

# Discovery of Aggregate Usage Profiles for Web Personalization

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**Abstract:** Web usage mining, possibly used in conjunction with standard approaches to personalization such as collaborative filtering, can help address some of the shortcomings of these techniques, including reliance on subjective user ratings, lack of scalability, and poor performance in the face high-dimensional and sparse data. However, the discovery of patterns from usage data by itself is not sufficient for performing the personalization tasks. The critical step is the effective derivation of good quality and useful (i.e., actionable) "aggregate usage profiles" from these patterns. In this paper we present and experimentally evaluate two techniques, based on clustering of user transactions and clustering of pageviews, in order to discover overlapping aggregate profiles that can be effectively used by recommender systems for real-time personalization. We evaluate these techniques both in terms of the quality of the individual profiles generated, as well as in the context of providing recommendations as an integrated part of a personalization engine.

## 1 Introduction

Today many of the successful e-commerce systems that provide server-directed automatic Web personalization are based on collaborative filtering. An example of such a system is NetPerceptions ([www.netperceptions.com](http://www.netperceptions.com)). Collaborative filtering technology [KMM+97, HKBR99, SM95], generally involves matching, in real time, the ratings of a current user for objects (e.g., movies or products) with those of similar users (nearest neighbors) in order to produce recommendations on other objects not yet rated by the user. There are, however, some well-known limitations to this type of approach. For instance, as noted in recent studies [OH99], it becomes hard to scale collaborative filtering techniques to a large number of items (e.g., pages or products), while maintaining reasonable prediction performance and accuracy. Part of this is due to the increasing sparsity in the ratings data as the number of items increase, as well as due to the increasing computational cost of determining user to user correlation in real time for a large number of

items and users. Furthermore, collaborative filtering usually performs best when explicit non-binary user ratings for similar objects are available. In many Web sites, however, it may be desirable to integrate the personalization actions throughout the site involving different types of objects, including navigational and content pages, as well as implicit product-oriented user events such as shopping cart changes, or product information requests.

Several recent proposals have explored Web usage mining as an enabling mechanism to overcome some of the problems associated with more traditional techniques [MCS99, Mob99, Yu99, NFJK99] or as a mechanism for improving and optimizing the structure of a site [PE98, CTS99, SPF99]. Data mining techniques, such as clustering, have also been shown to improve the scalability and performance of collaborative filtering techniques [OH99]. In general, Web usage mining systems [ZXH98, CMS99, BM99, SF99] run any number of data mining algorithms on usage or clickstream data gathered from one or more Web sites in order to discover interesting patterns in the navigational behavior of users. For an up-to-date survey of Web usage mining techniques and systems see [SCDT00].

However, the discovery of patterns from usage data, such as association rules, sequential patterns, and clusters of user sessions or pages, by itself is not sufficient for performing the personalization tasks. The critical step is the effective derivation of good quality and useful (i.e., actionable) "aggregate profiles" from these patterns. The discovery of aggregate usage profiles, through clustering as well as other Web mining techniques, has been explored by several research groups [YJGD96, SZAS97, SKS98, PE98, NFJK99]. However, in all of these cases, the frameworks proposed for the discovery of profiles have not been extended to show how these profiles can be used as an integrated part of recommender systems. In the case of [PE98], aggregate usage profiles were discovered using an algorithm called PageGather which uses as its basis clustering of pages based the Clique (complete link) clustering technique. While the generated profiles were not integrated as part of a

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recommender system, they were used to automatically synthesize alternative static index pages for a site.

In this paper we present and experimentally evaluate two Web usage mining techniques, each with its own characteristics, for the discovery of aggregate usage profiles that can be effective in Web personalization. The first technique, called PACT (Profile Aggregations based on Clustering Transactions), is based on the derivation of overlapping profiles from user transactions clusters. A preliminary version of this technique was first introduced in the context of a generalized framework for usage-based Web personalization in [Mob99]. The second technique, originally introduced in [MCS99], uses Association Rule Hypergraph Partitioning [HKKM97, HKKM98] to directly derive overlapping aggregate profiles from pageviews (rather than from user transactions). Each of these techniques generates overlapping profiles which capture aggregate views of the behavior of subsets of site users based their interests and/or information needs. The primary focus of this paper is the experimental evaluation of these techniques based on real usage data. To this end, we compare and evaluate both the quality of generated profiles, as well as the effectiveness the techniques when used as part of a recommender system for Web personalization. We also compare our techniques with the Clique-based clustering technique used in [PE98], described above. Finally, based on the experimental results we draw some conclusions as to the circumstances under which each technique is most appropriately used.

