Implicit Culture as a Tool for Social Navigation

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Abstract. Very often people tend to behave like other people behaved previously. This happens in many situations ranging from when one chooses the path in a forest to when she/he selects a link on 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 to behave according to the "usual" behavior of the community. This paper shows that Implicit Culture can be applied to Social Navigation problems and it presents a case study about the learning of user preferences.

1 Introduction

Ideas of Social Navigation [1, 2] have proven to be useful in the design of information systems [3–6]. The main objective of Social Navigation is to help people to take decisions by 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 a choice by looking at what other people with similar interests have chosen; *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 actions 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 the 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; the patterns are used to help another (or the same) group to behave similarly to the observed group. All this allows a person to use the information about others' behavior in similar situations.

This paper shows that Implicit Culture can be used as a tool for dealing with some Social Navigation problems, in particular, with the problem of guiding people to relevant information. We see this problem as one of the main problems arising in Social Navigation and it consists in providing efficient access to a possibly huge and dynamically changing amount of information available. We briefly present Implicit Culture in Section 2. Then, in Section 3 we describe how Implicit Culture can contribute to the design of different Social Navigation systems and we give an example of such a system in Section 4. We would like to stress that the purpose of the case study is to illustrate the use of Implicit

Culture as a tool for Social Navigation and the main contribution of the paper is not the system used in the case study, but the description of the relation between Implicit Culture and Social Navigation. We conclude the paper in Section 6.

2 Implicit Culture

When a person has to act in an unknown social environment his/her behavior is far from 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., culture shock). However, this 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 a "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 people with the environment and to encourage the newcomer(s) to behave similarly to more experienced people. Implicit Culture assumes that *agents* perform *actions* on *objects* in the *environment* (see [11] for more details). The actions are considered in the context of *situations*, and therefore we say that agents perform *situated actions*. The "culture" contains information about actions and their relation to situation, namely which actions are usually taken by the observed group in which situations. This information 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 navigate in a proper way) the knowledge transfer occurs. This knowledge transfer is performed by the SICS (System for Implicit Culture Support) and the relation characterized by this knowledge transfer is called *Implicit Culture* [11]: "Implicit Culture is a relation between a set and a group of agents such that the elements of the set behave according to the culture of the group" [11].

The general architecture of the SICS [11] consists of the following three components: the *observer*, which uses a database of observations to store information about actions performed by users in different situations; the *inductive module*, which analyzes the stored observations and applies data mining techniques to find a *theory* about the community culture; the *composer*, which exploits the information collected by the observer and the theory in order to suggest actions in a given situation. Further actions of the user can contain feedback to the suggestions. A part of the theory used by the composer can be specified a priori (domain theory), while the other part must be learnt by the inductive module and can evolve over time. For instance, in the presented case study (Section 4) the domain theory says that the system must recommend links which are likely to be accepted by the user, while the theory learnt by the inductive module contains information about which links are accepted for which keywords.

We illustrate Implicit Culture by the following example. Let us consider a child who does not know that it is common to clean the table after he/she has had dinner. Let us assume that he/she would be eager to do it, but this idea just does not come to his mind. Obviously, for an adult cleaning the table after the meal becomes automatic. If the system is able to use previous history to suggest that the child 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.

3 Applying Implicit Culture to Social Navigation

Establishing the Implicit Culture relation by means of SICSs can be considered as a particular case of Social Navigation. Implicit Culture-based systems manifest the two key properties of the Social Navigation phenomenon, namely *personalization* and *dynamism* [2]: when producing suggestions, the SICS focuses on a particular person and the situation this person currently encounters; suggestions of the SICS can change as new actions become common for the observed group in the same situations (the evolution of the theory). Also, both Implicit Culture and Social Navigation deal with processing of users' feedback in order to support information navigation. However, differently from Social Navigation, Implicit Culture allows for a formal description of the navigation process [11].

The work of Dieberger et al. [2] introduces several styles of Social Navigation systems. Here these styles are listed consistently with [2] and the possible use of Implicit Culture for each type is described.

