Collaborative Personalization Strategies for Web Search

Anushia Inthiran, Saadat M. Alhashmi & Pervaiz K. Ahmed

Information retrieval is not about providing users with multiple pages of results but providing users with relevant results. Relevant results can only be provided if search engine strategies are able to discern a user's information need. Collaborative personalization is an information retrieval strategy designed to provide users with relevant results. In this paper, we introduce the personalization process and review collaborative personalization features used in three feedback settings. We focus on the evolution of the following core features in collaborative personalization systems: group size, membership type, personalization technique, trust and privacy within each feedback setting. Finally, we conclude the paper by providing ideas for future development of personalization system.

Keywords: collaborative personalization, evolution of features, feedback setting, information retrieval, search process

The Internet has become the one stop centre for information retrieval. At this one stop centre, the search engine is tasked with locating answers to a user's query. Search engines are effective at retrieving results for 'look-up' search tasks but still struggle with other types of search tasks (Marchionini 2006). We believe this is due to three reasons: firstly, search engines have to battle with the obesity of the World Wide Web, secondly, users do not always know how to formulate effective queries, and thirdly search

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engines need to infer a user's query intent. From a user's point of view, searching on the Internet has become time consuming, tedious and unfulfilling (Teevan, Dumais & Horvitz 2005; Arapakis, Jose & Gray 2008).

Personalization is a strategy used by search engines to provide relevant results. Unlike other information retrieval strategies, personalization attempts to continuously learn and adapt to a users' information need. Personalization actively provides users with relevant results based on the query context, location, interest and preference of a user. Surveys suggest many tasks in a professional and casual setting can benefit from the ability to jointly search the web with others (Morris 2008). The survey reports job-related tasks, social planning tasks and general fact-finding are popular activities collaborated upon. Collaborative personalization boasts many advantages such as reducing difficulties faced by a single user (Reddy, Jansen & Krishnappa 2008) and the ability to locate the right information and the right time (Smyth *et al.* 2003).

The deployment of personalization strategies have been seamlessly integrated into web search. For example the *Cable News Network (CNN)* site allows personalized news to be provided to users. *Facebook* allows for instant personalization features and Google allows its registered members to utilize *iGoogle*, a service provided by Google to allow members to obtain personalized results based on search history and explicit preferences Besides focusing only on collaborative personalization strategies, researchers have ventured into the design and development of collaborative personalization interfaces (Price 2006; Tvarozek 2008; Morris 2008) and implementing specialized collaborative personalization techniques for specific domains (Kim & Yoon 2009; Dolog 2007). Ongoing research initiatives on collaborative personalization and evidence of personalization efforts being implemented on websites signify the importance of this technology. Personalization attempts to improve a users' search experience and increase the effectiveness of a search session. In most cases, users opt for personalized results as it enhances web search (Morris, Teevan & Bush 2008).

In this paper, we focus on three major feedback settings in collaborative personalization: explicit, implicit and combined. Feedback settings indicate the party/responsible to perform collaborative personalization. In explicit feedback, the user is responsible for personalization efforts. In implicit feedback, the system or technique assumes responsibility to perform personalization and in combined feedback the user and the system or technique work together to perform personalization. We analyse exemplary techniques and systems within these settings and provide an evolution of features within each setting based on the techniques and systems reviewed.

We acknowledge that the underlying operation of these techniques or systems within these settings is dissimilar. However, our intention is to better understand the evolution of features within each setting. In our opinion the best way to do this is to compare them in these settings. While dissimilar, they generally fall into these basic feedback settings (explicit, implicit, combined). The focus of this article is not about the technicality of personalization strategies. Rather, it is to provide insight on user related and soft-side issues such as trust, privacy, non-traditional search process and collaboration. We feel these issues are equally important but are often only an after-though and in some cases lost somewhere during the development of these techniques/systems.

The rest of the paper is organized as follows. In the next section we provide an overview of collaborative personalization. This is followed by examining systems and techniques within the three feedback settings. The discussion of systems and techniques is based on a review of their operational techniques and evolution of features. Finally we conclude the paper and provide future direction for personalization systems.

