A Novel Algorithm for Web Personalization through Integration of Web User Profiles and Behavioral Patterns

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***Abstract--*Web personalization recommends the tailored Web pages or forecasts the personalized Web matters to Web users as per their particular observations in terms of user profiles or behavioral patterns. Fundamentally, user profile is generated for demonstrating particular user directional patterns derived from Web usage mining. This is done by corresponding the present active user session with the learned usage patterns. Behavioral patterns are nothing but the frequent sequential patterns that are extracted from web usage data using frequent sequential pattern mining algorithms. In this paper, a novel algorithm for web personalization by integrating the knowledge from user profiles and behavioral patterns is proposed. Firstly, a set of active behavioral patterns and a set of user profiles along with the prediction period are read as input. Then, the pages are predicted by measuring the similarity between user profiles and behavioral patterns. The most significant behavioral patterns and user profiles are then selected to calculate the rank for each page. Finally, the top n-pages with the highest rank are recommended. Experiments have been conducted on two data sets obtained from KDDCUP and RNSIT websites. The results show that the proposed method gives significant information for predicting and recommending the customized web pages for Web user effectively. The maximum latency saving ratio achievable by our proposal is 7.5 allowing a reasonable traffic increase by a factor 6.3.**

Keywords: Web personalization, User profile, Behavioral patterns.

I. INTRODUCTION

It is outstanding that Internet has ended up being skilled stage to store, spread and recuperate information. Regardless, Web customers reliably encounter the evil impacts of the issues of information over-weight and suffocating due to immense and quick improvement in the measure of information and the amount of customers. Because of this, issues like slight precision and review rate are two vital stresses that customers need to oversee while searching for required information on Internet. On the other hand, the colossal measure of data/information abiding over the Internet contains a considerable measure of vital valuable discovering that could be found by method for bleeding edge data mining approaches. Web personalization is a methodology that uses the educational data picked up from Web mining as a learning base, then predicts customer potential get to slants, and recommends the changed Web substance by insinuating the data base. This could be content, usage and semantic information.

In this paper, a novel algorithm for web personalization by incorporating the information from client profiles and behavioral patterns is proposed. Firstly, an arrangement of dynamic behavioral patterns and an arrangement of client profiles alongside the expectation time frame are perused as information. At that point, the pages are anticipated by measuring the likeness between client profiles and behavioral patterns. The most critical behavioral patterns and client profiles are then chosen to ascertain the rank for each page. At long last, the top n-pages with the most elevated rank are prescribed and recommended to the web users.

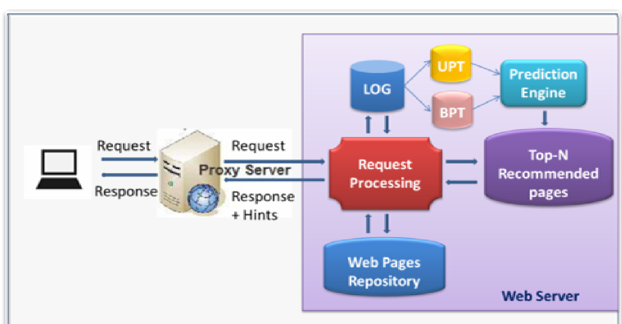
The remainder of this paper is organized as follows. Section 2 reveals the related work. Proposed system architecture is given in section 3. Novel algorithm for web personalization by incorporating the information from client profiles and behavioral patterns is proposed in section 4. Experimental results and discussions are provided at section 5. Section 6 concludes the paper with scope for further work.

