UNIVERSITY
OF TRENTO

DEPARTMENT OF INFORMATION AND COMMUNICATION TECHNOLOGY

38050 Povo – Trento (Italy), Via Sommarive 14
http://www.dit.unitn.it

IMPLICIT CULTURE AS A TOOL FOR SOCIAL NAVIGATION.

Aliaksandr Birukou, Enrico Blanzieri and Paolo Giorgini

March 2006

Technical Report # DIT-06-018

Implicit Culture as a Tool for Social Navigation

Aliaksandr Birukou, Enrico Blanzieri, and Paolo Giorgini

University of Trento, via Sommarive 14, 38050 Povo (Trento), Italy
{aliaksandr.birukou, enrico.blanzieri, paolo.giorgini}@dit.unitn.it,
WWW home page: http://dit.unitn.it/~implicit

Abstract. Very often people tend to behave as other people behaved previously. This happens in many different situations, for instance when one has to choose the path in a forest or when she/he has to select a link in the web. Social Navigation aims at providing assistance in such situations supporting the decision making process. Implicit Culture is a recent approach in which people are encouraged (induced) to behave according to usual behavior of the community. This paper shows similarities between Social Navigation and Implicit Culture and it presents a case study about user preferences learning.

1 Introduction

Ideas of Social Navigation [1, 2] are widely applied to the design of information spaces [3] and they also find application in the design of information systems [4–6]. The main objective of Social Navigation is to help people to take decisions using directly or indirectly information from other people. Dieberger et al. [2] introduce several styles of social navigation systems: *recommendation systems*, which help people to make choice by looking at what other people with similar interests have done; *populated spaces*, which use the idea of a populated space in which other people can be encountered; and *"history-enriched" systems*, which use the history of previous activities over information to guide the user.

Implicit Culture ideas have been recently introduced [7] and applied in several information systems [8–10]. The three main steps of Implicit Culture approach are the following: the behavior of a group of people is observed; then the behavior is analyzed and some behavioral patterns are discovered; patterns are used to help another (or the same) group of people to behave similarly to the observed group. All this allows a person to use information about others' behavior in similar situations.

We see the problem of guiding people to relevant information as one of the main problems arising in Social Navigation. The problem consists in providing an efficient access to a possibly huge and dynamically changing amount of available information. Information filtering problem has been addressed by techniques like Collaborative Filtering [11]. Implicit Culture is a generalization [7] of Collaborative Filtering and in this paper, we show that it can be used as a tool for Social Navigation, and in particular, for information systems. We describe how Implicit Culture can contribute to the design of different social navigation systems and we give an example of such a system.

The paper has the following structure. In Section 2 we describe the relation between Implicit Culture and Social Navigation and we show what problems can be solved using Implicit Culture. Section 3 presents the case study about Implicit Culture-based recommendation system for web search. We show that the system is able to learn community preferences about selecting links relevant to their interests. We conclude the paper in Section 4.

2 Applying Implicit Culture to Social Navigation

In this section we describe basic ideas of Implicit Culture and show the relation between Implicit Culture and Social Navigation.

When a person has to act in an unknown environment his/her behavior is far to be optimal. We can think of many situations where due to the lack of knowledge, it becomes hard for the person to take the right decision (e.g., cultural shocks). This, of course, is not the case for people that have been in similar situations previously. Indeed, they have acquired the necessary knowledge to act effectively in the environment. This knowledge, which we introduce as "community culture", very often results in being implicit, i.e. it is not represented by means of documents and/or information bases.

Implicit Culture is based on the assumption that it is possible to elicit the "community culture" by observing the interactions of other people with the environment and to encourage the newcomer(s) to behave similarly to more experienced (in these settings) people. This "culture" is then used to provide newcomers with information about others' behavior in similar situations. When newcomers start to behave similarly to the community culture (i.e. when they have been navigated in a proper way) we can speak of knowledge transfer. In Implicit Culture framework there is the so called SICS (System for Implicit Culture Support) to perform this knowledge transfer. The relation characterized by this knowledge transfer is called *"Implicit Culture"* [12].

For example, let us consider a child who does not know that it is common to clean the table after he/she had a dinner. Let us assume that he/she is eager to do it, but this idea just does not come to his mind. Obviously, for an adult cleaning the table after the meal just becomes automatic. If the system is able to use previous history to suggest the child to clean the table and he/she actually does it, then it is possible to say that he/she behaves in accordance with the community culture and that the Implicit Culture relation is established.