An Overview of Collaborative Personalization

"Prior to the digital era people often relied on the opinion of a network of friends with similar taste to filter information" (McLaughlin & Herlocker 2004, 329). Collaborative personalization strategies use this principle to store preferences and opinions of thousands of users of the system. When an active user would like a recommendation, the system finds users with similar taste and uses their opinions to generate a recommendation. Collaborative personalization emerged around the mid 90's with the development of systems such as *GroupLens* (Konstan *et al.* 1997) and *Fab* (Balabanovic & Shoham 1997). *GroupLens* supports collaborative filtering for *Usenet News* users, while *Fab* is a content-based collaborative recommendation system. The chronological order for these feedback settings is described in Figure 1. Note, Figure 1 only lists selected landmark systems for each feedback setting.

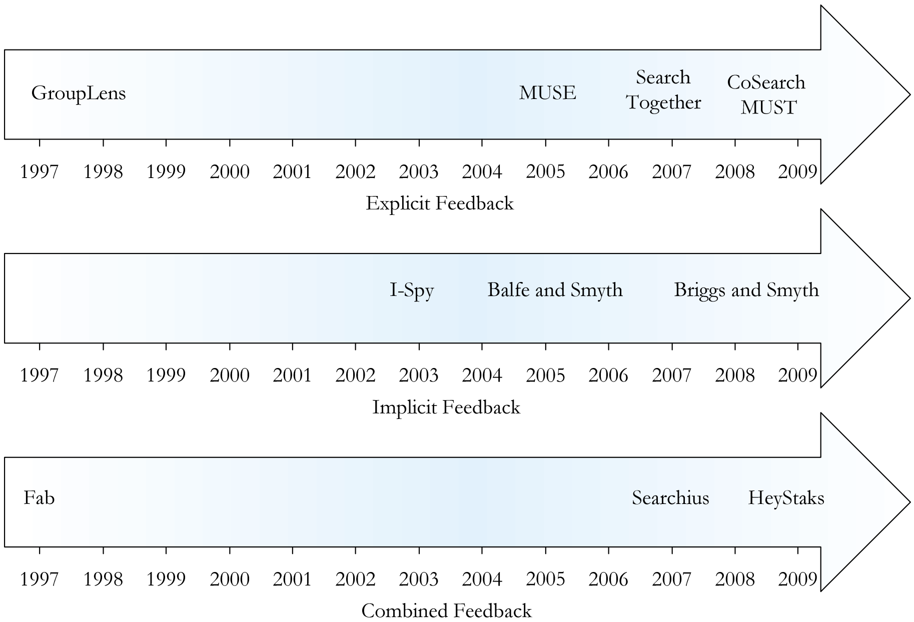

Figure 1: Timeline of landmark collaborative personalization systems for explicit, implicit and combined feedback setting

Various full-fledged systems were developed to perform personalization. The development of these systems somewhat indicates that researchers recognize the potential of personalization as an effective information retrieval strategy. In some cases instead of developing full-fledged systems, personalization techniques are developed to run on systems/networks to enable a non-personalized environment to behave in a personalized manner. Personalization techniques are usually heavy-duty algorithms developed for use in a non-personalized environment.

Systems were developed for explicit and combined feedback setting because in both settings users played an active role (explicit) or semi-active role (combined) in the personalization process. In implicit feedback the user does not play an active role in the personalization process. Rather, seamless background processing using algorithms is performed to place users into collaborative groups. Hence, algorithms (i.e. techniques) are commonly used to implement implicit personalization strategies.

There are two general methods as to how collaboration is performed. The first method is when users directly and actively collaborate in the personalization process. The second method is when the user is not directly involved in the personalization process. With the second method the system/technique places users in dynamic and invisible collaborative groups depending on the search activity of the user. There is no definitive technique as to which collaborative method is used in the three feedback settings. Thus, for the context of this paper we adopt a broad sense of the term collaboration to provide a realistic view of collaborative personalization strategies used on the World Wide Web.

A Review of Explicit Feedback Systems

We examine the following systems in the explicit feedback setting: *GroupLens* (1997), *Fab* (Balabanovic & Shoham 1997), *CoSearch* (Amershi & Morris 2008) *SearchTogether*, (Morris & Horvitz 2007), *Multi-User Search Engine* (*MUSE*) (Krishnappa 2005) and *Multi-User Search and Talk (MUST)* (Reddy, Jansen & Krishnappa 2008). These systems are chosen as representations of key steps in the evolution of techniques used in this setting.

