Implicit: A recommender system that uses implicit knowledge to produce suggestions

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Abstract

The number of accessible web pages in Internet increases every day and it becomes more and more difficult to deal with such a huge source of information. In literature many approaches have been proposed to provide users with high-quality links extracted from the thousands of irrelevant ones. In this paper, we present *Implicit*, a system that combines recommender system and multi-agent system approaches and is intended to be used within a community of people with similar interests. It complements the results obtained by search engines with suggestions obtained by means of implicit knowledge of the members of the community. Within the system, agents interact one another, share knowledge and use similarities among users' behaviors in order to increase quality of the recommendations.

1 Introduction

Although searching the Internet is a day-to-day task for many people, the problem of providing effective access to the information available on-line is still open. Due to the huge number of pages on the World Wide Web it is difficult to discover relevant and (or) interesting pages among those provided by a search engine. Therefore, web search is often a rather time-consuming task.

There exist several approaches aimed at solving the stated problem. Search engines are a common and prevailing tool for searching the Web. However, they have several shortcomings. For instance, a query can produce a huge quantity of the pages. Another drawback is a lack of personalization, namely that sometimes "different users may merit different answers to the same query" [Gori and Witten, 2005]. The first shortcoming could be alleviated by formulating an appropriate query for a search engine. Such a reformulation requires, however, a certain intuition and experience of the user. To overcome the lack of personalization, we see the need of supporting the user rather than simply responding to a keyword, which is context-free and impersonal.

Another solution is the use of Internet agents to assist the web browsing. In this field, we find personal assistants that collect observations of their users' behavior in order to recommend previously unseen relevant web pages. There exist also multi-agent systems, where personal agents collaborate with one another to improve the quality of the suggestions. This approach overcomes the shortcomings of the search engine approach from the personalization point of view. On the other hand, there are other drawbacks like the low number of suggestions generated or even the absence of them in the case of a keyword that has been previously unseen for the personal assistant agent. Sometimes personal agents require extra effort from the user, e.g. specifying his/her area of interests or answering additional questions.

Recommender systems can be also considered as tools for the effective access to the available information. They can be classified as content-based, collaborative filtering, or hybrid systems. Content-based systems produce recommendations by analyzing the content of previously browsed pages and using the obtained information to find pages with similar content. Collaborative filtering systems calculate similarity between the different users and provide the user with the pages that have been selected by the similar users. Hybrid recommender systems exploit both approaches to a certain extent. However, the majority of the recommender systems need user feedback and those systems that collect this feedback in explicit form force user to perform some extra work, like rating the items.

In this paper we present *Implicit*, a multi-agent recommender system. It combines Internet agents and a recommender system. *Implicit* uses a search engine in order to obtain a certain number of suggestions for any entered keyword. Personal agents communicate and collaborate in order to produce recommendations more suitable in the context of the current community[1]. Thus, we complement search engine results with the recommendations produced by the agents. This helps us to add personalization without decreasing significantly the number of the pages. As in many recommender systems we attempt to learn the user needs from the observations of his/her behavior.

This paper differs from the previous work in the field of recommender systems and advances the state of the art in the following ways. The system described here is designed to be used within a small organizational community of people,

[1]Here we do not give any precise definition of the *community*. We refer to the *community* in a general sense, a group of people working in the same environment and having common interests.

