Chapter 8
Web Page Recommendations Based on User Session Graph

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Abstract Web page recommender system provides users with recommendations to assist their navigation and increases the website usability and user satisfaction. In this chapter, Web page recommendation method is presented by constructing User Session Graph using user sessions from the navigation log. The node represents Web pages and weight on the edge is calculated by the number of times the Web pages present in the sessions. *new page problem* is solved by computing co-occurrence value between two terms present in titles. Web pages are recommended based on connected nodes in the graph and co-occurred terms. Experiments are conducted on user navigation data collected from Microsoft Website www.microsoft.com. The proposed method is compared with *TermNetWP* method and outperforms *TermNetWP* with higher precision and satisfaction values.

8.1 Introduction

Internet usage has increased excessively as a result of evolution in e-commerce, research, e-banking, education, news, music, movies and electronics devices. Hence, a huge amount of information is archived and it keeps growing rapidly without any control. The decreasing costs in secondary storage have made it easy to store a huge volume of information. The valuable information is beneficial to determine interesting and useful patterns that are used by many researchers for guiding the users to visit the Web pages during their activity on the Web. This type of system is called Recommender System and helps to predict the user request.

The Web page recommender system provides users with recommendations to assist their navigation. The objective is to discover which Web page user will access next. Web page recommendation increases the website usability and user

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K. R. Venugopal et al., *Web Recommendations Systems*,
https://doi.org/10.1007/978-981-15-2513-1_8

satisfaction. It is also useful in many applications like Web caching, prefetching and online advertising.

There are many problems in generating efficient Web page recommendation framework such as extracting useful information of the domain, efficiently determine knowledge and navigational patterns from available user navigational data, employing extracted knowledge to build a model and develop powerful Web page recommendation system.

Researchers have developed various methods to solve the above problems using available Web usage data. Probabilistic models and tree construction from Web log can effectively produce useful patterns [1–4] and are trained from navigational data to build links between Web pages. For a given Web page sequence as input to these trained models on previously visited pages, the Web pages user will access next can be predicted. These approaches requires more training dataset to get higher prediction accuracy and solely dependent on the Web usage data. Hence, if the input Web page is not present in usage data then it fails to predict the Web pages and is called *new page problem*.

The *new page problem* can be solved by incorporating semantic relation [5] and domain knowledge [6–8]. A semantic of Web pages of a website is represented by the domain ontology and combined with usage data to improve the Web page recommendation performance. Combining semantic knowledge to Web usage data has gained greater performance than traditional Web usage mining algorithms. However, the construction of efficient domain ontology and representation of semantic domain knowledge is a big challenge in these models.

In this chapter, Web page framework is presented where user session graph is constructed from sessions collected from user navigation log. In this graph, the nodes represent Web pages and an edge exists between two nodes if two Web pages are present in the session. The weight on the edge is calculated by the number of times the Web pages are present in sessions. This graph shows the relation between the two visited Web pages by the users. For a given Web Access Sequence (WAS) the connected Web pages with its weight are extracted for each page present in WAS. If any *new page* exists in WAS, then the Web pages are extracted based on co-occurred term calculation with its weight. Extracted Web pages are arranged in the descending order based on its weight and Top-*n* Web pages are recommended.

8.2 Related Works

In this section, various webpage recommendation techniques are discussed. Murat et al. [9] presented hybrid recommendation systems that combine existing recommendation methods based on Web usage. The comparative evaluation is presented by combining k-means models, Markov models, Association rule mining model and Click Stream Tree model. It shows the combination of various methods that affect the prediction accuracy.

Usually, in a website hierarchical link is created to organize webpages without any semantic relation. Hence, the traditional link-based algorithm for Web page retrieval gives poor performance. Li et al. [10] have proposed a Hierarchical Navigation Path based method for Web page retrieval. In this method, Web textual information such as page titles, anchor text and URLs are incorporated with website link structure for Web page retrieval. This method improves Web page retrieval accuracy compared to traditional link-based algorithm. However, the performance decreases with increase in path length. Markov models with semantic information is used for Web perfecting [11]. Semantic information is incorporated into Markov transition matrix. Hence, it can provide better prediction and solve the problem of contradicting prediction. This semantic information is used to prune states in Selective Markov models.

A technique that combines domain knowledge and Web navigation log is proposed [12] for prediction. It integrates the conceptual hierarchy of website and usage information based on biological sequence alignment. Similarity score between pages is computed based on conceptual hierarchy. Time spent on page and browsing order is incorporated in similarity calculation. A method that combines navigational patterns and page connectivity is proposed for Web page recommendation [2]. User concepts from Web log is used to extract navigational patterns and used to produce Web page recommendations by accomplishing navigational behaviour of a user. Recommended Web pages are ranked by computing hub score from page connectivity knowledge.