Recommendation systems. These systems help people to make a choice by looking at what other people with similar interests have done. It can also be considered as using of the traces of people's activities in the system. Implicit Culture ideas have been successfully applied in the recommendation system for web search, described in [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 recommendations not just from the system but from the other community members they are familiar with. Although it is a user's personal agent (not the user himself) who gives suggestions, it analyzes actions of the user to produce these suggestions. Therefore, suggestions can be considered as information 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 [12] are somehow addressed by the case study we present in Section 4.

Finally, 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 who 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].

4 A Case Study

In this section we briefly describe a concrete application of Implicit Culture to Social Navigation. The multi-agent recommendation system *Implicit* has been described in [8] and it helps to discover web links that are relevant to specific interests of a community of people. In *Implicit* users are assisted by their personal agents in searching the Internet. Agents run at the server side and process users' queries submitted via an html/php user interface at the client side. SICSs are used by the agents to produce suggestions, based on the history of interactions of users with the system. Suggestions, extracted from users' history and complemented with links provided by Google, are displayed in the user's browser.

The numerical results presented in [8] illustrated the utility of the suggestions produced by the system. In that paper we have shown that the system with the SICS outperformed, in terms of precision and recall, the system without the SICS in a simple simulated scenario. Here we use the same experimental scenario in order to explore the possibility of using rule mining algorithm for learning the theory that describes the community culture. Our motivation is to eventually include the algorithm in the inductive module of the SICS. The goal of the experiment presented in this section is twofold: (i) to show that the Apriori algorithm [13] is viable for learning associations between keywords and links and (ii) to see if there are differences between the specified community preferences and the way people actually select links using the system.

The Apriori algorithm deals with the problem of association rules mining. In our settings, this problem can be briefly formulated in the following way: given a database of requests and links, to find which links are accepted for which keywords. The mined rules have the form $keyword \rightarrow link$ and are characterized by confidence and support[1]. In the experiment, we focus on the confidence of the rules.

To conduct the experiment we used a simulator developed for *Implicit*. Interaction between agents and users is replaced with interaction between agents and user models. A user model contains a user profile which determines a sequence of search keywords and the 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. The model of user preferences similar to the model we used in this experiment is described in [14]. Also, in the presented experiment, we consider keeping queries intact, without splitting them into individual keywords. Since experimental settings are close to those described in [8], we refer the reader to that paper for additional information about adding noise and other details.

[1] *confidence* is the fraction of cases when the *link* has been accepted for the *keyword*; *support* is the fraction of the actions in the database which contain the rule

Table 1. Basic profile. The probabilities of acceptance of 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 models a user's search session and each keyword in the sequence corresponds to one query. For instance, 20 sequences of 50 keywords correspond to 20 sessions of 50 queries each. User's acceptance behavior is modelled as follows: given a keyword in the sequence, the accepted result is generated randomly according to the distribution specified in the profile; other links are marked as rejected. In the 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 learnt by the algorithm with the acceptance rate initially specified in the profile. For two of the keywords, the results averaged over the number of sessions are shown in Figure 1. These results illustrate the general trend, the average Euclidean distance between the composer's clickthrough rate and that specified in the profile (for all keywords) is 0.09408 (variance = 0.00039), 0.15933 (variance = 0.00032), and 0.13625 (variance = 0.00039) for 25, 50 and 100 searches correspondingly. The differences are limited in value and they change significantly as the number of searches changes. This means that the algorithm is effective in capturing the preference-driven behavior of the simulated users. Moreover, the results suggest that the Social Navigation phenomenon occurs in the system, namely interactions among people influence the way they select links, without changing their preferences. Of course, we must admit that the chosen user model may have an impact on the results obtained.