## 2 Mining Web Usage Data for Personalization

The data preparation and the usage mining tasks (for discovering usage profiles) are performed offline. The goal of the data preparation stage in Web usage mining is to obtain aggregate structures containing the preprocessed usage data to be used in the mining stage. These structures include a user transaction file capturing meaningful semantic units of user activity. We use the heuristics proposed in [CMS99] to identify unique user sessions from anonymous usage data and to infer cached references (path completion). *Pageview* identification is the task of determining which page file accesses contribute to a single browser display, and is heavily dependent on the intra-page structure, and hence requires detailed site structure information. Only relevant pageviews are included in the transaction file. Furthermore, among the relevant pageviews some may be more significant than others. For example, in an e-commerce site pageviews corresponding to

product-oriented events (e.g., shopping cart changes or product information views) may be considered more significant than others. Similarly, in a site designed to provide content, content pages may be weighted higher than navigational pages. A further level of granularity is obtained by identifying *transactions* within the sessions [CMS99]. The goal of transaction identification is to dynamically create meaningful clusters of references for each user, based on an underlying model of the user's browsing behavior. This allows each page reference to be categorized as a *content* or *navigational* reference for a particular user.

Finally, the transaction file can be further filtered by removing very low support or very high support pageview references (i.e., references to those pageviews which do not appear in a sufficient number of transactions, or those that are present in nearly all transactions). This type of *support filtering* can be useful in eliminating noise from the data, such as that generated by shallow navigational patterns of "non-active" users, and pageview references with minimal knowledge value for the purpose of personalization.

The above preprocessing tasks result in a set of  $n$  pageview records,  $P = \{p_1, p_2, \dots, p_n\}$ , appearing in the transaction file with each pageview record uniquely represented by its associated URL; and a set of  $m$  user transactions,  $T = \{t_1, t_2, \dots, t_m\}$ , where each  $t_i \in T$  is a subset of  $P$ . To facilitate various data mining operations such as clustering, we view each transaction  $t$  as an  $n$ -dimensional vector over the space of pageview references, i.e.,  $t = \langle w(p_1, t), w(p_2, t), \dots, w(p_n, t) \rangle$ , where  $w(p_i, t)$  is a weight, in the transaction  $t$ , associated with the pageview represented by  $p_i \in P$ . The weights can be determined in a number of ways, for example, binary weights can be used to represent existence or non-existence of a product-purchase or a documents access in the transaction. On the other hand, the weights can be a function of the duration of the associated pageview in order to capture the user's interest in a content page. The weights may also, in part, be based on domain-specific significance weights assigned by the analyst.

The transaction file obtained in the data preparation stage is used as the input to the profile generation methods. Ideally, profiles capture an aggregate view of the behavior of subsets of users based their interests and/or information needs. In particular, to be effective for personalization, aggregate profiles must exhibit three important characteristics:

1. they should capture possibly overlapping interests of users, since many users may have common interests up to a point (in their navigational history) beyond which their interests diverge;

2. they should provide the capability to distinguish among pageviews in terms of their significance within the profile; and
3. they should have a uniform representation which allows the recommendation engine to easily integrate different kinds of profiles, independently of the profile generation method used.

Given these requirements, we have found that representing *usage profiles* as weighted collections of pageview objects provides a great deal of flexibility. Each item in a usage profile is a URL representing a relevant pageview object, and can have an associated weight representing its significance within the profile. The profile can be viewed as an ordered collection (if the goal is to capture the navigational path profiles followed by users [SF99]), or as unordered (if the focus is on capturing associations among specified content or product pages). Another advantage of this representation for usage profiles is that these profiles, themselves, can be viewed as pageview vectors, thus facilitating the task of matching a current user session with similar profiles using standard vector operations. In the following sections, we present our two techniques for discovering overlapping usage profiles based on clustering of transactions and clustering of pageviews, respectively. We also discuss how these profiles are used by the recommendation engine to provide real-time personalization.

## 2.1 Discovery of Aggregate Profiles Based on Transaction Clustering

Given the mapping of user transactions into a multi-dimensional space as vectors of pageviews, standard clustering algorithms, such as *k-means*, generally partition this space into groups of transactions that are close to each other based on a measure of distance or similarity. Such a clustering will result in a set  $TC = \{c_1, c_2, \dots, c_k\}$  of transaction clusters, where each  $c_i$  is a subset of the set of transactions  $T$ . Dimensionality reduction techniques may be employed to focus only on relevant or significant features. Ideally, each cluster represents a group of users with similar navigational patterns. However, transaction clusters by themselves are not an effective means of capturing an aggregated view of common user profiles. Each transaction cluster may potentially contain thousands of user transactions involving hundreds of pageview references. Our ultimate goal in clustering user transactions is to reduce these clusters into weighted collections of pageviews which, as noted earlier, represent aggregate profiles.