GroupLens is a collaborative personalization system for *Usenet News*. It performs filtering based on user feedback on various news articles. In this setting, *GroupLens* has to deal with a constant high volume of news articles that have a short shelf-life based on popularity, relevance and association to recent events. To avoid bombarding users with a myriad of articles, this technique reduces information overload. Since *Usenet News* has a large user base, issues relating to sparsity due to continuously growing resources or 'cold start' where an article has insufficient ratings is somewhat reduced.

The development of explicit feedback settings progressed to systems that facilitate live searching and chatting. *MUSE* and *MUST* are systems that allow for people to work independently while sharing search results. *MUSE* is designed to facilitate collaboration between two people while *MUST* is a multiuser system. This setting automatically assumes users in collaborative groups to share a common search goal. When multiple users are involved in the search process, group dynamics affects the collaboration personalization process. If one user is an expert searcher and the other a novice, the novice searcher will benefit from the collaborative personalization effort. However, when all users are novice searchers, extensive chatting and 're-personalization' is necessary to obtain relevant results.

An example of a traditional non-digital collaboration technique is when users gather around a computer to perform a search. One user becomes the driver whilst others become observers or suggestion providers. *CoSearch* extends this principle to allow co-located people to search the web on a single computer. *CoSearch* allows for equal opportunity for all members as sometimes "drivers are overwhelmed with suggestions from observers and observers having their suggestions ignored by drivers" (Amershi & Morris 2008, 1650). However, using a single computer may result in navigation issues, cognitive overload and users getting distracted with having to manage too many search panels.

In *SearchTogether* (2007), an interface is provided to facilitate asynchronous and synchronous searching between authorized users. The interface allows for the exchange of queries and search results. Authorization to collaborative groups maintains privacy and reduces the possibility of users obtaining spam or unauthenticated results. However, users may be reluctant to collaborate when searching for sensitive or personal based information.

Evolution of Features in Explicit Feedback Setting

In this section, we analyse evolution of features for systems reviewed for the explicit feedback setting. These features are selected as they provide us with common ground to discuss the evolution of user and soft-side features within this setting. Evolution of features is discussed in relation to the chronological order of system inception (see Table 1.)

Collaborative Groups

GroupLens enrolls members based on membership to specific news groups. *MUSE*, *MUST* and *CoSearch* enrolls members in an unrestricted manner. *SearchTogether* enrolls users based on mutual authorization. Membership to collaborative groups is vital as it impacts search results. Usually, membership to collaborative groups is based on broad categories like interest or taste. We feel membership to collaborative groups need to be stringent to ensure the formation of tighter groups for effective personalization. Implicit user features like prior knowledge, preference and search goal have to be accounted for. Although these features may seem subtle, ignoring them would result in providing users with a less desirable result set.

MUSE restricted its group size to two. In our opinion, *MUSE* is suited for ad-hoc personal or work based searching amongst limited number of friends, family members or colleagues. On the other hand, *MUST* is suited for complex user intensive type searching. We foresee the future development of personalization systems driven by "purposeful searches or to fit specific domains of search" (Freyne & Berkovsky 2010, 386).

Personalization

GroupLense personalizes results based on a collection of votes. In other systems reviewed, personalization is viewed as recommending or sharing search results. We feel most systems have loosely adapted the term personalization. When users recommend or share search results with collaborators, the assumption is that they share a common search goal. If this is not the case, collaborators only receive 'semi-personalized' results. Users who receive semi-personalized results may require a second round of personalization.

In all systems reviewed, it was user ratings that drove the personalization process. However, in the event other elements require personalization, the user based personalization technique will fail. Riedl (2001) state personalization techniques need to consider a user's intent, goal and state of mind. Because it is possible when users drive the personalization process, provided results will be limited to the same set of topics. Over time, instead of providing a user with the 'right information at the right time' personalization strategies end up providing a 'one size fits all' result page. "A linear combination of multiple criteria is necessary to improve retrieved results*"* (Wolfe & Zhang 2009, 818).

