Access Support	/msaccesssupport
d_5	MS in Education	/education
d_6	Visual Fox Pro Support	/vfoxprosupport

Given this dataset, the extracted terms, for the sample (Table I), might be "MS", "Word", "Access", "Support", "Education", "Visual", and "Fox_Pro". Based on the extracted terms, we can generalize them to domain concepts in Step 2.

Step 2: Define the concepts

In this paper, we present the MS website as an example. This website focuses on the application software, such as MS Office, Windows Operating System, and Database. Therefore, the identified domain concepts of this website are Manufacturer, Application, Product, Category, Solution, Support, News, Misc, and SemPage , where the concept SemPage refers to the class of Web-pages, and the other concepts refer to the general terms in the MS website.

B. Semantic Domain Term Generation

One of the big challenges that these approaches are facing is the semantic domain knowledge acquisition and representation. Kearny et al. [10] also investigate how Web usage data may be combined with se-mantic domain knowledge to provide a deeper understanding of user behavior. The Semantic Web is based on a vision of Tim Berners-Lee, the inventor of the WWW. The great success of the cur-rent WWW leads to a new challenge:

A huge amount of data is interpretable by humans only; machine support is limited. Berners-Lee suggests enriching the Web by machine-processable information which supports the user in his tasks. For instance, today's search engines are already quite powerful, but still too of-ten return excessively large or inadequate lists of hits. Machine-processable

information can point the search engine to the relevant pages and can thus improve both precision and recall.

Algorithm to Automatically construct a TermNavNet WP

Input: TSC(Term sequence collection)

Output: G(TermNetWP)

Process:

Let TSC = {PageID, X= t1t2... tm, URL}

Initialize G

Let R= root or the start node of G

Let E= the end node of G

For eachPageIDand eachsequence Xin TSC{

Initialize a WPageobject identified as PageID

For eachterm ti ∈ X{

If node tiis not found in G, then

- Initialize an Instanceobject Ias a node of G

- Set I.Name= ti

Else

- Set I= the Instanceobject named tiin G

Increase LiOccurby 1

If (i==0) then

- Initialize an OutLink R-ti if not found

- Increase R-ti.iWeightby 1

- Set R-ti.fromInstance= R

- Set R-ti.toInstance= I

If (i>0& i<m) then

- Get preI= the Instanceobject with name ti-1

For instance, today it is almost impossible to retrieve information with a keyword search when the information is spread over several pages. Consider, e.g., the query for Web Mining experts in a company intranet, where the only explicit information stored are the relationships between people and the courses they attended on one hand, and between courses and the topics they cover on the other hand. In that case, the use of a rule stating that people who attended a course which was about a certain topic have knowledge about that topic might improve the results.

C. Conceptual Prediction Model

With the given dataset, meaningful terms are extracted by removing stop words, e.g., “the”, “a”, and “for”, or invalid words from the Web-page titles. For example, terms which are extracted from the sample dataset in Table 4-2 are “MS”, “Access”, “Support”, “SQL Server”, “Office”, “News”, “PowerPoint”, “Project”, and “Excel”. It is possible for some extracted terms to share same features, so they are better to be the instances of a concept rather than standalone concepts. As the scope of the domain has been stated in the requirements analysis, the considered domain concepts of the MS website are Manufacturer, Application, Product, Category, Solution, Support, News, Misc, and SemPage. In which, the concept SemPage refers to Web-pages, and other concepts refer to terms used in the MS website.

Regarding the non-taxonomic relationships, the relationship types, e.g. self-referencing, 1-M, and M-N relationships, which are often used in a relational database

except for the relationships between a super set and a sub set are considered. In the MS website example, the main types of non-taxonomic relationships are listed as below.

- The ‘provides’ relation describes the M:N relationship between concept Manufacturer and concepts Product, Solution, Support, and News. For example, the MS manufacturer might provide some products, e.g. MS Office, or some solutions, e.g. MS Solutions. The ‘isProvided’ relation is the inverse of the ‘provides’ relation.

- The ‘has’ relation describes the M:N relationship between concept Application and concepts Product, Solution, Support, and News. For example, the Office application might have some products, e.g. MS Office, MS Project, etc., or some supports, e.g. MS Office Support, MS Project Support, etc. The ‘isAppliedFor’ relation is the inverse of the ‘has’ relation.