A hybrid method is presented that minimizes repetitive Web surfing for personalized new recommendation [13]. Web pages of Web navigational log are classified by computing weight of terms and used to construct user's interest model. User's preference model is constructed from hyperlink of user navigational log. The recommendation probability for a user is computed by matching user's models and news content. Forsati and Meybodi [14] have proposed a hybrid algorithm based on weighted association rule and distributed learning automata for Web page recommendation. Users' navigational pattern is extracted by association rule mining and used for recommendation based on user's current status. In distributed learning automata, link analysis and behaviour of users are integrated to assign probability to the webpages. Recommendations are made based on structure of website and user behaviour patterns. HITS algorithm is used to extend the recommendation set.

A method that integrates prefetching and caching is presented to derive prefetching rules [15]. The cyclic behaviour and periodicity of Web access sequence is used to fetch profit-driven caching policy. The experiment results show that hit ratio is increased for the cached objects. The Probability of Correctness of Facts is proposed to compute Trustworthiness of websites to rank the Web pages [16]. Probability-based similarity function is used to extract correctness by matching facts provided by Web pages and Web pages' facts.

Collaborative social annotations method is applied for Web page recommendations [17]. Semantic clusters are generated from users' information and Web pages. Social annotation clusters are also generated from annotation and Web pages. Semantic and social annotation clusters are used to recommend Web pages. Collaborative filtering and Topic-aware Markov Model is used for personalized Web page recommendation [18]. User's navigational patterns is learned from topic aware Markov model. It acquires topical relevance of pages. Collaborative filtering is used to find user similarities and integrated to rank the recommended webpages.

8.3 Web Page Recommendations Framework and WRUSG Algorithm

8.3.1 Problem Definition

Given a Web Access Sequence (WAS) from user navigation *log*, the objective is to recommend webpages. It is assumed that the user is online and the user navigation *log* is available.

8.3.2 Web Page Recommendations Framework

In this section, Web Page Recommendation Framework is presented that solves new page problem. User session graph is constructed from the user navigation history in which nodes represent Web pages and edge represent navigation between the Web pages. For a given Web page sequence as an input, Web pages are recommended by travelling user session graph. For the new page problem, co-occurrence of domain terms is computed and later used to recommend Web pages. Here, first few terms are explained.

Web Pages: The domain consists of numerous pages with meaningful information. Each page has small description about it as a title of that page. A domain can be represented as $D = \{P_1, P_2, \ldots, P_m\}$ with m number of pages.

Domain Terms: A title consist of set of definite words which gives the knowledge of that page. Domain terms are the words present in the Web pages' titles for a particular domain and represents as $T = \{t_1, t_2, \ldots, t_n\}$.

Web Access Sequence (WAS): The user navigation log consists of user *id* and the sequence of Web pages a user has visited during browsing and it is called Web access sequence. This framework has the following steps:

Step 1: User Session Graph Construction

User session graph is constructed based on Web navigation history that gives us the knowledge about the users' Web access sequence. This sequence contains user clicked patterns, transactions or user interactions with Web resources. A session is the continuous Web access sequence visited by a user in a particular time period. It gives information about the visited pages and its association between Web pages. The visited Web page in a particular session can also be present in other sessions. The individual session cannot infer any kind of relationship between different Web pages. Hence, user session graph is constructed by combing all the user sessions.

Consider a Web navigation log with m number of sessions $S_m = \{S_1, S_2, \ldots, S_m\}$. Each session consists of Web pages visited by users $S = \{P_1, P_2, \ldots, P_n\}$. A User Session directed Graph $USG_{pp} = (V_{pp}, E_{pp})$ is constructed, where V_{pp} is the set of visited Web pages in the sessions S_m and E_{pp} is the set of edges between two Web pages. The edge (P_i, P_j) exist if and only if Web page P_i follows Web page P_j in a session S. The weight W_{pp} on the edge is calculated by number of times (P_i, P_j) present in sessions S_m. The weight should be normalized. The Directed user session graph is constructed using Function 8.1.

Consider a Web navigation log with five sessions $L = \{S_1, S_2, S_3, S_3, S_4\}$. The Web Access Sequence (WAS) in each session is shown in Table 8.1. Figure 8.1 shows the User Session directed Graph (USG) constructed from data present in Table 8.1. It is observed from the sessions that users have visited seven unique webpage during their navigation, hence the USG has seven nodes. In WAS, user has visited webpage P_1 to P_2 two times, hence the weight on that edge is two. Similarly, the weight on P_2 to P_4 is 2, P_4 to P_5 is 4 and so on.