The general architecture of the SICS [12] consists of the following three components: the *observer* that stores in a database of observations information about actions executed by users in different situations; the *inductive module* which analyzes the stored observations and applies data mining techniques to find which actions are common in which situations; the *composer* that exploits the information collected by the observer and analyzed by the inductive module in order to suggest actions in a given situation.

It is necessary to stress that although the SICS encourages the desired behavior of the community members, it does not control the decision-making process and it is the user that takes the final decision. The importance of all this with respect to Social Navigation in the online world has been described in Dieberger et al. [2].

Establishing an Implicit Culture relation by means of SICS's can be considered as a particular case of Social Navigation. The two key properties of the Social Navigation phenomena, *personalization* and *dynamism* [2], are present in Implicit Culture-based systems: when producing suggestions, the SICS is focused on a particular person and the situation this person currently encounters; suggestions of the SICS can change as new actions become common for the people in the same situations. Also, both approaches are dealing with processing of users' feedback in order to support information navigation.

In building information systems there is also the need for "[...] facilities that make us aware of other people's activities and select ones that seem appropriate for the task[...]" [2]. Implicit Culture provides a facility that helps a newcomer to obtain information about the behavior of other people.

The work of Dieberger et al. [2] introduces several styles of social navigation systems. Here we list these styles consistently with [2] and describe a possible use of Implicit Culture there.

Recommendation systems. These systems help people to make choice by looking at what other people with similar interests have done. It is also considered as using of the traces of people's activities in the system. Implicit Culture ideas are successfully applied in the recommendation system for web search [8] and in the system that helps a user to search for publications relevant to the topic he/she is interested in [9].

Populated spaces. Some Social Navigation tools use the idea of a populated space in which other people can be encountered. Partially, we have used this idea when developing the recommendation system for web search [8]: users of the system receive recommendation not just from the system but from the other community members they are familiar with. Although it is a user's personal agent who gives suggestion, it is the actions of the user which are analyzed to produce this suggestion. Therefore, a user can think of suggestions as of coming directly from a known person.

"History-enriched" systems. In this type of systems the history of previous activities over information is used to guide the user. Considered examples of selecting links based on recent traffic of the pages and other means of recording "footprints" of others [13] are somehow illustrated by the case study we present in Section 3.

3 A Case Study

In this section we shortly describe a concrete application of Implicit Culture to Social Navigation. We present a system that helps to discover web links that are relevant to specific interests of a community of people. We present also preliminary experimental results which proof the possibility of using Implicit Culture-based recommendation system for learning footprints of the community members in searching the Internet.

3.1 The System

In multi-agent recommendation system Implicit [8], Implicit Culture has been applied in the task of suggesting relevant links to the community members. In this system users are assisted by their personal agents in searching the Internet. Agents running at server side process users' queries submitted via an html/php user interface at the client side. SICS's are used by the agents to produce suggestions, based on the history of interactions of others with the system. Suggestions, extracted from users' history and complemented with links provided by Google are displayed in the user's browser. Figure 1 depicts the user interface of the system.

Implicit differs from existing tools, like, for example, common search engines, because it is intended for communities with specific common interests (e.g. PhD students of the same department, or members of the same project team) and helps to find links relevant to their specific interests.

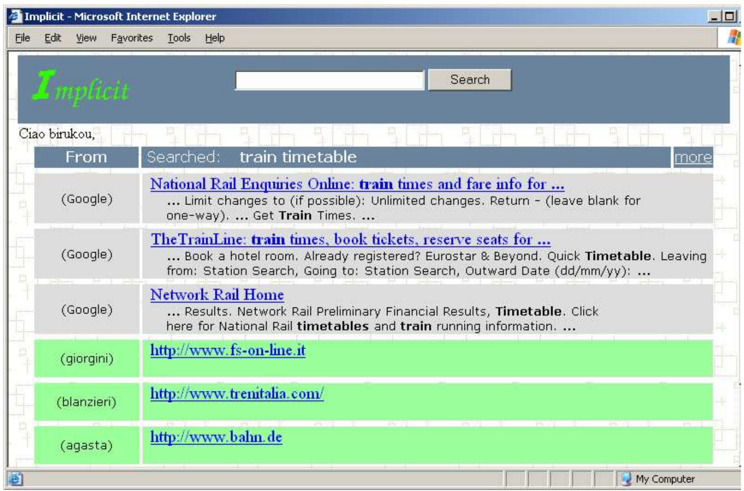

Fig. 1. User interface of Implicit. Suggestions from other users are depicted in the bottom part of the window, while Google links are shown in the top part.