II. RELATED WORK

The problem of providing recommendations to the visitors of a web site has received a significant amount of attention in the related literature. Most of the research efforts in web personalization correspond to the evolution of extensive research in web usage mining, taking into consideration only the navigational behavior of the (anonymous or registered) visitors of the web site [1, 2 and 3]. Pure usage-based personalization, however, presents certain shortcomings. This may happen when, for instance, there is not enough usage data available in order to extract patterns related to certain navigational actions, or when the web site's content changes and new pages are added but are not yet included in the web logs. Moreover, taking into consideration the temporal characteristics of the web in terms of its usage, such systems are very vulnerable to the training data used to construct the predictive model. As a result, a number of research approaches integrate other sources of information, such as the web content [4, 5 and 6] or the web structure [7, 8] in order to enhance the web personalization process. We should take into consideration that the web is not just a collection of documents browsed by its users. The web is a directed labeled graph, including a plethora of hyperlinks that interconnect its web pages. Both the structural characteristics of the web graph, as well as the web pages' and hyperlinks' underlying semantics are important and determinative factors in the users' navigational process. Several research studies proposed frameworks that express the users' navigational behavior in terms of ontology and integrate this knowledge in semantic web sites [9], Markov model-based recommendation systems [4], or collaborative filtering systems [10]. In [11], the authors displayed and investigated the handiness of succinct comprehensible client profiles with a specific end goal to improve framework tuning and assessment by method for client considers. Survey on few customized models for web data gathering has been given in [12] and correlation has been made amongst them and a framework in light of personalization of web information utilizing philosophy is presented. The creators in [13] made utilization of the two qualities for finishing up client's transient necessity. To start with is to adjust the level of client's every enthusiasm with time run movement. Second, web perusing logs identified with an action. To predict the web pages with high precision, a hybrid algorithm of clustering technique, All-K^{th}-Order Markov model, and neural network are presented in [14]. A recommendation approach that recommends a listing of pages based mostly upon client's historic pattern has been proposed by [15]. None of the aforementioned systems, however, exploits the notion of a web page's importance in the web graph and fully integrates link analysis techniques in the web personalization process. Hence, it is the need of great importance to integrate the behavioral patterns and user profiles for effective web personalization. The main objective of this paper is to propose a novel technique aimed at improving the overall effectiveness of the web personalization process through the integration of user profiles and the users' navigational patterns.

III. PROPOSED SYSTEM ARCHITECTURE

This paper proposes the integration of behavioral patterns and user profiles for web personalization and caching in client-side proxies. Proposed system architecture is depicted in Figure 1. The proxy is located near the Web clients to avoid repeated round-trip delays between the clients and the origin Web servers. The origin Web server in our architecture is an enhanced Web server which employs a prediction engine to predict the top-N pages that are to be recommended for personalization. As shown in Figure 1, the proxy serves the requests sent from the Web clients. In the case that a cache miss occurs, the proxy will forward the request to the origin Web server for resolution. Upon receiving the request, the origin server will log this request into record, fetch the requested page from the Web page repository, and check the top-N pages at the same time. If this request triggers some pages in the top-N pages, the pages will be piggybacked to the responding message as hints and returned to the proxy. After the proxy receives the response with the hints piggybacked from the origin Web server, the proxy will first send the requested page back to the client and then determine whether it is worth caching the piggybacked implied pages in the proxy. Note that, in the case that a cache hit is found (i.e., the client's request can be satisfied directly with the proxy's local cache), we assume that the proxy will still communicate with the origin Web server to obtain the personalization hints related to that request after the proxy has sent the response to the client. As such, we are able to investigate each request the personalization hints from the origin Web server to ensure that the discovered personalized hints are always up-to-date.



System Architecture for Web Personalization and Caching

Figure 1: System Architecture for Web Personalization and Caching

IV. NOVEL ALGORITHM FOR WEB PERSONALIZATION

Generally, a Web recommendation is to predict and customize Web presentations in a user preferable style according to the interests exhibited by individual or groups of users. This goal is usually carried out in two ways. On the one hand, we can take the current active user's navigational patterns into consideration and predict the preferable information to this specific user. On the other hand, by finding the most similar access patterns to the current active user from the learned user profiles of other users, we can recommend the tailored Web content. The former one is sometimes called memory-based approach, whereas the latter one is called model-based recommendation, respectively.