Step 2 : Compute Co-occurrence of Domain Terms

The user session graph is constructed based on user navigation history. If a Web page of a domain is not visited by a user then that page does not appear in the graph. Hence, Web pages cannot be recommended for unvisited pages. Relation between the domain terms plays an important role to overcome this problem. It acts as a bridge between the current page and the page to be recommended. Co-occurrence of domain terms revels relations between the terms explicitly. Higher the Co-occurrence value, more relation between the domain terms. This co-occurrence value is helpful to find relation between two Web pages based on the terms present in the title of that page. The co-occurrence between two terms t_i and t_j is represented as $C(t_i, t_j)$ and its value is set to 1 if t_i and t_j occurs together in the session. Further, it increments when they appear together in another session. The value of $C(t_i, t_j)$ is normalized by using Eq. 8.1.

$$NormalizedC(t_i, t_j) = CN(t_i, t_j) = \frac{C(t_i, t_j)}{C(t_i)} \tag{8.1}$$

Here, $C(t_i)$ is the number of times the term t_i that occurs in all the sessions.

Step 3: Extract Web Pages for new page problem using Co-occurrence Value

If any *new page* is present in the input sequence, then the domain terms D_i of that page are considered. The co-occurrence values of each term in D_i are computed as explained in step 2. Arrange the co-occurred terms according to their co-occurrence value in the descending order. All the Web pages that contain co-occurred term with the co-occurrence value as the weight $W_{co-occur}$ are extracted. Web pages are extracted for the *new page* using Function 8.2.

Function 8.1: Directed User Session Graph Generation

Function: GraphConstuction
Data: Consider User Navigation Log l, Generate Directed User Session Graph

Extract Web Access Sequence from Log l
For each user extract session from WAS
Let $Session_{count}$ = Total sessions in WAS
Let Directed User Session Graph $USG_{pp} = (V_{pp}, E_{pp})$ = NULL
// USG construction from WAS
for i = *1 to* $Session_{count}$ **do**
    for *each* $session_i$ **do**
        Let $Page_{count}$ = Number of visited pages in $Session_i$
        for j = *1 to* $Page_{count}$ **do**
            if $Page_j$ *and* $Page_{j+1}$ *is in* V_{pp} **then**
                Increment W_{pp} of $(Page_j, Page_{j+1})$
            else if $Page_j$ *is present in* V_{pp} *and* $Page_{j+1}$ *is not present* **then**
                Add $Page_{j+1}$ to V_{pp}
                Add edge between $Page_j$ and $Page_{j+1}$ to E_{pp}
                Set W_{pp} of $(Page_j, Page_{j+1}) = 1$
            else if $Page_{j+1}$ *is present in* V_{pp} *and* $Page_j$ *is not present* **then**
                Add $Page_j$ to V_{pp}
                Add edge between $Page_j$ and $Page_{j+1}$ to E_{pp}
                Set W_{pp} of $(Page_j, Page_{j+1}) = 1$
            else
                Add $Page_j$ and $Page_{j+1}$ to V_{pp}
                Add edge between $Page_j$ and $Page_{j+1}$ to E_{pp}
                Set W_{pp} of $(Page_j, Page_{j+1}) = 1$

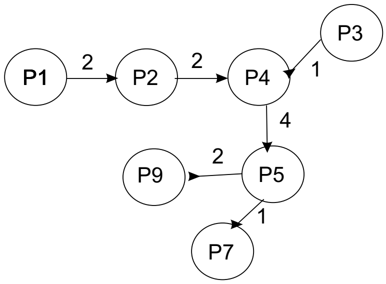
// Normalize weight of USG
Let $Node_{count}$ = Number of nodes in V_{pp}
for m = *1 to* $node_{count}$ **do**
    Let W_{node_m} = Number of times $node_m$ is present in WAS
    for *each connected node* C_{node} *from* $node_m$ **do**

$$NormalizeW(node_m, C_{node}) = \frac{W_{pp}(node_m, C_{node})}{W_{node_m}}$$

Table 8.1 Web access sequence in session

Session	Web access sequence
S_1	P_1, P_2, P_4, P_5, P_9
S_2	P_1, P_2, P_5
S_3	P_3, P_4, P_5, P_7
S_4	P_2, P_4, P_5
S_5	P_4, P_5, P_9

Fig. 8.1 User Session Graph



Function 8.2: Web Pages Extraction for *new page*

Function: NewPage
Data: Consider *new page* as Input and Web pages with its weight are extracted