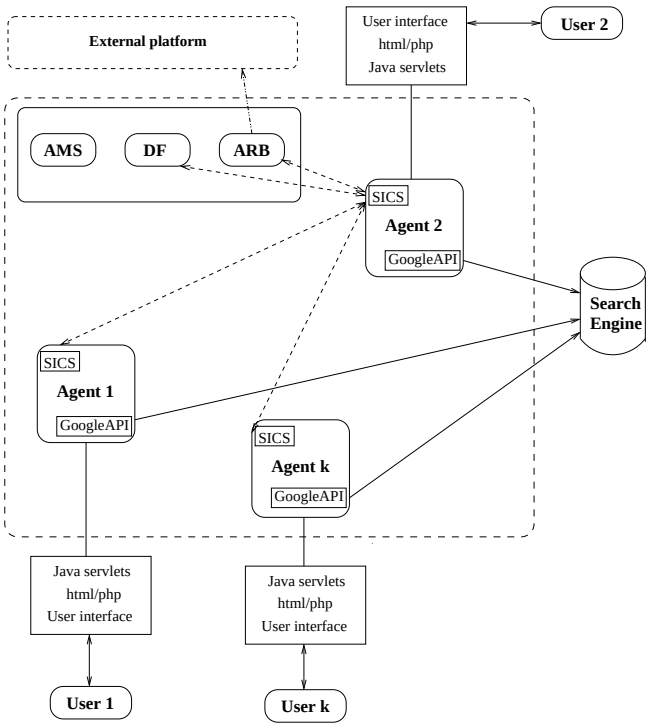

Figure 1: The architecture of the system. *Personal agents* process queries from *users* and interact with each other to exchange links; *SICS* is a part of the personal agent that is responsible for the recommendation creation process; *GoogleAPI* allows to query Google search engine; an *Agent Management System (AMS)* exerts supervisory control over the platform. It provides agent registration, search, deletion and other services; a *Directory Facilitator (DF)* provides agents with other personal agents' IDs. An *Agent Resource Broker (ARB)* deals with links to the services available on the other platforms.

but is not intended for big groups or emergent online communities. We use the universal filtering framework to produce different types of suggestions: links, which are shown to the user, and agents IDs, which are used internally to identify agents to contact. In order to access the information provided by the system, the user does not need to install ad-hoc plugins or a new browser, it is just necessary to register and then load the system homepage. Moreover, we use implicit feedback collection mechanism that requires no additional work from the user. The system structure is rather general in a sense that different data mining techniques can be implemented within the described framework. The methodology given here, once tested, can be moved to another domain, different from web search (see for instance [Sarini *et al.*, 2004]).

The rest of the paper is structured as follows. Section 2 describes the *Implicit* system in detail and Section 3 contains some experimental results on the use of our system. Final Sections 4 and 5 reviews related work and concludes the paper, respectively.

2 Structure of the System

In this section we present a detailed description of *Implicit*. The system exploits the notion of Implicit Culture [Blanzieri and Giorgini, 2000] to produce suggestions by means of peculiarities found in the community in which it works. Each user of the system has a dedicated personal agent whose task is to assist the user during his/her search and to provide him/her with the links in response to the entered keyword. For this purpose agents contact a search engine and produce recommendations by means of the Systems for Implicit Culture Support (SICS) module. This module uses implicit knowledge of the community members to find links that are considered relevant. Hereafter, by *relevant* links we mean links that are relevant to a certain keyword, from the agent's point of view. From the user's point of view, these links point to the relevant web pages. The framework that produces these links is universal in a sense that it is also exploited in order to discover which agents it would be useful to contact to obtain more relevant links. The general architecture of the system is represented in Figure 1.

Implicit consists of the client part and the server part. There is an html/php user interface on the client side. On the server side there are Java servlets and a multi-agent platform implemented using JADE (Java Agent Development Framework) [Bellifemine *et al.*, 2001]. JADE is a framework for developing multi-agent systems according to FIPA[2] standards. Here we present basic terms used in JADE and in our system.

A *personal agent* is an agent running on the server side that receives search tasks from its user and then produces recommendations in response to a query. The process of generating suggestions consists of several parts, implemented as behaviors. A *behavior* is a procedure that implements tasks, or intentions, of an agent. The agent is able to execute each task in response to different internal and external events. Behaviors are logical activity units that can be composed in various ways to achieve complex execution patterns and that can be concurrently executed. A *scheduler* is an internal agent component that automatically manages the scheduling of behaviors and determines which behavior to run now and what action to perform as a consequence. An *inbox* is a queue of incoming messages (ACL) from the user and from other agents. In order to produce recommendations agent uses its *resources* that consist of *beliefs* and *capabilities*. An agent's beliefs are the information available to the agent (e.g. information on user actions) and the capabilities are particular functionalities used in the behaviors (e.g. the SICS module). The structure of the personal agent is represented in Figure 2.

The basic sequence of actions while searching is as follows: a user logs into the system and enters a keyword. The interface generates a query message and sends it to the agent. When the agent receives the query message from the interface, it starts Search behavior. Search behavior produces results by means of internal (information about previous user searches) and external (communication with the agents) resources and these results are shown to the user.