SearchTogether and *CoSearch* demonstrate collaboration by allowing users to view search results. Traditionally, a search session is considered to be a two part process. The first part is issuing a query (query session) and the second part viewing search results (results session). For reviewed systems, collaboration takes place only at the results session. Personalization at this stage ignores a users search goal and context. Personalization for the entire search session will provide users with enhanced search results by reducing the effect of under or over personalization.

Non-Traditional Search Process

Traditionally, a query is required to initiate a search process. In *SearchGuide, MUSE, MUST and CoSearch* a user would likely obtain search results without having to issue a query. Collaborative systems automatically support this non-traditional search process by providing a chat function (*MUSE, MUST*), supporting asynchronous searching (*SearchTogether*) and the ability to view a collaborators search panel (*CoSearch*). Personalization is not limited to providing user with personalized results but is extended to supporting users in obtaining personalized results without having to issue a query.

We summarize the features explained above in Table 1.

	Dimensions and Systems		
Maximum number of searchers	Two (MUSE)	Unlimited (GroupLense, SearchTogether, CoSearch)	
Support function	Chat (MUSE, MUST)	Asynchronous search (SearchTogether)	
Personalization technique	Personalized search results (GroupLense)	Semi-personalized search results (MUSE, MUST, CoSearch, SearchTogether)	
Membership	Registered (GroupLense)	Inclusive (CoSearch, MUSE, MUST)	Exclusive (SearchTogether)

Table 1: Evolution of features – explicit feedback setting

In the next section, the implicit feedback setting is examined.

A Review of Implicit Feedback Systems and Techniques

In implicit feedback, users are not involved in the search process. We review the following exemplary implicit feedback systems/technique, *I-Spy* (2003), Balfe and Smyth (2005) and Briggs and Smyth (2008). The personalization technique developed by Balfe and Smyth (2005) is implemented as a new version on *I-Spy*. While *I-Spy* was first created in 2003, the newer version of *I-Spy* operated based on the technique created by Balfe and Smyth in 2005. As such, we first discuss *I-Spy (2003)* as a system to perform personalization and then discuss the newer version of *I-Spy* with reference to the technique developed by Balfe and Smyth (2005). The personalization technique developed by Briggs and Smyth (2008) is typically implemented on servers/workstations across networks. As such we are not able to discuss this personalization technique with reference to a specific system. Thus, we limit the discussion of this personalization technique to the algorithm. These systems and technique are reviewed as they are frequently appraised in collaborative personalization literature.

I-Spy Smyth et al., (2003) is a collaborative meta search engine that analyses the pattern of user queries and results selected. Collaborative groups are created based on anonymous form filing. A unique hit matrix is created for each community based on query issued and pages selected. This technique is beneficial when all users of the community express a query exactly the same. Unfortunately, users are likely to express queries differently although they share a common goal. A solution is to categorize queries into topics and create hit matrixes based on topics. At least, a user will be provided with 'semi-personalized' results as opposed to obtaining an empty result page. However, users are bound to obtain similar search results whenever the same query is issued. Personalization is applied only to the first set of results. This will persist until the result matrix is updated with new pages. Since group membership is bound to communities of interest, users are assured of obtaining relevant results.

In a newer version of *I-Spy* (Balfe and Smyth 2005), two similarity measures are used to perform personalization: query and behaviour. In query similarity, a hybrid metric is used to examine the difference between query terms. In behaviour similarity, the number of overlapping pages selected for a query is examined. Both techniques overcome issues highlighted in the earlier version of *I-Spy*. Furthermore, examining a user's click-through pattern allows for the capture of search context and indicators of relevance (Patil *et al.* 2005) while query similarity calculations enable variations of a query to be considered for personalization (White & Morris 2007).

Besides collaborating based on queries and page selection, Briggs and Smyth (2008) performed personalization based on sharing search experiences across a network. When a user performs a search, the query is used to access local search experiences to identify relevant results to be promoted. Collaboration takes place when connections between agents are formed. Personalization takes place when agents gather information across the network. The effectiveness of this personalization technique relates to the number of users and search experiences available on the network. In the event these are not sufficiently available the personalization process will temporarily halt. Nevertheless, this technique allows for similar context searches to be shared. To a certain extent, a searcher could leverage on the search experience of similar searches to minimize search time and effort.