Consider Domain terms $D = \{t_1, t_2, \ldots, t_n\}$ of $page_{newpage}$
for *each term t_i in D* **do**
    Co-occurred Terms C_{terms}[ ][ ] = Co-occurred terms, co-occurrence value
Arrange C_{terms}[ ][ ] in descending order of co-occurrence value
Extract web-pages which are containing Co-occurred terms
Return extracted web-pages and their corresponding Co-occurred terms' Weight as $W_{co-occur}$

Step 4: Web Page Recommendation

In this step, the strategy is defined for recommending the Web pages. User session graph is constructed with training sessions as explained in step 1. From the testing sessions, Web access sequence is given as an input to the graph and for each page in the sequence, Web pages connected to that page with the weight W_{pp} are considered. If any *new page* is present in the input sequence then the Web pages are extracted as explained in step 3 with their weight $W_{co-occur}$. The resultant Web pages are arranged in the descending order based on the weight and top-n Web pages are recommended.

8.3.3 WRUSG Algorithm

The method to recommend the Web pages is shown in Algorithm 8.1.

Algorithm 8.1: WRUSG : Web Page Recommendation using User Session Graph

Input : User Navigation Log l
Output: Recommended Web pages

begin
  USG_{pp} = Construct Directed User Session Graph by using Function $GraphConstuction(l)$
  Let $GraphInput$[ ] = WAS
  for *each page* $Page_{curr}$ *in* $GraphInput$*[ ]* **do**
    if $Page_{curr}$ *is present in* USG_{pp} **then**
      $Connected_{node}$[ ][ ][ ] =$page_{curr}$, connected node of $page_{curr}$ $C_{pagecurr}$, W($page_{curr}$, $C_{pagecurr}$)
    else
      New_{page}[ ][ ] = NewPage($page_{curr}$)
      $Connected_{node}$[ ][ ][ ] = $page_{curr}$, New_{page}[ ][ ]
  Arrange $Connected_{node}$[ ][ ][ ] in descending order of $W(page_{curr}, C_{pagecurr})$
  Recommend top-n pages from $C_{pagecurr}$

8.4 Experiments

8.4.1 Data Collection

In this experiment, user navigation data is collected from Microsoft Website www.microsoft.com [19]. This dataset contains 294 unique Web pages and 37711 user sessions. Each Web page has a description of it as a title and each title is a collection of words. The dataset contains 641 total words and 330 unique words in Web pages titles.

8.4.2 Experimental Setup

The proposed model is compared with the combination of *TermNetWP* and Conceptual Prediction Model (CPM) presented in [20] and also solves *new page problem*.

The setup of *TermNetWP* + CPM is as follows: Titles of the Web pages are collected and term sequence from titles are extracted. Term frequency of each term is computed and terms are mapped to respective Web pages as per their order of occurrence in title. Co-occurrence value of co-occurred words is computed. CPM is computed using co-occurrence value and term frequency of terms. For a given Web Access Sequence (WAS), domain terms are extracted for each page in WAS and co-occurred words are considered for each domain term. Co-occurred terms are arranged in the descending order and Web pages are recommended that contain co-occurred terms. If there are two co-occurred terms are present, then the set-up is called $TermNetWP_1$. If there are three co-occurred terms present, then the setup is called $TermNetWP_2$.

The setup of the proposed method Web Page Recommendations based on User Session Graph (WRUSG) is as follows: The directed user session graph is constructed from user sessions. Co-occurrence value of co-occurred words is computed. For the given Web access sequence, connected Web pages are extracted for each page from the graph with its weight. If any new page occurs in a Web access sequence, then the domain terms are extracted for each page and co-occurred terms are considered for each domain terms. Web pages are extracted that contains co-occurred terms with co-occurrence value as weight. Top-*n* Web pages are recommended based on their weight.

8.4.3 Performance Metrics

The performance metrics used for evaluation are Precision and Satisfaction [21]. The Precision measures the probability that user visits one of the recommended Web pages. The satisfaction measures the probability that user visits next recommended Web pages after visiting one of the recommended pages. Web page recommendation rule needs to be set to compute Precision and Satisfaction.

Web Page Recommendation Rule: Let $WAS = \{p_1, p_2, \ldots, p_m\}$, $m \geq 2$. Web pages are recommended by giving input as $WAS = \{p_1, p_2, \ldots, p_{m-1}\}$ and stored in $Recom = \{rec_1, rec_2, \ldots, rec_n\}$. For any $p_k (1 \leq k \leq m-1)$ (1) If $Recom$ contains p_{k+1} then $Recom$ is *correct*. (2) If $Recom$ contains p_{k+1} to p_m then $Recom$ is *satisfied*. (3) If $n = 0$ the $Recom$ is *empty*.