The agent's Search behavior consists of the Google search behavior and the Platform search behavior, which comprises the Internal search behavior and the External search behavior. During the Google search behavior the agent process query

[2]FIPA. Foundation for Intelligent Physical Agents. `http://www.fipa.org/`.

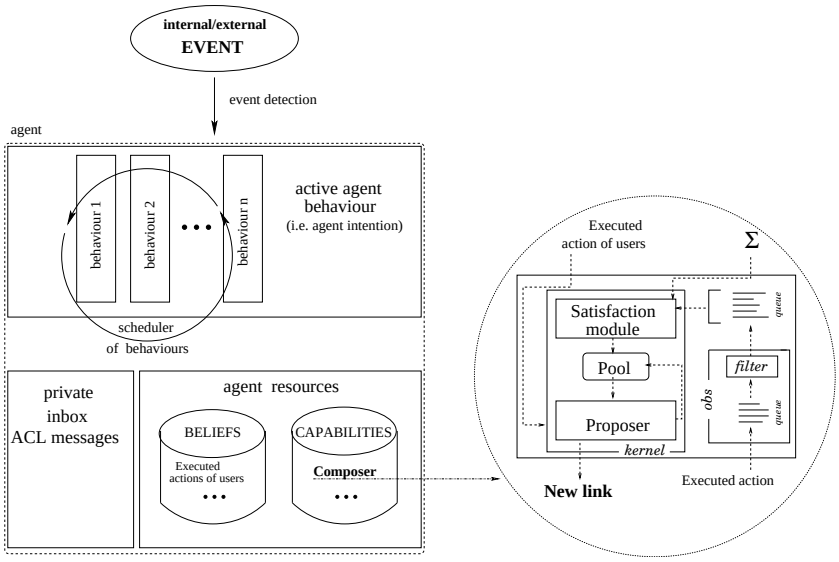

Figure 2: The internal architecture of the personal agent. Agent executes a *behavior* in response to different internal and external events. A *scheduler* manages execution of the behaviors. ACL messages received from the user or from other agents are stored in *inbox*. The *resources* consisting of *beliefs* (information available to the agent) and *capabilities* (available functionality) are used to produce suggestions. The *satisfaction module* selects links to the *pool* using behavior patterns produced by the *inductive module* from the observations on executed actions. The *proposer* selects the best link from the pool.

to Google search engine [Brin and Page, 1998] using Google Web API. As soon as the agent receives the answer, it shows the obtained links to the user and starts the Internal search behavior. In the Internal search the goal of the SICS module is to generate the http, ftp or resource links based on the past user actions. All the generated links are stored in the memory and the External search behavior is started. This behavior also uses the SICS, but the goal of the SICS in this case is to propose agents to contact. If there are no suggestions then agent contacts Directory Facilitator. Directory Facilitator (DF) according to the FIPA standards is a special agent that provides yellow pages service on the agent platform. Actually, in our case, DF simply provides the agent with the IDs of other personal agents on the platform. Having filled the list of agents to contact, personal agent starts an interaction — it sends a query to every member of the list. When all the agents are contacted the External search behavior queries new agents that were suggested during the search and so on. When all suggested agent queries have been answered the system shows all the obtained links to the user.

In the present implementation, the agent performs the three types of search in the following order: first the Google search, then the Internal search and finally, the External search. Agents may also query each other and in this case the respondent does not use the capability of contacting a search engine, because the questioner has this capability too. Agent-responder runs the Internal search behavior and uses its own observation history in order to produce links that the user of the agent-questioner will probably accept. It also starts the External search behavior in order to recommend to the questioner other agents to contact. The techniques used within these two behaviors are the same and are implemented within the SICS module.