Evolution of Features in Implicit Feedback Setting

In this section, we analyse evolution of features for systems reviewed for the implicit feedback setting. These features are selected as they provide us with common ground to discuss the evolution of user and soft-side features within this setting. Evolution of features is discussed in relation to the chronological order of system/technique inception (see Table 1.)

Collaborative Groups

With the exception of *I-Spy*, other systems use an unrestricted method to create collaborative groups. In Balfe and Smyth (2005), users are bound to shift from one group to another depending on queries entered or pages selected. As users perform searching for a multitude of goals, restricting a user's collaborative group undermines the collaboration process.

Personalization

In Balfe and Smyth (2005), we attribute the effectiveness of the personalization technique to the query similarity measure and the degree of query variance expressed amongst users. However, we are mindful that natural language issues and expanding query lengths may mar the similarity calculation process. Teevan, Dumais and Liebling (2008) state personalization is only beneficial for ambiguous queries. Automatically performing similarity calculation without examining the query may provide users with irrelevant search results.

For page similarity, we note users 'irrational search behavior' (Jansen, Spink & Bateman 1998) affects page similarity calculation. Recent research findings indicate "specific personalization techniques (query suggestion, destination page) are suited for specific type of searches" (White, Bilenko & Cucerza 2007, 166). We foresee the future development of personalization systems with the ability to identify a query type before applying specialized personalization techniques.

In all three collaborative methods, systems had to be able to cater for adequate processing power and ample storage. Efficient algorithms and complex calculations are necessary to locate queries or to perform query and page similarity calculation. The availability of sufficient resources and calculation complexity may influence the effectiveness of this personalization technique.

Privacy and Security

'Growing privacy concerns' (Gauch *et al.* 2007) may prevent personalization techniques from gathering information from a user's search history log. Privacy concerns tie in with security. Acquiring search history logs require a change in security settings. This may make a computer vulnerable to security threats. However, since *I-Spy* (2003) is based on anonymous membership, hence an acceptable level privacy and security can supposedly be maintained.

Trust

There are two meanings of trust. First, trusting members in a collaborative group and secondly, trusting search results. In some cases, both of them influence each other and in other cases they are treated separately. When members of collaborative groups are unknown to each other, users may not necessarily trust provided results. On the other hand, if members are known, will users trust their collaborators not to maliciously recommend or provide spam search results? Developers of personalization systems might want to consider implementing trust features in order to facilitate trust-based algorithms for validating search results.

We summarize the features explained above in Table 2.

	Dimensions and Systems		
Maximum number of searchers	Non-dynamic (I-Spy)	Dynamic (Balfe and Smyth, Briggs and Smyth)	
Membership	Exclusive (I-Spy)	Inclusive (Balfe and Smyth, Briggs and Smyth)	
Is trust and security maintained?	Yes (I-Spy, Balfe and Smyth)	Unlikely (Briggs and Smyth)	
Is privacy maintained?	Yes (I-Spy)	Unlikely (Balfe and Smyth, Briggs and Smyth)	
Personalization technique	Based on query (Balfe and Smyth, Briggs and Smyth)	Based on page (Balfe and Smyth)	Based on interest and query (I-spy)

Table 2: Evolution of features – implicit feedback setting

In the next section, combined personalization techniques are examined.

A Review of Combined Feedback Systems

In combined feedback, users are partly responsible for the personalization process. We examine the following systems which demonstrate the latest development for combined feedback setting: *Fab* (1997), *Searchius* (Papagelis & Zaroliagis 2007) and *Heystaks* (Smyth *et al.* 2009).

Fab is a hybrid content collaborative recommendation system for digital libraries. *Fab* utilizes two methods to perform personalization: classical grouping of users with similar interest and article content preference. Users initially rate articles to build a personal and content-based profile. Collaboration is seamlessly performed by agents who gather, compare and analyse data in profiles. This technique requires a sufficient number of users and rated articles to work effectively. Since the domain of implementation is a digital library, using user interest and article content preference to perform personalization enables users to obtain enhanced search results.