5 Related Work

Although Implicit Culture has been already presented in a number of papers (see e.g. [7, 11]) and applied in a number of applications [8–10], its relation to Social Navigation has not been discussed before. Essentially, Implicit Culture and Social Navigation are very similar and have been applied in alike settings. Implicit Culture does not cover all the scope of the Social Navigation problems, and it has been formally defined [11] as a relation between groups of agents. The definition emphasizes the implicit transfer of knowledge between groups

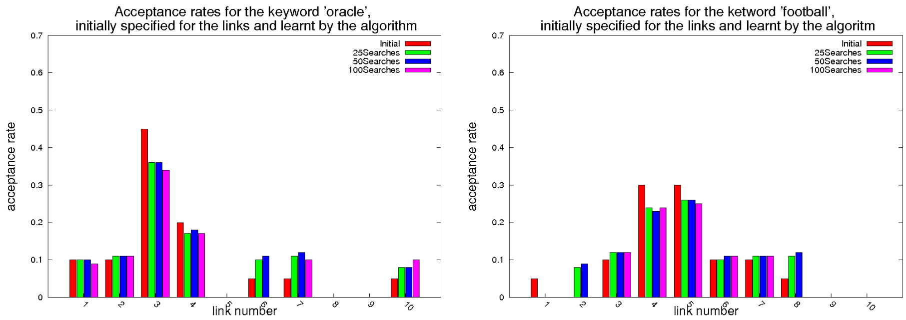

Fig. 1. Acceptance rate for the keywords "oracle" and "football" specified initially and the confidence of the rules learnt after 25, 50 and 100 searches

and permits to evaluate whether the Implicit Culture relation arises from some system usage. It can be argued that some effective Social Navigation systems produce such a relation. On the other hand, Social Navigation systems supporting awareness (e.g. social proxies [15]) do not necessarily produce the Implicit Culture relation. We foresee the possibility of using Implicit Culture as a tool for building, assessing and evaluating Social Navigation systems.

The Implicit Culture approach (with respect to its application to web search) is particularly related to the problem of Social Navigation on the Internet (online navigation), described in [16] and to the social search engines, like I-Spy [6] and Eurekster[2]. However, our approach differs from these systems. Firstly, Implicit Culture focuses more on an organizational community, rather than on an emergent or online one. Secondly, it uses collaboration and interactions among agents to improve suggestions. Finally, the Implicit Culture approach has applications not only in web search, but in a number of completely different areas, see e.g. [10] for the work on supporting biologists in their working activities or assisting designers in choosing a design pattern [17].

Mathé and Chen [18] provide a mechanism for user-centered adaptive information retrieval and navigation. This work focuses on customized information access for individual users and groups of users. Implicit Culture focuses more on the culture of the whole group, though it still takes into account behavior of an individual user. Differently from Mathé and Chen, the main goal of Implicit Culture mechanism is to help a user to deal with an unfamiliar situation while they focus on repetitive ones, providing a "goody book" that contains information about the user's behavior with respect to various tasks performed on regular basis.

According to Konstan and Riedl, "[...]some forms of Social Navigation are very closely related to Collaborative Filtering[...]" [19]. In [7] it has been shown that Collaborative Filtering(CF) is a particular case of the general SICS architecture: the theory is specified a priori and is not updated over time, therefore

[2] Eurekster. http://www.eurekster.com/

the inductive module is not necessary. The composer module in the SICS for CF plays the main role in the process of producing recommendations. It selects potentially relevant items by comparing actions of "rating". In the general architecture of the SICS, actions are not restricted to the actions of "rating". Moreover, the theory can evolve over time, incorporating the essence of the history of observations. Since Implicit Culture is a generalization of CF, it can be used instead of CF in Social Navigation systems. It allows for the use of a wide set of algorithms in the inductive module of a SICS, e.g. the Apriori algorithm for mining association rules.

The Implicit Culture approach applied in the selected case study is related to swarm intelligence theories (in particular, to trail laying, or ant foraging). These theories have been applied in Social Navigation systems [20, 21] to guide people (e.g. learners) to relevant information using the data from previous interactions with the system. Unlike these approaches, which suggest that the user follow trails taken by the majority, in the Implicit Culture approach the user's actions are compared with actions of the whole community and not necessarily the most popular ones are suggested. More precisely, taking into account user's past actions, the system can offer actions which are less popular in general, but are common among the part of the community which is the most similar to the user.