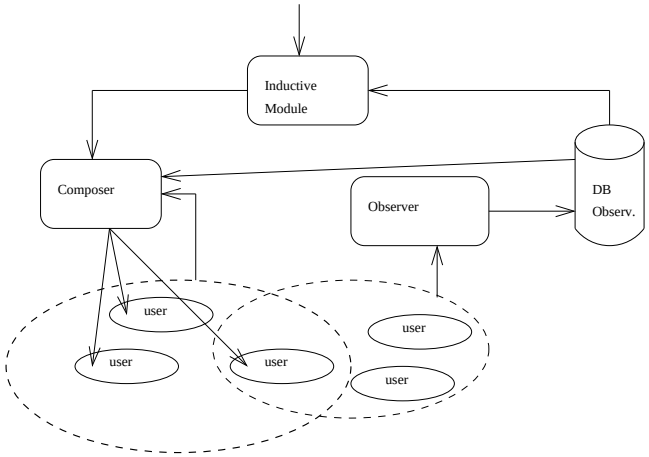

Figure 3: The System for Implicit Culture Support. The basic architecture for the System for Implicit Culture Support consists of the following three basic components: the *observer* that stores in a database (DB) the information about the executed user actions in order to make it available for other components; the *inductive module* that analyzes the executed actions in order to discover patterns of user behaviors; the *composer* that produces the links to suggest the user

The basic architecture for the SICS is shown in Figure 3 and consists of the following three basic components: the *observer module* is the part of the SICS that watches and records the actions performed by the user during the use of the system; the *inductive module*, analyzes the stored observations and implements data mining techniques to discover patterns in the user behavior; the *composer* exploits the information collected by the observer and analyzed by the inductive module in order to produce better suggestions to its user or to

other agents.

The SICS architecture requires the solution of two learning problems: a problem of browsing patterns learning (inductive module) and a problem of prediction of links the user will accept (composer). The inductive module problem is a rather standard learning problem: inducing the behavior patterns of the groups from the observations. The problem is not solved yet. The solution of the composer problem exploits the principles of instance-based learning (namely, memory-based or lazy learning). For more general description of these two problems see the work of Blanzieri et. al [2004].

The structure of the SICS allows the system to find out relevant links from the observations and to discover relevant agents using the same mechanism. The SICS calculates the similarity between the community members in order to produce suggestions. Therefore, it personalizes user's web search to a certain extent. For more detailed description of the SICS module, we refer the reader to the paper of Blanzieri et. al [2004].

Agents use Agent Communication Language (ACL) and standard FIPA protocols for link and agent ID exchange. There is also a feedback protocol for the exchange of information about accepted/rejected links. A feedback from one agent to another is sent as the result of the user browsing behavior. We illustrate the use of communication protocols by the following short example. More detailed description of the message passing and communication between agents an be found in [Birukov *et al.*, 2005].

For instance, a user searches information about *"train timetable"* and asks his/her personal agent, *pagent*. *Pagent* starts the Google search, the Internal and the External searches. After the Google search has finished the user has information about the links (we consider only the first three links for this example) provided by Google: *www.nationalrail.co.uk/planmyjourney, www.thetrainline.com* and *www.railtrack.co.uk*. The Internal search is then started in which the SICS module uses data mining techniques to select agents that performed similar actions and then selects the link accepted for the keyword *"train timetable"* by the agent with the highest similarity. During the External search behavior the SICS module selects agents that performed similar actions and chooses an agent likely to propose a link that will be accepted by the user. Let us suppose that SICS suggested the link *www.fs-on-line.it* during the Internal search and another agent to contact, *agent1*, during the External search. The personal agent sends a request to *agent1* using FIPA Iterated Contract Net Protocol. *Agent1* receives the request from *pagent* and uses its SICS module in order to produce suggestions. Let us consider that the Internal search behavior of *agent1* produced the link *www.trenitalia.it* selected from the links accepted by the *agent1*'s user in the past. As a result, *pagent* receives the link *www.trenitalia.it* and shows it to the user. If the user accepts the link *www.trenitalia.it* then *pagent* stores the information that this link has been accepted and sends this information (using feedback protocol) to *agent1* because it provided *pagent* with *www.trenitalia.it*. When the user leaves *Implicit* or starts a new search all the unaccepted links are considered rejected and all the agents involved in the dialog receive the communication. In our example, if the user does not accept *www.trenitalia.it* then *agent1* receives the message that this link is rejected. One of the benefits of our approach is that feedback is collected without any effort from the user, such as giving ratings to the items or specifying his/her interests.

It is possible to have some special agents in the platform. Although each agent encapsulates the ability of contacting the external search engine, it is also possible to use agents called wrappers for transferring the queries to other search engines like Yahoo! or Vivisimo. The Agent Resource Broker (ARB) is the special agent whose main purpose is to provide personal agents with the links to the services available on other platforms (wrappers for example). The system can use some sort of the locally available knowledge, e.g. "yellow pages" reference or bookmarks.