In this work, we adopt the model-based technique in our Web recommendation framework. As discussed in our previous work, frequent sequential patterns are extracted from web usage data using effective FSP mining algorithms. These represent the behavioral patterns. From the discovered user session clusters, we generate user profiles. Given a User Profile Table (UPT) and the Behavioral Pattern Table (BPT), we present an algorithm called ***RPUPBP*** that predicts and recommends Web pages for a user/group based on integration of UPT and BPT. We utilize the commonly used cosine function to measure the similarity between the behavioral pattern and the user profile. We, then, choose the most significant behavioral pattern and user profile. Finally, we generate the top-N recommendation pages. The detailed procedure is described as follows.

Algorithm [RPUPBP]: *Recommendation of Web pages for a user/group based on integration of User Profile Table (UPT) and Behavioral Pattern Table (BPT)*

Input: Active set of behavioral patterns BPT and a set of user profiles UPT and the prediction period τ = {Weekly, Fortnightly, and Monthly}

Output: Set of top-N pages predicted / recommended for the user/group within τ

Steps:

1. If new user? Then extract the *BPs* and build the *UP*. Identify the group for which user belongs to and update the corresponding UPT and BPT.

2. For each user/group, read the *UPT* and *BPT* for the prediction period τ. The *BPs* and *UPs* are modeled as n-dimensional vectors over the page space within the web site. For example, k^{th} BP and UP are given as follows:

   $BP_k=[a_1,a_2,a_3,\ldots,a_n]$ a_i = *1- if accessed already, 0 – otherwise for pages* $p_1,p_2,p_3,\ldots,p_n$
   $UP_k=[w_1,w_2,w_3,\ldots,w_n]$ w_i *represent the weight/frequency of the page* p_i *in* UP_k

3. Predict the pages by measuring similarity between BPs and Ups

   $$Similarity\,(BP_k,UP_k) = (BP_k.UP_k)/(\,\|BP_k\|_2\,\|UP_k\|_2)$$

   $$where\;\; BP_k.UP_k = \sum_{i=1}^{k} w_i^k.a_i^k, \qquad \|BP_k\|_2 = \sqrt{\sum_{i=1}^{k}(a_i^k)^2}$$

   and $\|UP_k\|_2 = \sqrt{\sum_{i=1}^{k}(w_i^k)^2}$

4. Choose/Select the BP and UP with maximum similarity called the most significant BP and UP (BP_s, *UPs*)
   (BP_s, *UPs*) = Max($Similarity\,(BP_k,UP_k)$) for k = 1,2,..,n

5. From the selected BP_s *and UPs*, calculate the *rank* $r(p_i)$ for each page p_i
   $r(p_i) = \sqrt{Similarity\,(BP_s,UP_s) * w_i^s}$
   Thus each page is assigned a *rank* between 0 and 1. Note that the *rank* will be 0 if the page is already visited in the current session

6. Sort the *ranks* in descending order and select the top-N pages with the highest ranks and construct the top-N recommend pages *RPs*
   $$RPs = \{\, p_i^s \mid r(p_i^s) > r(p_{i+1}^s), for\ i = 1,2,3,\ldots,n-1 \,\}$$

V. RESULTS AND DISCUSSIONS

Experiments have been conducted on two real world data sets obtained from log files of KDDCUP (www.ecn.purdue.edu/kddcup/) and RNSIT (rnsit.ac.in) web sites to evaluate the effectiveness of the proposed algorithm. KDDCUP consists of 69 pages and 6305 user sessions after preprocessing. RNSIT consists of 48 pages and 5043sessions after preprocessing. These data sets are articulated as usage-matrices with each column as page and each row as session. We use these matrices as an input data source and extract usage information and quiescent semantic associations. Then we apply the proposed algorithms to make Web recommendations. From tables 1 and 2, it is observed that each user profile is represented by a sequence of important pages together with corresponding support expressed in a normalized form. Table 1 depicts two user profiles generated from KDD dataset from our previous work.