On the other hand, a horizontal search engine like *Searchius* performs personalization based on collecting and analyzing users' URL collections. Votes for a page are tabulated to determine the rank of a page. This tech-nique provides a direct indication of a user's preference for a page. A user who uses this search engine automatically becomes a member of a single collaborative group. The effectiveness of the personalization technique is dependent on the collection of bookmarked pages. It is likely that *Searchius* is not able to provide results for specialized searches: for example a country- or government-specific type search. However, *Searchius* is most useful for general, well-known and popular types of searches.

From developing special search engines, personalization techniques progressed to developing underlying services for search engines. An example of such a system is *Heystaks*. *HeyStaks* allows users to organize and share search sessions and search results using stacks[1]. The user has the ability to control the setting of a stack by making it private or public. The exchange of information in a private stack is performed when explicit permission is obtained from the stack owner. Information in public stacks is made available for everyone. Since *HeyStaks* allows for public and private search sessions, we hypothesize private search stacks are used for personal searches. *HeyStaks* allows for users to cluster and share search results. It also allows users to review queries that have been previously used, to resume a previously halted session and also to view latest search results for a previous query.

Evolution of Combined Feedback Features

In this section, we analyze evolution of features for system reviewed in the combined feedback setting. These features are selected as they provide us with common ground to discuss the evolution of features within this setting. Evolution of features is discussed in relation to the chronological order of system inception (see Table 1.)

Collaborative Groups

Group membership for *Fab* and *Searchius* is inclusive, while *SearchGuide* is based on registered membership. *Heystaks* allows for two types of membership depending on the setting of a stack. This setting allows users to control the degree of collaboration as well as the type of search collaborated upon. In a private stack, users are able to control the size of the group. We believe group size and membership type influence the personalization technique to be used. When ranking, filtering and voting techniques are used to personalize, a large group size and inclusive membership type allow for greater personalization ability. When personalization techniques recommend or share search results, collaborative group size tend to be small and the membership is required to be exclusive.

Personalization

Searchius provide users with recommended results while *Heystaks* provides the ability for users to share results. Both techniques allow users to receive semi-personalized results. Since recommended results originate from users and are not randomly generated, it would be interesting to investigate if recommended-personalized systems outperform personalized systems.

Non-Traditional Search

When users share a common goal in *Heystaks,* it is possible for a user to obtain search results without having to issue a query. A view of a public stack is sufficient to commence and complete a search session.

Privacy and Security

Inclusive membership to collaborative groups observed in *Fab*, *Searchius, and public HeyStaks* highlights issues with privacy. Future design and development of systems require features to account for privacy and security. The *Platform for privacy preferences (P3P) project*[2] is such an initiative to solve privacy issues.

Trust

Inclusive membership to collaborative groups observed in *Fab*, *Searchius* and public *Heystaks* highlights issues with trust. Trust is a long term issue and has to be observed during all search sessions. A system providing trust-worthy results today may not provide trustworthy results tomorrow. Personalization systems have to incorporate the design of an 'anti-spam' feature akin to anti-virus software to be able to account for trust.

We summarize the features explained above in Table 3.

	Dimensions and Systems	
Maximum number of searchers	Unlimited (Fab, Searchius, Public Heystak)	Limited (Private Heystak)
Membership	Exclusive (Private Heystak)	Inclusive (Fab, Searchius, Public Heystak)
Is trust and security maintained?	Yes (Fab, Private Heystak)	Unlikely (Searchius, Public Heystak)
Is privacy maintained?	Yes (Fab, Private Heystak)	Unlikely (Searchius, Public Heystak)
Is personalization employed	Yes (Fab)	Semi-personalized (Heystaks, Searchius)

Table 3: Evolution of features – combined feedback setting

Conclusion and Future Direction

In this section, we review common features across collaborative personalization settings and discuss areas that require further study. Collaboration took place in various stages for each setting. In most cases collaboration took place in the result session, and it rarely took place in the query session. We acknowledge collaboration performed throughout an entire search session is tedious. A study to investigate credible stages to perform collaboration would enable a system to provide users with enhanced personalized results.