Preliminary results [Mob99] have identified one potentially effective method for the derivation of

profiles from transaction clusters. To obtain aggregate profiles from transaction clusters, we employ a technique analogous to concept indexing methods used to extract document cluster summaries in information retrieval and filtering [KE00]. We call this method PACT (Profile Aggregations based on Clustering Transactions). For each transaction cluster  $c \in TC$ , we compute the mean vector  $m_c$ . The mean value for each pageview in the mean vector is computed by finding the ratio of the sum of the pageview weights across transactions in  $c$  to the total number of transactions in the cluster. The weight of each pageview within a profile is a function of this quantity thus obtained. In generating the usage profiles, the weights are normalized so that the maximum weight in each usage profile is 1, and low-support pageviews (i.e. those with mean value below a certain threshold  $\mu$ ) are filtered out. Thus, a usage profile associated with a transaction cluster  $c$ , is the set of all pageviews whose weight is greater than or equal to  $\mu$ . In particular, if we simply use binary weights for pageviews, and the threshold  $\mu$  is set at 0.5, then each profile will contain only those pageviews which appear in at least 50% of transactions within its associated transaction cluster.

The primary difference between PACT and the concept indexing method proposed in [KE00] is that we start with clusters of transactions (rather than document clusters), and that the weights associated with items (in this case pageviews) are obtained differently.

To summarize, given a transaction cluster  $c$ , we construct a usage profile  $pr_c$  as a set of pageview-weight pairs:

$$pr_c = \{ \langle p, weight(p, pr_c) \rangle \mid p \in P, weight(p, pr_c) \geq \mu \}$$

where the significance weight,  $weight(p, pr_c)$ , of the pageview  $p$  within the usage profile  $pr_c$  is given by

$$weight(p, pr_c) = \frac{1}{|c|} \cdot \sum_{t \in c} w(p, t)$$

and  $w(p, t)$  is the weight of pageview  $p$  in transaction  $t \in c$ . Each profile, in turn, can be represented as vectors in the original  $n$ -dimensional space.

## 2.2 Discovery of Aggregate Profiles Based on Pageview Clustering

The second profile generation method we consider is to directly compute clusters of pageview references based on how often they occur together across user transactions (rather than clustering transactions, themselves). In general, this technique will result in a

different type of usage profiles compared to the transaction clustering technique. The profiles obtained by reducing transaction clusters group together pages that co-occur commonly across "similar" transactions. On the other hand, usage clusters tend to group together frequently co-occurring items across transactions, even if these transactions are themselves not deemed to be similar. This allows us to obtain clusters that potentially capture overlapping interests of *different types* of users.

However, traditional clustering techniques, such as distance-based methods generally cannot handle this type clustering. The reason is that instead of using pageviews as features, the transactions must be used as features, whose number is in tens to hundreds of thousands in a typical application. Furthermore, dimensionality reduction in this context may not be appropriate, as removing a significant number of transactions as features may result in losing too much information.

We have found that the Association Rule Hypergraph Partitioning (ARHP) technique [HKKM97, HKKM98] is well-suited for this task since it can efficiently cluster high-dimensional data sets without requiring dimensionality reduction as a preprocessing step. Furthermore, the ARHP provides automatic filtering capabilities, and does not require distance computations. The ARHP has been used successfully in a variety of domains, including the categorization of Web documents [HBG+99].

*Association rules* capture the relationships among items based on their patterns of co-occurrence across transactions. In the case of Web transactions, association rules capture relationships among pageviews based on their co-occurrence in navigational patterns of users. The association rule discovery methods such as the Apriori algorithm [AS94], initially find groups of items (which in this case are the URLs appearing in the transaction file) occurring frequently together in many transactions. Such groups of items are referred to as *frequent item sets*.

Given a set  $IS = \{I_1, I_2, \dots, I_k\}$  of frequent itemsets, the *support* of  $I_i$  is defined as

$$\sigma(I_i) = \frac{|\{t \in T: I_i \subseteq t\}|}{|T|}$$

Generally, a support threshold is specified before mining and is used by the algorithm for pruning the search space. The itemsets returned by the algorithm satisfy this minimum support threshold.

In the ARHP, the set  $IS$  of large frequent itemsets are used as hyperedges to form a hypergraph  $H = \langle V, E \rangle$ , where  $V \subseteq P$  and  $E \subseteq IS$ . A hypergraph is an extension of a graph in the sense that each

hyperedge can connect more than two vertices. The weights associated with each hyperedge can be computed based on a variety of criteria such as the confidence of the association rules involving the items in the frequent itemset, the support of the itemset, or the "interest" of the itemset. In our experiments, we weight each hyperedge using a function of the interest of the itemset which is defined as:

$$Interest(I) = \frac{\sigma(I)}{\prod_{i \in I} \sigma(i)}$$

The hypergraph  $H$  is then partitioned into a set of clusters  $C$ . Each partition is examined to filter out vertices that are not highly connected to the rest of the vertices of the partition. The connectivity of vertex  $v$  (a pageview appearing in the frequent itemset) with respect to a cluster  $c$  is defined as:

$$conn(v, c) = \frac{\sum_{e \subseteq c, v \in e} weight(e)}{\sum_{e \subseteq c} weight(e)}$$

A high connectivity value suggests that the vertex has strong edges connecting it to other vertices in the partition. The vertices with connectivity measure greater than a given threshold value are considered to belong to the partition, and the remaining vertices are dropped from the partition.