Table 1. Sample user-profiles built from KDDCUP dataset

Profile#	Page #	Page title	Support
Profile -1	29	/Main-shopping_cart.html	1.00
	4	/Products-productDetailleagwear.html	0.86
	27	/Main-Login2.html	0.67
	8	/Main-home.html	0.53
	44	/Check-express_Checkout.html	0.38
	65	/Main-welcome.html	0.33
	32	/Main-registration.html	0.32
	45	/Checkout-confirm_order.html	0.26
Profile -2	11	/Main-vendor2.html	1.00
	8	/Main-home.html	0.40
	12	/Articles-dpt_about.html	0.34
	13	/Articles-dpt_about_mgmtteam.html	0.15
	14	/Articles-dpt_about_broadofdirectors.html	0.11

Table 2. Sample user-profiles built from RNSIT dataset

Profile#	Page #	Page title	Support
Profile - 1	3	/Admissions.html	1.00
	6	/Placement.html	0.41
	9	/sports&culture.html	0.24
	28	/awards.html	0.21
	29	/accolades.html	0.11
	46	/aboutus.html	0.11
Profile - 2	14	/campus.html	1.00
	7	/hostel.html	0.35
	5	/library.html	0.32
	30	/bestteachers.html	0.13
	1	/index.html	0.11
Profile - 3	1	/index.html	1.00
	12	/courses.html	0.78
	21	/pp_cse.html	0.40
	35	comp-visited.html	0.17
	6	/Placement.html	0.12

Similarly from Table 2, three profiles are generated. We can observe from the generated profiles that most of the profiles show specific navigational behavior whereas few represent multiple interests.
Table 3 shows sample behavioral patterns extracted from RNSIT dataset.

Performance Evaluation Metrics:
The performance of the algorithm has been evaluated by using the main metrics related to the users' perceived latencies, personalization costs and prediction performance. Notice that prediction performance can be measured at different moments or in different elements of the architecture. For instance, when the algorithm makes the prediction and when personalization is applied in the real system. Therefore, each prediction index has a dual index; e.g., we can refer to the precision of the prediction engine and to the precision of the personalization process.

Table 3. Sample Behavioral Patterns(FSPs) extracted from RNSIT dataset

#User	#FSPs – Page Ids	#User	#FSPs – Page Ids
U_{23}	P_{13}, P_{14}	U_{67}	P_7,P_5
	P_{23}, P_{14}		P_7,P_{22}
	P_{23}, P_{13}		P_5,P_{22}
U_{10}	P_{23},P_5		P_5, P_5
	P_{23}, P_{18}		P_{22}, P_7
	P_5 ,P_{18}		P_{22}, P_5
U_{32}	P_1,P_9	U_7	P_{22} ,P_4
	P_1 ,P_{14}		P_{22},P_{21}
	P_9 ,P_{14}		P_4,P_{21}
	P_9, P_1		P_4, P_{22}
	P_{14}, P_1		P_{21}, P_{22}
	P_{14}, P_9		P_2, P_4
U_{68}	P_7,P_5	U_{55}	P_{42},P_8
	P_7,P_{23}		P_{42},P_4
	P_5 ,P_{23}		P_8 ,P_4
	P_5, P_7		P_8, P_{42}
	P_{23}, P_7		P_4, P_{42}
	P_{23}, P_5		P_4, P_8

- *Recall (Rc):* The percentage of pages requested by the user that were previously predicted (or personalized). The recall measures the ratio of user requested pages that were previously predicted and personalized.
  Rc = #hits/ #User requests
- *Precision (Pc):* The ratio of good predictions (or personalized pages) to the number of predictions. The precision measures the ratio of pages that were predicted, personalized and then finally requested by the user (hits) versus the total number of pages that were predicted and personalized.
  Pc = #hits / #Predicted
- *Latency per page ratio (Lp):* It is the ratio of the latency per page that personalization achieves to the latency with no personalization. The latency per page is calculated by comparing the time between the browser initiation of an HTML page GET and the browser reception of the last byte of the last embedded image or object for that page. The page latency is obtained by performing an experiment without personalization, and these values are used as a baseline for comparison purposes in the experiments. The page latency (ΔPL) is calculated as:

ΔPL = Average Page Latency with Personalization / Average Page Latency without personalization

Similarly, the page latency saving percentage (ΔPL(%)) is calculated as:

*ΔPL(%) = (1 - Average Page Latency with Personalization / Average Page Latency without personalization) * 100*

This work uses the page latency saving as the main performance index for measuring prediction and personalization effectiveness because our aim is to study the maximum benefit perceived by web users.