- The ‘hasPage’ relation describes the M:N relationship between a domain concept, such as Application or Product, and the concept SemPage. For example, the MS Word application has some Web-pages describing its general information and features. The ‘isAbout’ relation is the inverse of the ‘hasPage’ relation, which means when we define a page about a certain term instance, that term instance has the page as its object property value.

IV. EXPERIMENTAL RESULTS

In order to evaluate the effectiveness of the proposed models of knowledge representation and the recommendation strategies along with the queries, we implement these models, algorithms and strategies to test their performance of Web-page recommendation using a public dataset. In this section, we firstly list the measures for the performance evaluation of Web-page recommendation strategies, and then present the design of the experiments, followed by the comparisons of experimental results.

A. Performance Evaluation

The performance of Web-page recommendation strategies is measured in terms of two major performance metrics: Precision and Satisfaction according to Zhou [14]. In order to calculate these two metrics, we introduce two definitions: Support and Web-page recommendation rules, as follows:

Definition 13 (Support). Given a set Δ of WAS and a set $P = \{P_1, P_2, \dots, P_n\}$ of frequent (contiguous) Web access sequences over Δ , the support of each $P_i \in P$ is defined as:

$$\sigma(P_i) = \frac{|\{S \in \Delta : P_i \subseteq S\}|}{|\Delta|}, \text{ where } S \text{ is a WAS.}$$

In the context of Web usage knowledge discovery using PLWAP-Min, Support is used to remove infrequent Web-pages and discover FWAP from WAS. This is accomplished by setting a Minimum Support (MinSup) and using it as a threshold to check WAS. The Web access sequences whose Support values are greater than, or equal to

MinSupare considered as FWAP. The smaller MinSup is set, the more FWAP are discovered.

Definition 14 (Web-page recommendation rules): Let $S = s_1s_2 \dots s_k s_{k+1} \dots s_n$ ($n \geq 2$) be a WAS. For each prefix sequence $\text{Sprefix} = s_1s_2 \dots s_k$ ($k \leq n-1$), a Web-page recommendation rule is defined as a set of recommended Web-pages generated by a Web-page recommendation strategy, denoted as $RR = \{r_1, r_2, \dots, r_M\}$, where r_i ($i \in [1..M]$) is a recommended Web-page. A Web-page recommendation rule is deemed as correct, and/or satisfied, or empty based on the following conditions:

- If $s_{k+1} \in RR$, RR is correct.
- If $\exists s_i \in RR$ ($k+1 \leq i \leq n$), RR is satisfied.
- If $M = 0$, RR is empty.

Given a set of recommendation rules, $R = \{RR_1, RR_2, \dots, RR_N\}$, where RR_i ($1 \leq i \leq N$) is a recommendation rule, and $|R| = N$ is the total number of recommendation rules in R including empty rules, the performance of Web-page recommendation strategies is measured in terms of two major performance metrics: Precision and Satisfaction according to Zhou [14]. The precision is useful to measure how probable a user will access one of the recommended Web-pages. Besides, we also need to consider if a user accesses one of the recommended Web-pages in the near future. Actually, the next page accessed by a user may not be the target page that user wants. In many cases, a user has to access a few intermediate pages before reaching the target page. Hence, the satisfaction is necessary to give the precision that the recommended pages will be accessed in the near future.

B. Design of Experimental Cases

We aim to compare the performance of different techniques ranging from the traditional Web-page recommendation approach, such as PLWAP-Mine; through the semantic-enhanced approach based on domain ontology of Web-pages (DomainOntoWP), which is constructed manually based on the developer's knowledge, and the DomainOntoWP-based semantic Web usage knowledge (TermNavNet); to the semantic-enhanced approach based on a semantic network of Web-pages (TermNetWP), which is automatically constructed based on the Web usage dataset, and the TermNetWP-based semantic Web usage knowledge (TermNavNet).

Case 1 (R.PLWAP). Set the threshold of the traditional Web-page recommendation approach using the best Web usage mining (WUM) algorithm, i.e. PLWAP-Mine. The Web-page recommendations are generated based on the PLWAP-Mine algorithm. We refer to this case as the base case.