The hypergraph is recursively partitioned until a stopping criterion for each partition is reached. The stopping criterion is determined according to a threshold on the ratio of the weights of the cut edges to the weights of uncut edges in the partition. Once the partitioning is completed, vertices can be "added back in" to clusters depending on the user defined overlap parameter. For each partial edge that is left in a cluster, if the percentage of vertices from the original edge that are still in the cluster exceed the overlap percentage, the removed vertices are added back in. This will allow some vertices to belong to more than one cluster. In the ARHP method, additional filtering of non-relevant items can be achieved using the support criteria in the association rule discovery components of the algorithm.

The connectivity value of an item (pageviews) defined above is important also because it is used as the primary factor in determining the weight associated with that item within the profile. As noted earlier, the weights associated with pageviews in each profile are used as part of the recommendation process when profiles are matched against an active user session (see below).

## 2.3 A Recommendation Engine Using Aggregate Profiles

The goal of personalization based on anonymous Web usage data is to compute a *recommendation set* for the current (active) user session, consisting of the objects (links, ads, text, products, etc.) that most closely match the current user profile. The recommendation engine is the online component of a usage-based personalization system. If the data collection procedures in the system include the capability to track users across visits, then the recommendation set can represent a longer term view of potentially useful links based on the user's activity history within the site. If, on the other hand, profiles are derived from anonymous user sessions contained in log files, then the recommendations provide a "short-term" view of user's navigational history. These recommended objects are added to the last page in the active session accessed by the user before that page is sent to the browser.

Maintaining a history depth may be important because most users navigate several paths leading to independent pieces of information within a session. In many cases these *sub-sessions* have a length of no more than 3 or 4 references. In such a situation, it may not be appropriate to use references a user made in a previous sub-session to make recommendations during the current sub-session. We capture the user history depth within a sliding window over the current session. The sliding window of size  $n$  over the active session allows only the last  $n$  visited pages to influence the recommendation value of items in the recommendation set. The notion of a sliding session window is similar to that of *N-grammars* discussed in [Cha96]. Structural characteristics of the site or prior domain knowledge can also be used to associate an additional measure of significance with each pageview in the user's active session. For instance, the site owner or the site designer may wish to consider certain page types (e.g., content versus navigational) or product categories as having more significance in terms of their recommendation value. In this case, significance weights can be specified as part of the domain knowledge.

Usage profiles, obtained using any of the techniques described in the previous section, are represented as sets of pageview-weight pairs. This will allow for both the active session and the profiles to be treated as  $n$ -dimensional vectors over the space of pageviews in the site. Thus, given a usage profile  $C$ , we can represent  $C$  as a vector

$$C = \{w_1^C, w_2^C, \dots, w_n^C\}$$

where

$$w_i^C = \begin{cases} \text{weight}(p_i, C), & \text{if } p_i \in C \\ 0, & \text{otherwise} \end{cases}$$

Similarly, the current active session  $S$  is also represented as a vector  $S = \langle s_1, s_2, \dots, s_n \rangle$ , where  $s_i$  is a significance weight associated with the corresponding pageview reference, if the user has accessed  $p_i$  in this session, and  $s_i = 0$ , otherwise. In our experiments, discussed in the next section, we simply used binary weighting for the active session. We compute the profile matching score using the normalized cosine similarity measure for vectors:

$$\text{match}(S, C) = \frac{\sum_k w_k^C \cdot S_k}{\sqrt{\sum_k (S_k)^2 \times \sum_k (w_k^C)^2}}$$

Note that the matching score is normalized for the size of the clusters and the active session. This corresponds to the intuitive notion that we should see more of the user's active session before obtaining a better match with a larger cluster representing a user profile. Given a profile  $C$  and an active session  $S$ , a recommendation score,  $\text{Rec}(S, p)$ , is computed for each pageview  $p$  in  $C$  as follows:

$$\text{Rec}(S, p) = \sqrt{\text{weight}(p, C) \cdot \text{match}(S, C)}$$

If the pageview  $p$  is in the current active session, then its recommendation value is set to zero. We obtain the usage recommendation set,  $\text{UREC}(S)$ , for current active session  $S$  by collecting from each usage profile all pageviews whose recommendation score satisfies a minimum recommendation threshold  $\rho$ , i.e.,

$$\text{UREC}(S) = \{w_i^C \mid C \in UP, \text{ and } \text{Rec}(s, w_i^C) \geq \rho\}$$

where  $UP$  is the collection of all usage profiles. Furthermore, for each pageview that is contributed by several usage profiles, we use its maximal recommendation score from all of the contributing profiles.