3 Experimental Results

In this section we present the experimental results obtained with the proposed platform. We also define the measures (precision and recall) estimating the quality of the recommendations produced by the SICS.

The aim of the experiment is to understand how the insertion of a new member into the community affects the relevance, in terms of precision and recall, of the links produced by the SICS. We also want to check the hypothesis that after a certain number of interactions, personal agents will be able to propose links accepted in previous searches.

In our experiment, interaction between agents and models of users replaces interaction between agents and actual users. A user model contains sequence of search keywords and results about link acceptance. The results are among the first m links provided by Google for each keyword and the rank of the list is adopted as an identifier. The links provided by Google for a certain keyword are reordered very quickly, therefore before the experiment we store the links in a dataset. During the simulation we use the dataset instead of contacting Google. User profile is a set of probabilities of choosing a specified link for a specified keyword. The profile is built using n keywords $k_1,\ k_2,\ \ldots,\ k_n$ and determining the probabilities $p(j|k_i)$ of choosing the j-th link, $j \in \{1, \ldots, m\}$ while searching with the i-th keyword. We assume that the user accepts one and only one link during search for the keyword k_i, so $\sum_{j=1}^{m} p(j|k_i) = 1$. The user profile can be seen as a set of association rules with a probability of acceptance of a certain link for a given keyword search. In our experiment the number of keywords n is equal to 10, the number of the links provided by Google, m is equal to 10, the user profile is represented in Table 1.

We use the following performance-related notions in order to evaluate the quality of the suggestions:

- Link is considered to be **relevant** to a particular keyword if the probability of its acceptance, as specified in the user profile, is greater than some pre-defined relevance threshold.
- **Precision** is the ratio of the number of relevant links suggested to the total number of irrelevant and relevant links suggested.

Table 1: Basic profile. The probabilities of acceptance links for a set of keywords. Links are numbered 1..10.

	Google rank of the link									
keyword	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
tourism	0	0	0.05	0.4	0.05	0.2	0.1	0.05	0.1	0.05
football	0.05	0	0.1	0.3	0.3	0.1	0.1	0.05	0	0
java	0.35	0.3	0.05	0.05	0.05	0.05	0.05	0.1	0	0
oracle	0.1	0.1	0.45	0.2	0	0.05	0.05	0	0	0.05
weather	0	0.3	0	0	0.5	0	0	0.1	0.1	0
cars	0	0	0.05	0.4	0.05	0.2	0.1	0.05	0.1	0.05
dogs	0.05	0	0.1	0.3	0.3	0.1	0.1	0.05	0	0
music	0.35	0.3	0.05	0.05	0.05	0.05	0.05	0.1	0	0
maps	0.1	0.1	0.45	0.2	0	0.05	0.05	0	0	0.05
games	0	0.3	0	0	0.5	0	0	0.1	0.1	0

- **Recall** is the ratio of the number of relevant links proposed to the total number of relevant links.

We compute recall in a slightly different way. The total number of relevant links is adjusted by adding a number of relevant links proposed by the agents to a number of relevant links presented in the user profile. We do it despite the fact that in reality the links from the agents already exist in the user profile, because in this way model of interactions becomes more similar to a real-life situation, where users (and their agents as well) have different collections of links. However, with such an interpretation of recall, the quality of system suggestions is underestimated.

Assuming that all the users are members of the same community and have similar interests, the profile for each user is derived from the basic profile given in Table 1. In order to make the users different, we add noise uniformly distributed in [0.00,...,0.05] to each entry of the profile. Then we renormalize entries in order to keep the sum of each row equal to one. Following this procedure we generate five different profiles.

From our set of 10 keywords for each agent we generate 25 sequences of 25 keywords by extraction with repetition. Each sequence is used for a search session modelling the user query behavior. We also need to model the user acceptance behavior. Given a keyword in the sequence of keywords, an accepted result is generated randomly according to the distribution specified in the profile. Other links obtained from the agents are marked as rejected.

In a simulation we run 25 search sessions for each agent in the platform. At the end of each session the observation data were deleted. The search sessions were repeated several times in order to control the effect of the order of the keywords and link acceptance. We run five simulations for 1,2,3,4 and 5 agents. With one agent in the platform, the agent acts alone without interactions with the others. With five agents there is a small community where agents interact with each other. We set the relevance threshold used to determine the relevance of links equal to 0.1.