- *Traffic Increase (Δ Tr):* The bytes transferred through the network when personalization is employed divided by the bytes transferred in the non-personalization case. Notice that this metric includes both the extra bytes wasted by predicted pages that the user will never use and the network overhead caused by the transference of the personalization hints. The traffic increase quantifies, in bytes, the extra traffic incurred by the personalized pages that are never requested by the user.

  $\Delta Tr_B = (\textit{Pages not used}_B + \textit{Network overhead}_B + \textit{User requests}_B) / \textit{User requests}_B$

Cost-Benefit Analysis Methodology

Despite the fact that personalization has been also used to reduce the peaks of bandwidth demand, its primary goal is usually the reduction of the user's perceived latency. Therefore, performance comparison between personalization approaches should be made from the user's point of view and using a cost-benefit analysis. When predictions fail, personalized pages waste user and/or server resources, which can lead to performance degradation either to the user himself or to the rest of users. Since in most proposals the client downloads the predicted pages in advance, the main cost to achieve the latency reduction is the increment of the network load. This increment has two effects: the first is the increase in the amount of bytes transferred (measured through the *Traffic Increase* metric), and the second is the increase in the server requests (measured through the *Traffic Increase* metric). As a consequence, the performance analysis should consider the benefit of reducing the user's perceived latency at the expense of increasing the network traffic and the amount of requests to the server. Each simulation experiment in our personalization environment considers as input the user's behavior, their available bandwidth and the personalization parameters. The main results obtained are the traffic increase and the latency per page ratio. Trace-driven experiments are performed to show the impact of the proposed technique on the users perceived latency and what traffic increase is required to accomplish it. To this end, several experiments are conducted varying the threshold of the prediction algorithms, because it affects the personalization aggressiveness.

Precision and *Recall* for time window of *Weekly,Fortnightly and Monthly* are shown in Figures 2, 4 and 6 respectively. Similarly, The *page latency (ΔPL) and* the *page latency saving percentage (ΔPL(%)* for time window of *Weekly,Fortnightly and Monthly* are shown in Figures 3, 5 and 7 respectively.