User based collaboration is an upcoming trend. Liu *et al.* (2010) state using implicit indicators of user behaviour enables enhancement of the personalization process. Another alternative is to collaborate based on task, query context or query semantics. In a Search Strategies Expo and Conference held in 2009, researchers indicate emphasis on semantic-content is essential to elicit a searchers' search intent. Collaborative techniques based on these features would make the personalization process more focused.

Personalization was demonstrated in various flavours. For some systems, sharing search results is an instance of personalization. In others, recommending results is regarded as personalization. Teevan, Dumais and Lieblig (2008) state personalization should only occur when users want a different result set than most people. Similarly, Riedl (2001) states when users are in the mood to browse, personalization features should be turned off. Automatically applying personalization techniques without examining if there is a need to do so negatively affect a user's search experience. We suggest personalization techniques are designed to investigate the 'state' of the query or user to determine the necessity for personalization.

Privacy, trust and security are major issues for the implicit and combined feedback setting. Current research initiatives hardly demonstrate advances to combat these issues. Collaborative personalization systems are also unable to address issues in relation to long term search goals and parallel searching. To cater for long term searching, collaborative systems require the ability to store and retrieve previous search results or to resume a halted search session. As more users demonstrate parallel searching behaviour, collaborative personalization systems have to develop techniques to support this feature.

To the best of our knowledge, collaborative personalization techniques/systems are evaluated based on quantitative measures of precision and recall. In most cases, one system is compared against the performance of another. The system providing higher precision and recall results is deemed the 'better' system. These systems are tested computationally on large datasets. Rarely is testing performed by users. Since these techniques/systems are developed for users, it is our opinion that the performance of these systems should be evaluated by users. To holistically evaluate techniques/systems, we feel it is necessary for a standardized list of features besides precision and recall be developed.

We further suggest researchers to explore the idea of developing specific techniques to fit the domain of search. For example, in a music domain personalization techniques based on genre, band name, artist, song title and lyrics seem more realistic compared to using query similarity, interest or search experience. We also suggest creating collaborative groups by "categorizing users into narrow sub-groups" (Wolfe & Zhang 2010, 818) for a streamlined personalization technique.

Systems like *MusicFX* and *GroupCast* (McCarthy 2001) extend collaborative personalization techniques to the physical world. These systems adapt to visual and aural aspects of users who are in a physical space. We suggest some examples where the same principle can be adapted in the digital world: applying personalization techniques to serendipitous browsing and personalization based on data gathered from eye-tracking devices. In our opinion, effective personalization requires a balancing act amongst different features and options. Though this is tedious, once the right balance is struck, users are provided with a compelling search experience.

Anushia is a PhD candidate at the faculty of Information Technology, Monash University Sunway Campus. She holds a Bachelor's Degree in Computing from Monash University and a Masters Degree in Technology Management from Staffordshire University. She served as an IT Security Analyst for six years with Standard Chartered Bank before becoming a lecturer. Her research interest lies in web search personalization, interactive information retrieval and domain specific information retrieval. She is also a life time member of the Golden Key International Honour Society.
Contact: anushia.inthiran@monash.edu
www.infotech.monash.edu.my/postgraduates/aint2.html

Dr Alhashmi is an active researcher in the field of Multimedia and Information retrieval and Social Media. His articles are regularly published in mainstream newspapers. Prior to taking up his current appointment, he has taught at a university in the Sultanate of Oman and has also worked as a Research Assistant at Sheffield Hallam University, U.K for an EU-funded project
Contact: alhashmi@monash.edu

Pervaiz K. Ahmed is Professor and Chair in Management in School of Business, Monash University Sunway Campus. Currently, he is Head of Management Department and Director of the Strategy Research Group. He has published extensively in international journals including Journal of Strategic Information Systems, Journal of Strategic Marketing, European Journal of Information Systems, International Journal of Management Reviews, Journal of Business Ethics, R&D Management Journal, European Journal of Marketing, etc. He has been an invited speaker at many international venues, and served as editor and sits on the editorial boards of a number of international journals.
Contact: pervaiz.ahmed@monash.edu

Notes

1. Stack – repository of result recommendations and search history
2. www.w3.org/P3P

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