We compute precision and recall of the links proposed by the agents. In Figure 4, line 1 represents precision of the links produced by the personal agent only. The SICS module incorporated in the agent produces these links by analyzing stored observations. Line 2 represents precision of the links proposed by all the agents including the personal one. The agents were discovered at the External search stage or provided by the DF. In Figure 5 we have analogous curves for

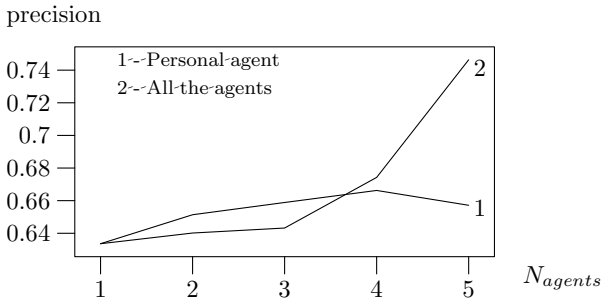

Figure 4: Average precision of 25 simulations with different number of agents.

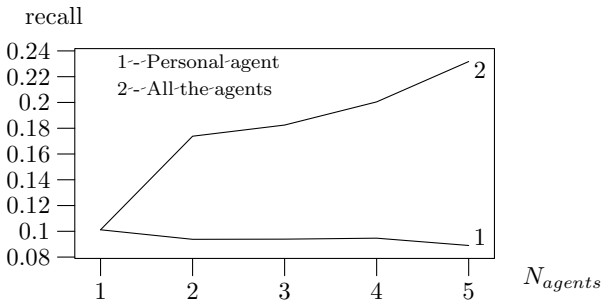

Figure 5: Average recall of 25 simulations with different number of agents.

recall.

From these figures we can note that the increase of community members causes the increase of the agents' recall. It is probably conditioned by the fact that when we have more agents we also have more interactions between them. The agents provide each other with only one link. The growth of the number of links provided by the agents during the search results in an increase of the percentage of relevant links proposed by the agents and causes an increase of recall. Moreover, the increase of recall appears without a decrease of precision and the precision keeps on a rather high level — from 0.63 to 0.75. The value of recall is also rather good and changes from 0.09 to 0.23. Because we limit ourselves to the small number of agents, the growing number of interactions does not really influence the characteristics. We also studied the statistical significance of the difference between agents with the same profile and in different simulations. We performed t-Tests with Bonferroni correction, namely dividing p-value by the number of tests we have performed, in order to control type I error. These tests prove that the average recall for 4 and 5 agents is consistently better ($p < 0.01$) than the average recall of the simulations with smaller number of agents. The results also prove the hypothesis that after a certain number of interactions, agents are able to propose links based on the past user actions.

In other words the obtained results prove that our method of complementing search engine with recommendations, produced as a result of collaboration, makes sense and allows a more qualitative web search.

For the moment we did not run yet any experiment for

a number of agents bigger than five. Therefore this paper contains only preliminary experimental results. We suppose, though we can not strongly claim that after a number of agents reaches a certain level, the increase of the community members causes only a moderate increment of the performance characteristics.

4 Related Work

In this section we briefly discuss related work.

A market-based recommender system is presented by Wei et. al [2003]. It is a multi-agent system where agent acts on behalf of its user and sells the slidebar space where recommendations can be displayed. Other agents participate in this auction in order to show their links on this slidebar. The agent-initiator of the auction chooses the most profitable offers and displays them to the user. Providers of the links accepted by the user receive reward. Agents adopt multiple heterogeneous recommendation methods and try to make better suggestions in order to increase their profit. The paper focuses more on the dynamic market behavior than on the recommendation quality evaluation.

A multi-agent recommender system is considered by Yu and Singh [2002]. MARS is a referral system for knowledge management that assigns software agent to each user. The agents interact in order to produce answers to the queries of their users. The agents are also able to give each other referrals to other users. There is a complex model of interactions in the system in a sense that it is important from who the query comes — there could be a different set of actions for the different agents. The system uses pre-determined ontologies, shared among all the agents, to facilitate knowledge sharing between them, while we emphasize the implicit support of knowledge by managing documents, links and references to people. Differently from our system, the agents do not answer all questions but only those related to their own user interests. The paper is focused more on knowledge (in general) search rather than on web search. Finally, the system is mail-based while *Implicit* is a web-based system that adopts FIPA standards and JADE platform.