## 3 Experimental Evaluation

We used the access logs from the Web site of the Association for Consumer Research (ACR) Newsletter ([www.acr-news.org](http://www.acr-news.org)) for our experiments. The site includes a number of calls-for-papers for a variety of conferences and Journals related to consumer behavior and marketing, an archive of editorial articles, and a

variety of pages related to organizational matters. After preprocessing and removing references by Web spiders, the initial log file (from June 1988 through June 1999), produced a total of 18342 transactions using the transaction identification process. The total number of URLs representing pageviews was 112. Support filtering was used to eliminate pageviews appearing in less than 0.5% or more than 80% of transactions (including the site entry page). Furthermore, for these experiments we eliminated short transactions, leaving only transactions with at least 5 references (which was the average transaction size in the whole data set). Approximately 25% of the transactions from the final set were randomly selected as the evaluation set, and the remaining portion was used as the training set to which we applied the profile generation methods described earlier. The total number of remaining pageview URLs in the training and the evaluation sets was 62.

For the PACT method, we used multivariate k-means clustering to partition the transaction file. Overlapping aggregate profiles were generated from transaction clusters using the method described earlier. For Association Rule Hypergraph Partitioning, the frequent itemsets were found using the Apriori algorithm [AS94]. Each pageview serves as a vertex in the hypergraph, and each edge represents a frequent itemset with the weight of the edge taken as the interest for the set. Since interest increases dramatically with the number of items in a rule, the log of the interest is taken in order to prevent the larger rules from completely dominating the clustering process.

As mentioned in the Introduction section, for comparison purposes, we also generated usage profiles using the Clique-based clustering technique used in [PE98]. We used a similarity threshold of 0.5 to form the similarity graph among pairs of pageviews. Profiles were then generated from the completely connected components of the graph. The weight of items in each Clique profile was determined by measuring the similarity of the item vector (a vector of transactions) to the cluster centroid.

In all cases, the weights of pageviews were normalized so that the maximum weight in each profile would be 1. In the case of PACT and Hypergraph, the maximum overlap among any pairs of profiles was already less than 50%, however, the Clique method tends to generate a large number of highly overlapping clusters, often differing by only 1 or 2 items. In order to rectify this situation we employed the overlap reduction method discussed in [PE98].

The profiles were ranked according to average similarity of items within the profiles, and then the lower ranking profiles which had more than 50% overlap with a previous profile were eliminated.

As an example of aggregate profiles, Table 1 depicts 3 of the profiles generated using the PACT method for the ACR site. Only pageview URLs with weights of at least 0.5 have been shown in each profile. The first profile in Table 1 represents the activity of users who are primarily interested in general ACR sponsored conferences. The second profile, while containing some overlap with the first, seems to capture the activity of users whose interests are more focused on specific conferences or journals related to marketing and consumer behavior. Finally, the third profile captures the activity of users interested in news items as well as specific columns that appear in the "Online Archives" section of the ACR site.

Weight	Pageview ID
1.00	Conference Update
0.89	ACR 1999 Annual Conference
0.82	CFP: ACR 1999 Asia-Pacific Conference
0.83	CFP: ACR 1999 European Conference
0.56	ACR News Special Topics

Weight	Pageview ID
1.00	Call for Papers
1.00	CFP: Journal of Consumer Psychology I
0.72	CFP: Journal of Consumer Psychology II
0.61	CFP: Conf. on Gender, Marketing, Consumer Behavior
0.54	CFP: ACR 1999 Asia-Pacific Conference
0.50	Conference Update
0.50	Notes From the Editor

Weight	Pageview ID
1.00	President's Column - Dec. 1997
0.78	President's Column - March 1998
0.62	Online Archives
0.50	ACR News Updates
0.50	ACR President's Column
0.50	From the Grapevine

**Table 1. Examples of aggregate usage profiles obtained using the PACT method**

### 3.1 Evaluation of Individual Profile Effectiveness

As a first step in our evaluation, we computed the *average visit percentage* for the top ranking profiles generated by each method. This evaluation method,

introduced by Perkowitx and Etzioni [PE98], allows us to evaluate each profile individually according to the likelihood that a user who visits any page in the profile will visit the rest of the pages in that profile during the same transaction. However, we modified the original algorithm to take the weights of items within the profiles into account. Specifically, let  $T$  be the set of transactions in the evaluation set, and for a profile  $pr$ , let  $T_{pr}$  denote a subset of  $T$  whose elements contain at least one page from  $pr$ . Now, the weighted average similarity to the profile  $pr$  over all transactions is computed (taking both the transactions and the profile as vectors of pageviews) as:

$$\sum_{t \in T_{pr}} (\bar{t} \cdot \bar{pr}) / |t|$$

The (weighted) average visit percentage (WAVP) is this average divided by the total weight of items within the profile  $pr$ :

$$\left( \sum_{t \in T_{pr}} \frac{\bar{t} \cdot \bar{pr}}{|t|} \right) / \left( \sum_{p \in pr} weight(p, pr) \right)$$

Profiles generated by each method ranked according to their WAVP. Figure 1 depicts the comparison of top ranking profiles.