3.2 Apriori algorithm

In the version of the system used in the experiment the SICS implements Apriori algorithm. This algorithm has been described by Agrawal and Ramakrishnan [14] and it deals with the problem of association rules mining which in our settings can be briefly formulated in a following way: given a database of requests and links to find which links are accepted for which keywords. Not going into the details of the algorithm, we say that mined rules have the form $keyword \rightarrow link$ and are characterized by confidence and support. In our settings, the *confidence* of a rule denotes the fraction of cases when the *link* from the rule was accepted for the *keyword* from the rule. The *support* denotes the fraction of the actions in the database which contain this rule. In the experiment, we are focused on the confidence of the rules.

3.3 Experiment

In [8] we presented numerical results which illustrated, in terms of precision and recall, the utility of the suggestions produced by the system. The goal of the experiment described below was to show that SICS is capable of learning web surfing behavior of the community that uses the system.

To conduct experiment we used a simulator developed for Implicit. Interaction between agents and users is replaced with interaction between agents and user models. Differently from the scenario used in [8], where each personal agent used SICS for creating recommendations, we use only one SICS in the community that collects the information about actions of all users. A user model contains user profile which determines a sequence of search keywords and click-through rate of the acceptance of the results. In our experiment, each profile contains 10 keywords and 10 links for each keyword (see Table 1). From this profile we generated 5 similar profiles, slightly varying entries by adding noise. Each profile with noise represented one user model in our simulations. Since experimental settings are close to those described in [8] we refer the reader to that paper for additional information about profiles construction mechanism and other details.

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

From our set of 10 keywords for each agent we generated 20 sequences of 25 keywords, 20 sequences of 50 keywords, and 20 sequences of 100 keywords by extraction with repetition. Each sequence is used for a search session modelling the user query behavior. User acceptance behavior is modelled as follows: given a keyword in the sequence, accepted result is generated randomly according to the distribution specified in the profile; other links are marked as rejected. In a simulation we run 20 search sessions for each agent, deleting observation data after each session. We performed simulations for 25, 50 and 100 keywords in a search session.

We compared the confidence of the rules learned by SICS with the acceptance rate initially specified in the profile. For one of the keywords, the results averaged out the number of sessions are illustrated in Figure 2. The results suggest that the system is capable of learning users' preferences with respect to the selection of links. The learned preferences can be used for navigating people towards relevant information. For examples, the way the experts select links relevant to their interests can be used to guide novices.

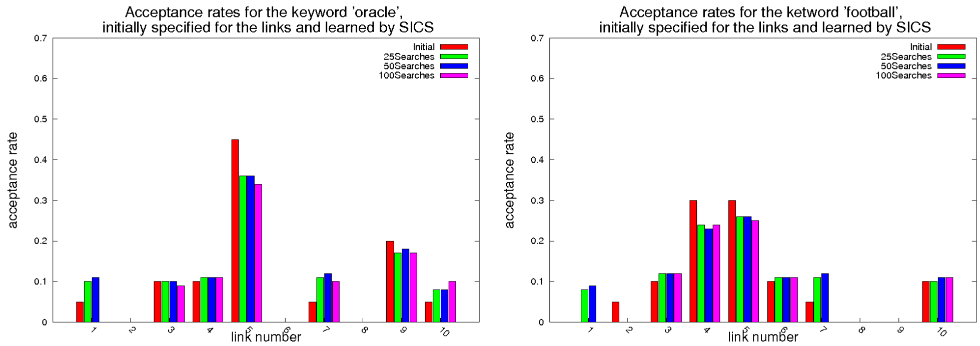

Fig. 2. Acceptance rate for the keywords "oracle" and "football" specified initially and the confidence of the rules learned after 25, 50 and 100 searches

4 Conclusion

Implicit Culture ideas have been already presented in a number of papers (see e.g. [7, 12]). This paper introduces and discusses the relation between Implicit Culture and Social Navigation. We have briefly presented Implicit Culture concept and showed that it can be used as a tool for Social Navigation.

Our approach is particularly related to the problem of Social Navigation on the Internet (online navigation), described in [15]. Konstan and Riedl claim that "[...]some forms of Social Navigation are very closely related to Collaborative Filtering[...]" [16]. Implicit Culture is more general than Collaborative Filtering [11], being able to filter not only items based on the given ratings, but actions in general [7]. Since Implicit Culture is a generalization of Collaborative Filtering, it can be use instead of Collaborative Filtering in Social Navigation systems. It allows using a wide set of algorithms in the inductive module of a

SICS, e.g. Apriori algorithm for mining association rules, which use has been illustrated in this paper.