Balabanović and Shoham present a recommender system Fab [Balabanović and Shoham, 1997] that combines collaborative and content-based filtering techniques. Personal selection agents analyze content of browsed web-pages and corresponding user ratings in order to maintain users profiles. Obtained profiles are compared using collaborative filtering algorithms and previously unseen items are recommended. Oppositely to using implicit feedback, the authors of this paper use explicit ratings, what requires a user to spend some time after browsing. Agents in Fab are divided into collection agents, who proactively gather pages relevant to a number of topics, and selection agents, who are dealing with discarding already browsed pages from the batch of the recommendations. The difference between Fab and *Implicit* is that our system filters not only links, but also agents. The framework we present is more general in a sense that different data mining algorithms can be implemented in order to produce recommendations. The ideas described in this paper can be deployed within different domains, e.g. Sarini et. al [Sarini *et al.*, 2004] describe application of Implicit Culture ideas to support the work of biologists in their laboratories. Yet another difference is that profiles in *Implicit* are not stored somewhere explicitly, but are spread around the agents and there is no explicit items ranking.

Freyne et. al [Freyne *et al.*, 2004] describe I-SPY meta-search engine that re-rank search results by taking into account previous searches of the similar users. The system architecture differs from the architecture of *Implicit* significantly, but the goals and the techniques are very similar. The engine uses adapters in order to query several external search engines. These queries then pass through the component that re-rank search results according to the hit matrix of previous searches. The system tends to capture preferences of the users and therefore adapts to the community where it is deployed. While I-SPY has fully centralized architecture, *Implicit* is technically centralized, but conceptually it is distributed due to the fact that profiles are spread around the agents. It uses collaboration between the agents to improve results. We also focus more on an organizational community rather than on an emergent or online one.

A collaborative multi-agent web mining system "Collaborative Spiders" is given by Chau et. al [2003]. There are different types of agents responsible for retrieving web pages, performing post-retrieval analysis, interacting with users, sharing information about user search sessions, performing profile matching and carrying out retrieval and analysis tasks according to a schedule. Before a search the user has to specify the area of the interests and privacy or publicity of the search. One of the sufficient differences between this system and *Implicit* is that the user should analyze excessive output looking through a number of similar already finished search sessions.

Zhu et. al [2005] present WebICLite - a recommender system that uses behavior models to predict relevant web pages. They conceptualize web browsing as a search for a specific well-defined information need and make assumption that this need can be identified from the pages visited by the user and from the actions that he/she performs on the pages. Several specific algorithms for identifying information-need-revealing patterns are considered and compared. The algorithms are used in order to turn the inferences about the user information needs into the queries for a standard search engine which does the actual retrieval of recommended pages. The system is browser-integrated and reformulates a query of the user without any collaboration and communication between different users.

Macedo et. al [2003] apply a recommender system approach to assist and to augment the natural social process of asking for recommendations from other people. WebMemex is a system that provides recommendations based on the browsing history of the people well-known to the users. To obtain the list of such users, a contact list from Yahoo Messenger is used. The system allows the user to keep privacy of web search by hiding his/her browsing for a certain time. The recommendations generated within the system are based on the links between the related documents visited by the users. On the server side there are no agents, but components that capture user behavior and generate recommendations.

5 Conclusion and Future Work

In this paper we have presented an agent-based recommender system that extracts implicit knowledge from user browsing behavior. The knowledge is necessary to suggest links or agents to a group of people and to their personal agents. Personal agents use universal mechanism to produce suggestions about links and agents IDs. Learning capabilities are used by agents to produce results even without an interaction. Interactions allow a user to use the already acquired experience of the members of his/her community. This increases the quality of the search. The process of collecting feedback and producing recommendations is completely hidden from the user and therefore does not require any kind of extra work from the user.

Implicit can be modified in several ways. It could be enhanced with the capability of analyzing content of visited web pages. In this way it would combine content-based and collaborative approaches. Classification of the users on "experts" and "novices" could also be implemented in order to take into account information about the author of the recommendation.

We use rather simple user model in this paper in order to test our system, and results presented here are preliminary. In the future, we plan to conduct some experiments with the participation of the real users.

6 Acknowledgements

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