The top ranking profiles generated by the Hypergraph method perform quite well under this measure, however, beyond the top 2 or 3 profiles, both Hypergraph and the Clique methods seem to perform similarly. On the other hand the PACT method, overall, performs consistently better than the other techniques. It should be noted that, while WAVP provides a measure of the predictive power of individual profiles, it does not necessarily measure the "usefulness" of the profiles. For instance, the Hypergraph method tends to produce highly cohesive clusters in which potentially "interesting" items, such as pageviews that occur more deeply within the site graph, dominate. This is verified by our experiments on the recommendation accuracy of the method as a whole, discussed below.

### 3.2 Evaluation of Recommendation Effectiveness

Our recommendation engine, discussed in the previous section, can potentially contribute items to the recommendation set from multiple profiles. Thus, the average visit percentage for individual profiles is not, by itself, sufficient to measure the effectiveness of a recommender system based on aggregate profiles as a whole. In addition, recommendation accuracy may be

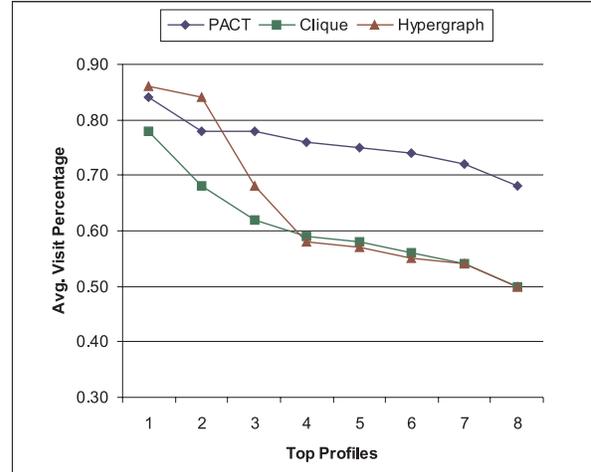


Figure 1. Comparison of top profiles based on Weighted Average Visit Percentage

affected by factors such as the size of the active session window and the recommendation threshold that filters out low scoring pages.

In order to evaluate the recommendation effectiveness for each method, we measured the error rate to compute the accuracy of the recommendation set produced for each transaction in the evaluation set. The basic methodology used is as follows. For a given transaction  $t$ , and an active session window size  $n$ , we randomly chose  $|t| - n + 1$  groups of items from the transaction as the surrogate active session window. For each of these active sessions, we produced a recommendation set and compared the set to the remaining items in the transaction by computing the percentage of visited pages for which a recommendation was produced. The final score for transaction  $t$  is the mean score over all of the  $|t| - n + 1$  surrogate active sessions. Finally, the mean over all transactions in the training set was computed as the evaluation score. To determine a recommendation set based on an active session, we varied the recommendation threshold from 0.2 to 0.9. A page is included in the recommendation set only if it has a recommendation score above this threshold.

Clearly, fewer recommendations are produced at higher thresholds, while higher evaluation scores are achieved at lower thresholds (with larger recommendation sets). Ideally, we would like the recommendation engine to produce few but highly relevant recommendations. Table 2 shows the results produced by the recommendation engine for the 3 profile generation methods using a session window size of 2. For example, at a threshold of 0.7, the PACT method produced an evaluation score of 0.82 with an average recommendation set size of 10 over all trials.

Roughly speaking, this means that on average 82% of unique pages actually visited by users in the evaluation set transactions matched the top 10 recommendations produced by the system.

In order to compare the overall relative recommendation accuracy among all 3 methods, the evaluation score percentage was divided by the size of the recommendation set. Thus, a higher number according to this measure corresponds to better overall performance by the recommendation engine.

The results for session window sizes of 2 and 3 are depicted in Figures 2 and 3, respectively. It is clear from these results that the PACT method provided better overall performance, especially for higher threshold values. The Hypergraph method tended to give better relative performance for lower threshold values when session window size was smaller. Also, as expected, all 3 methods did better when the window size used by the recommendation engine was increased to 3, however, the improved performance due to larger window size was more dramatic for PACT than the other two methods. Despite the fact that the Hypergraph method scored lower in than PACT in these experiments, casual observation of the recommendation results show that the Hypergraph methods tends to produce more "interesting" recommendations. In particular, this method more often gives recommended pages that occur more deeply in the site graph as compared to top level (and more frequently visited pages). This is in part due to the fact that interest of the itemsets was used to compute the weights for the hyperedges.