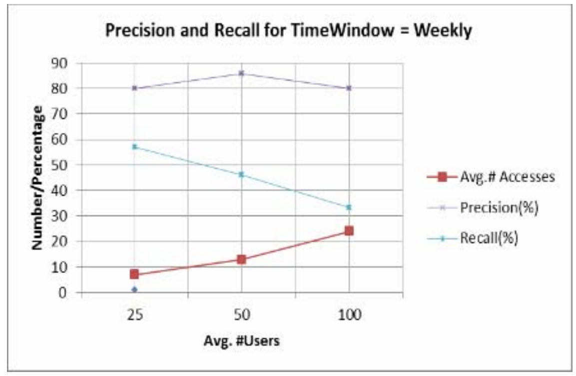


Figure 2: Precision and Recall for ***TimeWindow***=Weekly

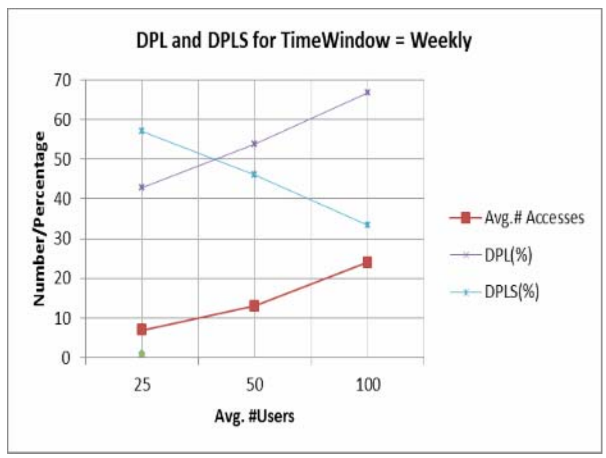


Figure 3: DPL and DPLS for ***TimeWindow***=Weekly

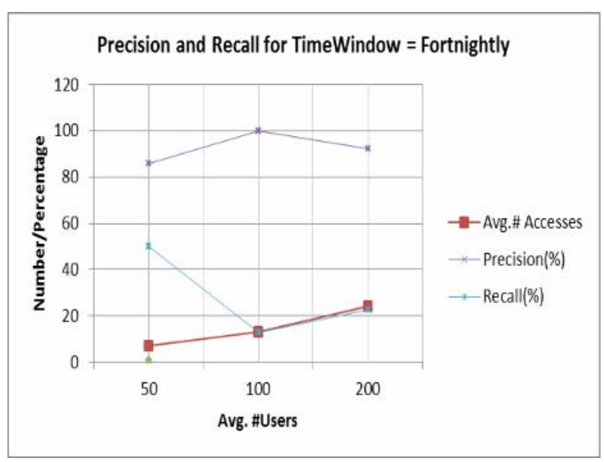


Figure 4: Precision and Recall for ***TimeWindow***=Fortnightly

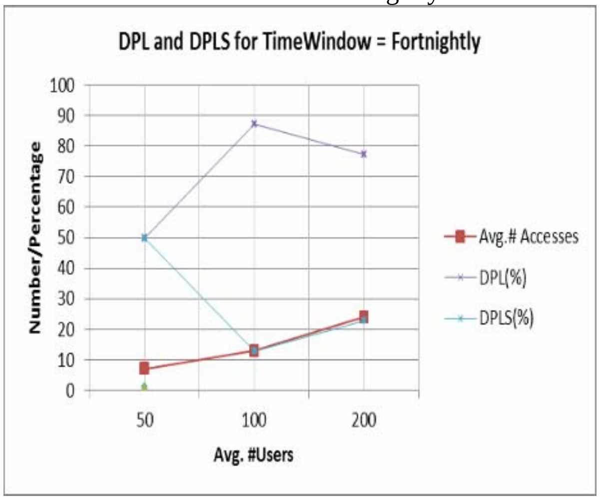


Figure 5: DPL and DPLS for ***TimeWindow***=Fortnightly

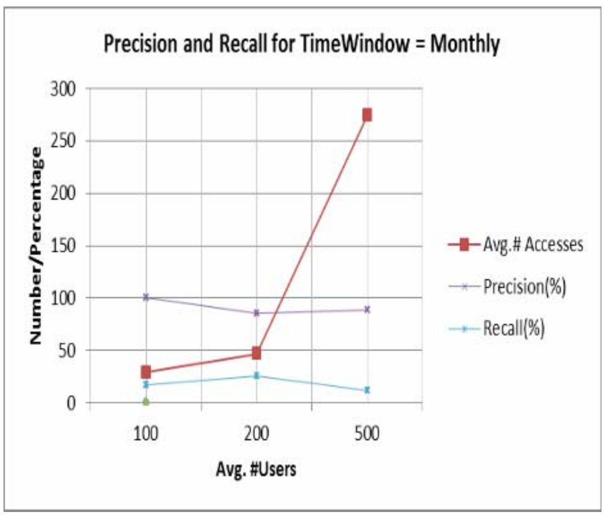


Figure 6: Precision and Recall for ***TimeWindow***=Monthly

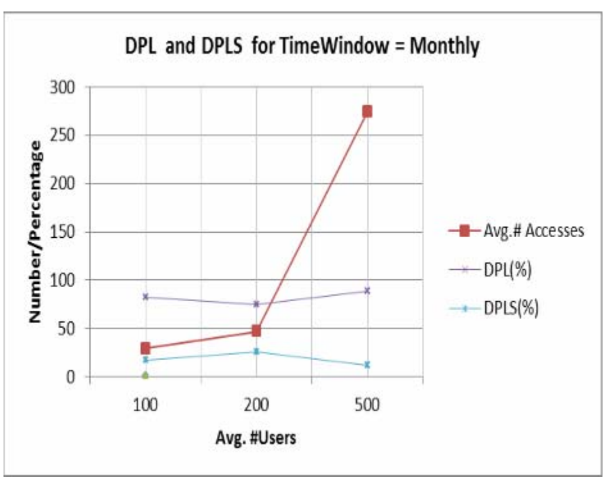


Figure 7: DPL and DPLS for ***TimeWindow***=Monthly

Table 4 gives the statistics about average number of users, accesses, predicted pages, recall, precision, latency for look ahead window size: weekly, fortnightly and monthly. Table 5 shows the statistics giving latency save ratio and network traffic increase.

Table 4. Statistics showing average number of users, accesses, predicted pages, recall, precision, latency for look ahead window size: weekly, fortnightly and monthly

Period	Avg. # Users	Avg.# Accesses	Web Personalization							
			#Pages Predicted	#Hits	Recall (%)	Precision (%)	Avg. Lp	Avg. LNp	DPL(%)	DPLS(%)
Weekly	25	7	5	4	57.14	80.00	3	7	42.86	57.14
	50	13	7	6	46.15	85.71	7	13	53.85	46.15