Precision and Satisfaction are computed using Eqs. 8.2 and 8.3, respectively.

$$Precision = \frac{| Recom_{correct} |}{| Recom |} \tag{8.2}$$

$$Satisfaction = \frac{| Recom_{satisfie} |}{| Recom |} \tag{8.3}$$

Here, $Recom_{correct}$ is the total number of correct recommendations for given WASs. *Recom* is the total number of recommendations for given WASs. $Recom_{satisfie}$ is the total number of satisfied recommendations for given WASs.

8.4.4 Performance Evaluation

In this section, results are presented and discussed. Performance metrics are used to compare the results of the proposed model and *TermNetWP* + CPM [2]. Experiments have been conducted on 4 GB memory and Intel(R) Core(TM) i5-5200U CPU @ 1.80 GHz processor. The dataset used for evaluation for both the methods are the same as explained in Data collection. Dataset is divided into training and testing dataset. Training and testing dataset contains 32711 and 5000 sessions, respectively. The user session graph is constructed with 32711 sessions in the proposed method. The graph contains 233 nodes and 2448 edges. The minimum support threshold $Threshold_{min}$ is set in order to evaluate the performance of Web access patterns.

Let Web Access Sequences in the testing dataset are $WASs = \{W_1, W_2, \ldots, W_m\}$. Each WAS $W_i = \{p_1, p_2, \ldots, p_n\}$. Threshold of each WAS_i is computed using Eq. 8.4.

$$Threshold_{WAS_i} = \frac{Total_{WAS}}{\mid WASs \mid} \tag{8.4}$$

Here, $Total_{WAS}$ = Number of times WAS_i occurs in *WASs*. The *WASs* whose $Threshold_{WAS_i}$ is greater than or equal to $Threshold_{min}$ are considered as frequent Web access sequence. If the value of $Threshold_{min}$ is set to smaller value then more number of frequent WAS are found.

Tables 8.2 and 8.3 shows comparison of the precision and satisfaction values for $TermNetWP_1$, $TermNetWP_2$ and the WRUSG. It is observed that the values of precision and satisfaction is higher in WRUSG in comparison with *TermNetWP* models. The precision of the WRUSG is increased by 23.688% and 27.3% in comparison with $TermNetWP_1$ and $TermNetWP_2$ method, respectively. The satisfaction of the WRUSG is increased by 25.736% and 30.816% in comparison with $TermNetWP_1$ and $TermNetWP_2$ method respectively. The WRUSG considered user history first and if any *new page* occurs only semantic knowledge is used to recommend Web pages, while *TermNetWP* combines user history and domain knowledge to recommend Web pages. Hence the WRUSG outperforms the *TermNetWP* method.

8.5 Summary

Web page recommendation method is presented by considering user sessions and co-occurred terms in titles of the Web pages. User session graph is constructed using user sessions from the navigation log in where nodes are Web pages and edges are present

Table 8.2 Comparison of precision values

Minimum support	0.4	0.5	0.6	0.7	1.0
Number of WASs	165	139	120	110	74
$TermNetWP_1$	0.3505	0.3602	0.3839	3725	0.5448
$TermNetWP_2$	0.2720	0.2965	0.3601	0.3856	0.4871
WRUSG	0.6149	0.6397	0.6339	0.6176	0.6602

Table 8.3 Comparison of satisfaction values

Minimum support	0.4	0.5	0.6	0.7	1.0
Number of WASs	165	139	120	110	74
$TermNetWP_1$	0.3084	0.3137	0.3273	0.3104	0.4935
$TermNetWP_2$	0.2203	0.2377	0.2886	0.3169	0.4358
WRUSG	0.5938	0.6127	0.6011	0.5915	0.6410

if those two Web pages exist in sessions. The weight on the edge is computed by the number of times the Web pages are present in sessions. To solve *new page problem*, co-occurrence value between two terms present in titles is computed that is helpful to find relation between the two Web pages. Web pages are recommended based on the connected nodes in the graph and co-occurred terms. Experiments are conducted on the user navigation data collected from Microsoft Website www.microsoft.com. The WRUSG method is compared with $TermNetWP$ method [20] and outperforms $TermNetWP$ by increased precision value of 23.688% and 27.3% and satisfaction value of 25.736% and 30.816% in comparison with $TermNetWP_1$ and $TermNetWP_2$ method, respectively.

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