Intuitively, we may consider a recommended object (e.g., a page or a product) more interesting or useful if a larger amount of user navigational activity is required to reach the object without the recommendation engine. In our experimental data set, these objects correspond to content pages that are located deeper in the site graph (as opposed to top level navigational pages).

In order to evaluate the effectiveness of the 3 profile generation methods in this context, we filtered out the top-level navigational pages in both the training and the evaluation sets and regenerated the aggregate profiles from the filtered data set. All other parameters for profile generation and the recommendation engine were kept constant. Figure 4 depicts the relative performance of the 3 methods on the filtered evaluation set.

As these results indicate, filtering the data set resulted in better performance for all 3 methods. There was moderate improvement for Clique, while the improvement was much more dramatic for Hypergraph and (to a lesser degree) PACT. In particular, the Hypergraph method performed consistently better than the other two methods in these experiments, supporting our conjecture that it tends to produce more interesting recommendations.

To see the impact of filtering more clearly, Figure 5 depicts the relative improvement of the PACT and Hypergraph methods when comparing the results for filtered and unfiltered data sets.

Threshold	Clique		PACT		Hypergraph	
	Eval. Score	Avg. Number of Recs.	Eval. Score	Avg. Number of Recs.	Eval. Score	Avg. Number of Recs.
0.9	0.50	4.3	0.54	3.8	0.65	5.9
0.8	0.71	7.2	0.75	7.0	0.69	7.3
0.7	0.81	9.5	0.82	10.0	0.76	10.1
0.6	0.87	12.3	0.88	13.3	0.83	12.0
0.5	0.92	16.8	0.92	16.7	0.87	13.4
0.4	0.95	21.6	0.95	21.6	0.89	14.8
0.3	0.95	24.4	0.98	25.8	0.89	16.8
0.2	0.95	25.2	0.98	28.7	0.90	17.3

**Table 2. Evaluation scores and the average size of the recommendation set produced by the recommendation engine using a session window size of 2.**