6 Conclusion and Future Work

The paper has illustrated the relation between Implicit Culture and Social Navigation. Essentially, the approaches are very similar and Implicit Culture can be considered as an attempt to provide a tool for dealing with some Social Navigation problems. The experimental results presented in this paper are preliminary. We are planning to include the Apriori algorithm in the inductive module of SICS as a part of future work.

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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. Brusilovsky, P., Chavan, G., Farzan, R.: Social adaptive navigation support for open corpus electronic textbooks. In: AH 2004, Eindhoven (2004) 24–33
4. 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
5. Svensson, M., Höök, K.: Social Navigation of Food Recipes: Designing Kalas. In: Designing Information Spaces: The Social Navigation Approach. Springer (2003) 201–222
6. Smyth, B., Balfe, E., Freyne, J., Briggs, P., Coyle, M., Boydell, O.: Exploiting query repetition and regularity in an adaptive community-based web search engine. User Modeling and User-Adapted Interaction **14**(5) (2005) 383–423
7. Blanzieri, E., Giorgini, P.: From collaborative filtering to implicit culture: a general agent-based framework. In: Proc. of the Workshop on Agents and Recommender Systems, Barcelona (2000)
8. Birukov, A., Blanzieri, E., Giorgini, P.: Implicit: An agent-based recommendation system for web search. In: AAMAS '05, ACM Press (2005) 618–624
9. Birukou, A., Blanzieri, E., Giorgini, P.: A multi-agent system that facilitates scientific publications search. In: AAMAS '06, ACM Press (2006) 265–272
10. Sarini, M., Blanzieri, E., Giorgini, P., Moser, C.: From actions to suggestions: supporting the work of biologists through laboratory notebooks. In: Proc. of 6th International Conference on the Design of Cooperative Systems (COOP2004), French Riviera, France, IOSPress (2004) 131–146
11. Blanzieri, E., Giorgini, P., Massa, P., Recla, S.: Implicit culture for multi-agent interaction support. In: CooplS '01: Proc. of the 9th International Conference on Cooperative Information Systems, Springer (2001) 27–39
12. Brusilovsky, P., Farzan, R., Ahn, J.: Comprehensive personalized information access in an educational digital library. In: JCDL '05: Proc. of the 5th ACM/IEEE-CS joint conference on Digital libraries, ACM Press (2005) 9–18
13. Agrawal, R., Srikant, R.: Fast algorithms for mining association rules in large databases. In: VLDB '94, Morgan Kaufmann (1994) 487–499
14. August, K.G., Hansen, M.H., Shriver, E.: Mobile web searching. Bell Labs Technical Journal **6**(2) (2001) 84–98
15. Erickson, T., Kellogg, W.A.: Social Translucence: Using Minimalist Visualisations of Social Activity to Support Collective Interaction. In: Designing Information Spaces: The Social Navigation Approach. Springer (2003) 17–41
16. Dieberger, A.: Supporting social navigation on the world wide web. Int. J. Human-Computer Studies **46** (1997) 805–825
17. Birukou, A., Blanzieri, E., Giorgini, P.: Choosing the right desing pattern: the implicit culture approach. In: Proc. of the Workshop on Multi-Agent Systems and Simulation at the Industrial Simulation Conference 2006 (ISC-2006). (2006)
18. Mathé, N., Chen, J.R.: User-centered indexing for adaptive information access. User Modeling and User-Adapted Interaction **6** (1996) 225–261
19. Konstan, J.A., Riedl, J.: Collaborative Filtering: Supporting Social Navigation in Large, Crowded Infospaces. In: Designing Information Spaces: The Social Navigation Approach. Springer (2003) 43–82
20. Dron, J.: Control, termites and e-learning. In: Proc. of IADIS International Conference Web Based Communities 2005. (2005) 103–110
21. van den Berg, B., van Es, R., Tattersall, C., Janssen, J., Manderveld, J., Brouns, F., Kurvers, H., Koper, R.: Swarm-based sequencing recommendations in e-learning. In: Proc. of the 5th International Conference on Intelligent Systems Design and Applications (ISDA05). (2005)