	100	24	10	8	33.33	80.00	16	24	66.67	33.33
Fortnightly	50	12	7	6	50.00	85.71	6	12	50.00	50.00
	100	31	4	4	12.90	100.00	27	31	87.10	12.90
	200	53	13	12	22.64	92.31	41	53	77.36	22.64
Monthly	100	29	5	5	17.24	100.00	24	29	82.76	17.24
	200	47	14	12	25.53	85.71	35	47	74.47	25.53
	500	274	36	32	11.68	88.89	242	274	88.32	11.68

Figure 8 shows the Latency Save Ration v/s Cache Size for ***TimeWindow***=Monthly. Similarly, Network Traffic Increase v/s Cache Size for ***TimeWindow***=Monthly is shown in Figure 9. Figures 10 and 11 demonstrates the Hit Ratio v/s Cache Size for ***TimeWindow***=Fortnightly and Monthly respectively. The maximum latency saving ratio achievable by our proposal is 7.5 as observed in Figure 8 allowing a reasonable traffic increase by a factor 6.3 as observed in Figure 9.

Table 5. Statistics showing latency save ratio and network traffic increase

Cache Size	Avg. Lp	Avg. LNp	LSR Without Personalization	LSR With Personalization	Network Traffic Increase Without Personalization	Network Traffic Increase With Personalization
1	3	7	42.86	47.14	57.14	52.86
2	6	12	50.00	55.00	50.00	45.00
4	7	13	53.85	59.23	46.15	40.77
8	16	24	66.67	73.33	33.33	26.67
16	41	53	77.36	85.09	22.64	14.91
32	27	31	87.10	95.81	12.90	4.19