The experimental results presented in this paper are preliminary in a sense that the possibility of using learned footprints for guiding people is not yet shown. We are planning to elaborate it as a part of future work.

5 Acknowledgements

This work is funded by research projects EU SERENITY "System Engineering for Security and Dependability", COFIN "Artificial Intelligence Techniques for the Retrieval of High Quality Information on the Web" and by Fondo Progetti PAT, MOSTRO "Modeling Security and Trust Relationships within Organizations" and QUIEW (Quality-based indexing of the Web), art. 9, Legge Provinciale 3/2000, DGP n. 1587 dd. 09/07/04.

References

1. Dourish, P., Chalmers, M.: Running out of space: Models of information navigation, short paper. In: HCI'94, Glasgow (1994)
2. Dieberger, A., Dourish, P., Höök, K., Resnick, P., Wexelblat, A.: Social navigation: Techniques for building more usable systems. interactions **7**(6) (2000) 36–45
3. Höök, K., Benyon, D., Munro, A.J., eds.: Designing information spaces: the social navigation approach. Springer-Verlag, London, UK (2003)
4. Brusilovsky, P., Chavan, G., Farzan, R.: Social adaptive navigation support for open corpus electronic textbooks. In: Adaptive Hypermedia and Adaptive Web-Based Systems, Third International Conference, AH 2004, Eindhoven, The Netherlands (2004) 24–33
5. Dieberger, A., Guzdial, M.: CoWeb - Experiences with Collaborative Web spaces. Computer Supported Cooperative Work. In: From Usenet to CoWebs: Interacting with Social Information Spaces. Springer (2003) 155–166
6. Svensson, M., Höök, K.: Social Navigation of Food Recipes: Designing Kalas. In: Designing Information Spaces: The Social Navigation Approach. Springer Verlag (2003) 201–222
7. Blanzieri, E., Giorgini, P.: From collaborative filtering to implicit culture: a general agent-based framework. In: Proceedings of the Workshop on Agents and Recommender Systems, Barcellona (2000)
8. Birukov, A., Blanzieri, E., Giorgini, P.: Implicit: An agent-based recommendation system for web search. In: AAMAS '05: Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems, ACM Press (2005) 618–624
9. Birukou, A., Blanzieri, E., Giorgini, P.: A multi-agent system that facilitates scientific publications search. In: AAMAS '06: Proceedings of the fifth international joint conference on Autonomous agents and multiagent systems. To appear. (2006)
10. Sarini, M., Blanzieri, E., Giorgini, P., Moser, C.: From actions to suggestions: supporting the work of biologists through laboratory notebooks. In: Proceedings of 6th International Conference on the Design of Cooperative Systems (COOP2004), French Riviera, France, IOSPress (2004) 131–146

11. Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., Riedl, J.: Grouplens: an open architecture for collaborative filtering of netnews. In: CSCW '94: Proceedings of the 1994 ACM conference on Computer supported cooperative work, Chapel Hill, North Carolina, United States, ACM Press (1994) 175–186
12. Blanzieri, E., Giorgini, P., Massa, P., Recla, S.: Implicit culture for multi-agent interaction support. In Batini, C., Giunchiglia, F., Giorgini, P., Mecella, M., eds.: CooplS '01: Proceedings of the 9th International Conference on Cooperative Information Systems. Volume 2172 of Lecture Notes in Computer Science (LNCS)., London, UK, Springer-Verlag (2001) 27–39
13. Brusilovsky, P., Farzan, R., wook Ahn, J.: Comprehensive personalized information access in an educational digital library. In: JCDL '05: Proceedings of the 5th ACM/IEEE-CS joint conference on Digital libraries, New York, NY, USA, ACM Press (2005) 9–18
14. Agrawal, R., Srikant, R.: Fast algorithms for mining association rules in large databases. In: VLDB '94: Proceedings of the 20th International Conference on Very Large Data Bases, San Francisco, CA, USA, Morgan Kaufmann Publishers Inc. (1994) 487–499
15. Dieberger, A.: Supporting social navigation on the world wide web. Int. J. Human-Computer Studies **46** (1997) 805–825
16. Konstan, J.A., Riedl, J.: Collaborative Filtering: Supporting Social Navigation in Large, Crowded Infospaces. In: Designing Information Spaces: The Social Navigation Approach. Springer Verlag (2003) 43–82