Case 2 (R.DO.1st). Test the effectiveness of the semantic-enhanced Web-page recommendation by integrating the domain ontology (DomainOntoWP) with TermNavNet using the first-order CPM. The recommendation strategy (R.DO.1st) is used.

Case 3 (R.DO.2nd). Test the effectiveness of the semantic-enhanced Web-page recommendation by integrating the domain ontology (DomainOntoWP) with TermNavNet using

the second-order CPM. The recommendation strategy (R.DO.2nd) is used.

Case 4 (R.TN.1st). Test the effectiveness of the semantic-enhanced Web-page recommendation by integrating the semantic network of Web-pages (TermNetWP) with TermNavNet using the first-order CPM. The recommendation strategy (R.TN.1st) is used.

Case 5 (R.TN.2nd). Test the effectiveness of the semantic-enhanced Web-page recommendation by integrating the semantic network of Web-pages (TermNetWP) with TermNavNet using the second-order CPM. The recommendation strategy (R.TN.2nd) is used.

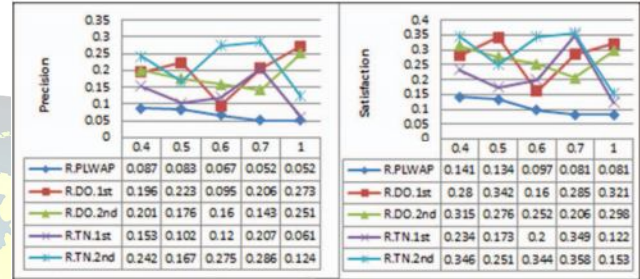


Fig. 2. Results for experimental cases 1-5 (Rec.Len = 5)

In overall, the proposed method depends less on the MinSup than PLWAP-Mine, because Web-pages are reasoned based on their semantics. Although an increase in MinSup leads to a decrease in the FWAP, that is the Web-page recommendation capability declines, the proposed method can query for the relevant terms of Web-pages and enrich the pool of recommended Web-pages. As a result, the proposed recommendation models which are based on not only the accessed Web-pages, but also the semantics of Web-pages can outperform the PLWAP-Mine-based recommendation model. Moreover, it has been shown that the second-order prediction model based on TermNetWP is more accurate than the first-order one. However, this is contrary to the DomainOntoWP-based prediction models. Regarding the Web-page recommendation performance of approaches to semantic knowledge representation of Web-pages, the TermNetWP-based models are by large more effective than the DomainOntoWP-based models. In particular, the TermNetWP-based second-order prediction model is the best approach for Web-page recommendation. That is because:

- TermNetWP allows sorting of terms and Web-pages in the queries, so the most possible items are taken into account in the term prediction and Web-page recommendation processes.

- TermNetWP fully models terms of Web-pages of user interest, and the relationships between terms and Web-pages. Hence, the interesting.

V. CONCLUSION AND FUTURE ENHANCEMENT

This paper aims to address the challenges and/or problems in developing Web-page recommender systems,

such as the “new page” problem, the challenges of manual knowledge construction, and the “heterogeneous knowledge bases” problem. We discussed how Semantic Web Mining can improve the results of Web Mining by exploiting the new semantic structures in the Web; and how the construction of the Semantic Web can make use of Web Mining techniques. The example provided in the last section shows the potential benefits of further research in this integration attempt.

Three important directions for further interdisciplinary cooperation between mining and application experts in Semantic Web Usage Mining have been identified: (1) the development of ontologies of complex behaviour, (2) the deployment of these ontologies in Semantic Web description and mining tools, and (3) continued research into methods and tools that allow the integration of both experts’ and users’ background knowledge into the mining cycle.

Finally, we concluded with the description of the recommendation engine’s operation and presented an algorithm for making effective recommendations. Compared with one of the most advanced Web usage mining method, i.e. PLWAP-Mine, the proposed method can substantially enhance the performance of Web-page recommendation in terms of precision and satisfaction. More importantly, this method is able to alleviate the “new-page” problem mentioned in the introduction because it based on not only the Web usage knowledge, but also the semantics of Web-pages.

Future work will focus on further experiments with different combinations of the system’s functionalities, further contextualization possibilities from the Semantic Web Mining area, and an evaluation of the proposed approach with respect to learning support and to open-corpus learning.

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