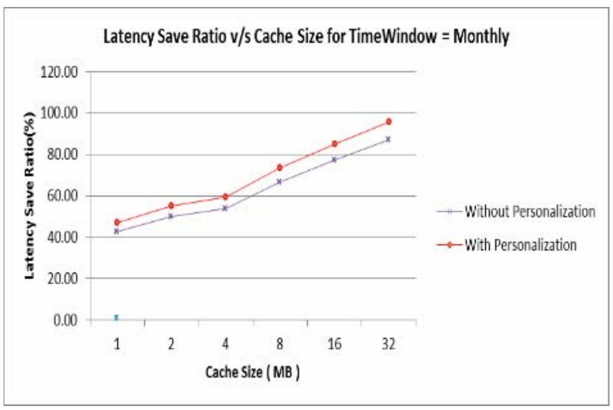


Figure 8: Latency Save Ration v/s Cache Size for ***TimeWindow***=Monthly

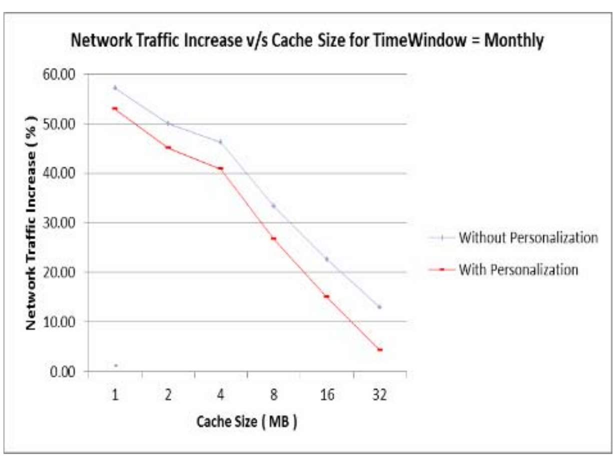


Figure 9: Network Traffic Increase v/s Cache Size for ***TimeWindow***=Monthly

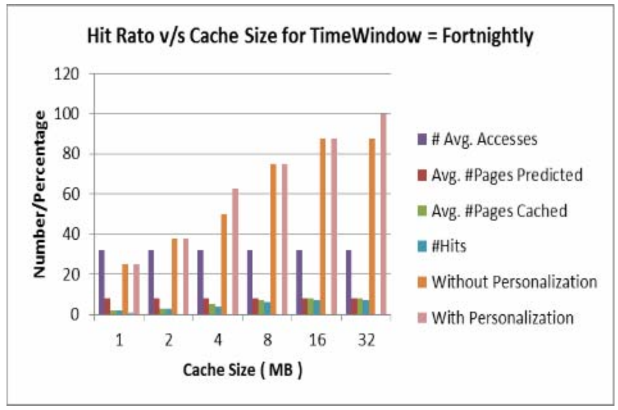


Figure 10: Hit Ratio v/s Cache Size for ***TimeWindow***=Fortnightly

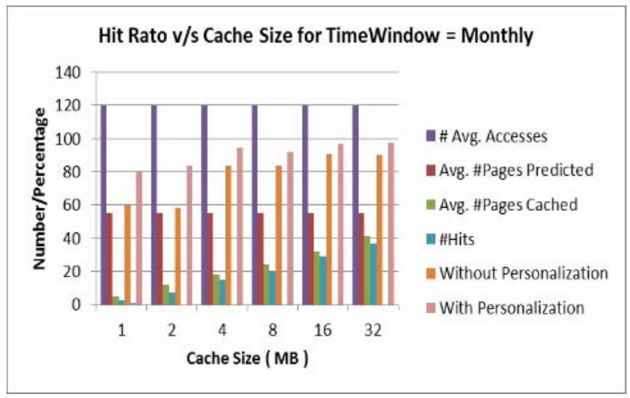


Figure 11: Hit Ratio v/s Cache Size for ***TimeWindow***=Monthly

VI Conclusion

The users' navigation in a web site is typically content-driven. The users usually search for information or services concerning a particular topic. Therefore, the underlying user profiles and behavioral patterns semantics should be dominant factors in the process of web personalization. A novel algorithm for web personalization by incorporating the information from client profiles and behavioral patterns has been presented in this paper. Firstly, an arrangement of dynamic behavioral patterns and an arrangement of client profiles alongside the expectation time frame were perused as information. At that point, the pages were anticipated by measuring the likeness between client profiles and behavioral patterns. The most critical behavioral patterns and client profiles were then chosen to ascertain the rank for each page. At long last, the top n-pages with the most elevated rank were predicted and recommended to the web users. Experiments have been conducted on two datasets to validate the effectiveness of the proposed algorithm. The maximum latency saving ratio achievable by our proposal is 7.5 allowing a reasonable traffic increase by a factor 6.3. The results shows that the proposed approach effectively predict the pages for recommendation to web users.

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