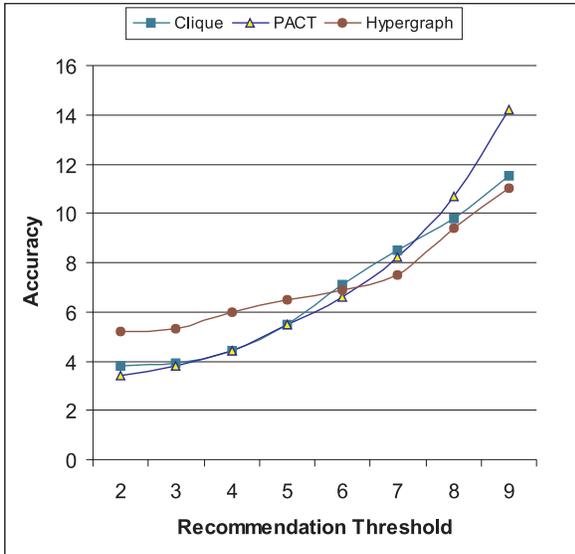


Figure 2. Comparison of recommendation accuracy using session window size 2

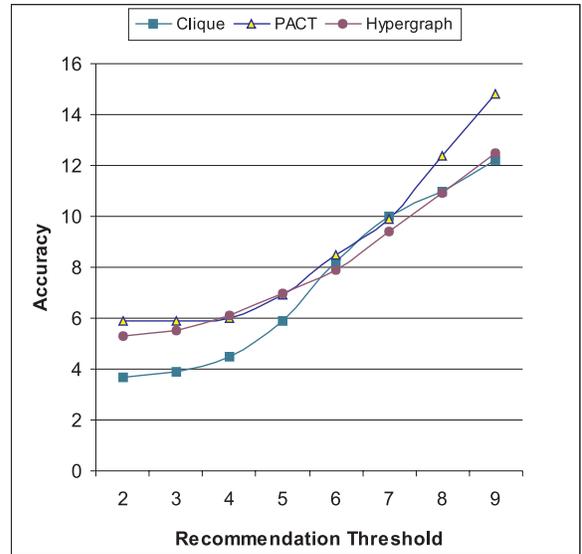


Figure 3. Comparison of recommendation accuracy using session window size 3

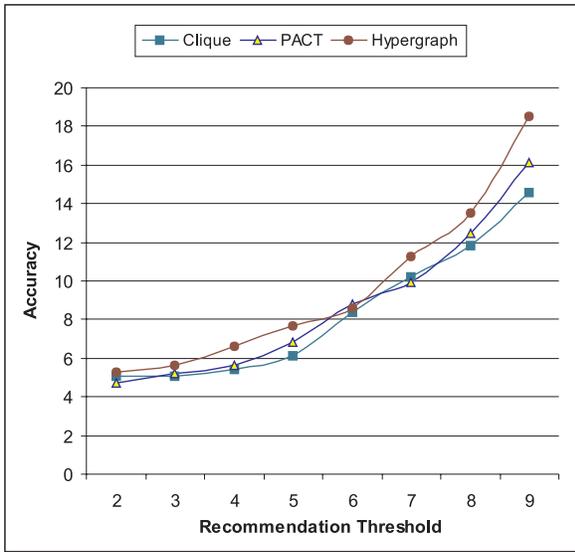


Figure 4. Comparison of recommendation accuracy using session window size 2 on the filtered data set.

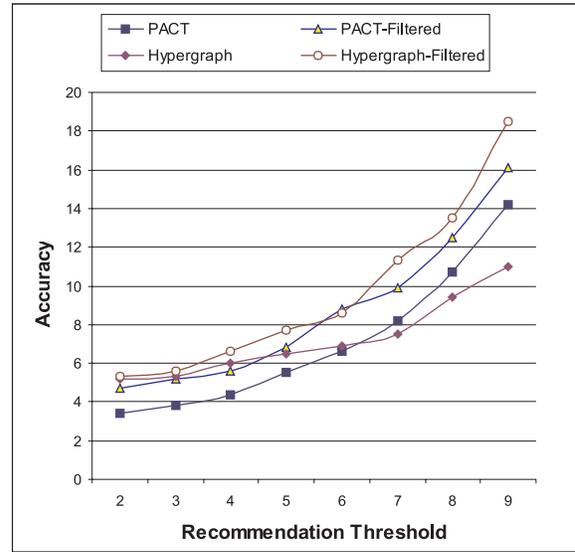


Figure 5. The impact of filtering on the accuracy of recommendations for the PACT and Hypergraph methods (window size = 2).

### 3.3 Discussion

We conclude this section by summarizing some of our observations based on the above experimental results. First it should be noted that we have performed a similar set of experiments using the data from another site resulting in similar and consistent conclusions. We

used the Clique method, as used by Perkowit and Etzioni [PE98] in their PageGather algorithm, for comparative purposes. In general, this technique for profile generation is not as useful as our two proposed methods, partly due to prohibitive cost of computing a distance or similarity matrix for all pairs of pageviews, especially in a large, high traffic site. Furthermore, the overall performance of PACT and Hypergraph

methods is better both when considering individual profiles as well as in their use as part of the recommender system.

In comparing PACT and Hypergraph, it is clear that PACT emerges as the overall winner in terms of recommendation accuracy. However, as noted above, Hypergraph tends to perform better at lower recommendation thresholds when the session window size is smaller. Furthermore, Hypergraph does dramatically better when we focus on more "interesting" objects (e.g., content pages). In general, the Hypergraph method seems to produce a smaller set of high quality, and more specialized, recommendations, even when a smaller portion of the user's clickstream is used by the recommendation engine. On the other hand, PACT provides a clear performance advantage when dealing with all the relevant pageviews in the site, particularly as the session window size is increased.

Whether PACT or Hypergraph methods should be used in a given site depends, in part, on the goals of personalization. Based on the above observations, we conclude that, if the goal is to provide a smaller number of highly focused recommendations, then Hypergraph may be a more appropriate method. This is particularly the case if only specific portions of the site (such as product related pages) are to be personalized. On the other hand, if the goal is to provide a more generalized personalization solution integrating both content and navigational pages throughout the whole site, then using PACT as the underlying aggregate profile generation method seems to provide clear advantages.

## 4 Conclusions

The practicality of employing Web usage mining techniques for personalization is directly related to the discovery of effective aggregate profiles that can successfully capture relevant user navigational patterns. Once such profiles are identified, they can be used as part of usage-based recommender system, such the one presented in this paper, to provide real-time personalization. The discovered profiles can also be used to enhance the accuracy and scalability of more traditional personalization technologies such as collaborative filtering. We have presented two effective techniques, based on clustering of transactions and clustering of pageviews, in which the aggregate user profiles are automatically learned from Web usage data. This has the potential of eliminating subjectivity from profile data as well as keeping it up-to-date. We have evaluated these techniques both in terms of the quality of the individual profiles generated, as well as in the context of providing recommendations as an

integrated part of a personalization engine. Our evaluation results suggest that each of these techniques exhibits characteristics that make it a suitable enabling mechanism for different types of Web personalization tasks. A local version of the ACR site which uses the PACT method and the recommendation engine described in this paper has been made available for demonstration purposes. This site can be accessed at the location: <http://aztec.cs.depaul.edu/scripts/ACR2>.

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