"The Devil You Know Knows Best" – How Online Recommendations Can Benefit From Social Networking

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ABSTRACT
The defining characteristics of the Internet today is an abundance of information and choice. Recommender Systems (RS), designed to alleviate this problem, have so far not been very successful, and recent research suggests that this is due to the lack of the social context and inter-personal trust. We simulated an online film RS with 60 participants, where recommender information was added to the recommendations, and a subset of these were attributed to friends of the participants. Participants overwhelmingly preferred recommendations from familiar recommenders with whom they shared interests and a high rating overlap. When recommenders were familiar, rating overlap was the most important decision factor, whereas when they were unfamiliar, the combination of profile similarity and rating overlap was important. We recommend that RS and social networking functionality should be integrated, and show how RS functionality can be added to an existing social networking system by visualising profile similarity.

Categories and Subject Descriptors
H.5.3. Information interfaces and presentation (e.g., HCI): Group and Organization Interfaces - Collaborative Computing.

General Terms
Design, Human Factors.

Keywords
Recommender systems, online advice-seeking, social networking, decision support.

1. INTRODUCTION
The Internet has evolved significantly since its early days as a mere source of information. Where previously users would predominantly interact with content offered by professional services, today they actively contribute to the content they and others consume. Some of the most successful sites today let users create and share content, connect and communicate with like-minded users and thus provide a richer and more interactive user experience. In producing and consuming content at the same time the emerging web 2.0 [14] has created *prosuming* users.

Recommender systems (RS) have been built to help consumers deal with the abundance of data available on the web. However, recent research suggests that current RS do not offer sufficient utility, and user experience is not satisfactory [4]. It has been argued that RS could be significantly improved by drawing on features from social systems [3].

Social networking systems such as Facebook[1], mySpace[2] or Orkut[3], which have attracted millions of users (mySpace has more than 100 million[4] users) have become popular communication platforms for its users to share digital content and socialise. The increased popularity in recent years has greatly extended active participation and content production of the web as these systems often include blogs, photo galleries and other means for sharing digital content. However, they are in danger of becoming victims of their own success: with rapidly increasing number of users, identifying like-minded fellow users has become difficult. While many users provide rich profile information, it is currently not used to provide effective user matching and recommendation potential.

The research presented in this paper takes a new view of RS in the light of the above developments: we investigate the effect of real friends as recommenders on people's choices. We begin with a brief overview of RS research, and discuss how current social networking systems relate to this. This lays the groundwork and motivation for our online RS simulation, which was completed by 60 participants and examined *real* (rather than simulated ones) recommender characteristics such as *familiarity*, *profile similarity* and *rating overlap* on participants' choices in an RS context. We predicted that, given recommendations by unknown and familiar persons, participants would be more likely to adopt recommendations from familiar ones, and that a high degree of profile similarity and ratings overlap would further increase uptake of recommendations. The results show that all 3 variables had significant impact on what type of recommender participants chose to trust (i.e. accept a recommendation from) although the relative weight of each variable changes with the context of the choice. Based on these results, we present an example how profile similarity can be integrated into the interface of a popular social networking system.

2. Background

2.1 Recommender systems
Filtering and evaluating potential choices from the Internet has become a day–to-day activity for many people shopping for items such as CDs and DVDs, or choosing a restaurant or movie Generally, the number of choices available by far exceeds what can be considered by an individual: take, for instance, the number of available CDs on a site like

[1] www.facebook.com

[2] www.myspace.com

[3] www.orkut.com

[4] According to mySpace primary network

Amazon.com. RS are meant to alleviate this problem by filtering the available options according to the consumers' individual preferences.

RS strategies can be divided into the following categories (see [1] for a more detailed overview):

(1) **content-based recommendations** – items that are similar to ones a users have previously liked will be recommended

(2) **collaborative filter recommendations (CF)** – users receive recommendations based on people who have similar tastes and preferences

(3) **hybrid approaches** – a combination of content and collaborative methods

RS research to date has predominantly focused on designing algorithms for more *effective and efficient computation* of rating predictions [5,8,12]. Even *trust* has been examined from an algorithmic perspective [7,11,13]. The main approaches to RS trust research aim to include trust measures in the form of trust ratings in the algorithms computing recommendations. Their aim was to address shortcomings of Collaborative Filter algorithms, such as the *cold start problem*, [11] or increasing the precision of recommender algorithms [13].

Human Computer Interaction (HCI) research into RS to establish interaction design guidelines has been limited to evaluation of existing RS [9,16]. Swearingen & Sinha [16] stress that users need to understand how recommendations are computed (*system transparency*). Herlocker et al. [9] conducted an extensive study examining what effect explanations for collaborative filtering results have on the user's perception of the system. They found that explanations are important to users as they were less likely to trust recommendations when they did not understand *why* certain items were recommended to them. Herlocker et al. [9] suggested that a rating histogram of the user's closest neighbours is the most effective way of explaining the results of collaborative filtering.

Bonhard & Sasse [4] have argued for a new HCI approach to RS design: they examined existing psychology literature on advice-seeking and decision-making, and conducted a qualitative study on when and why people want recommendations. They found that people prefer to consult familiar advisors, and that the *situatedness* or *social embedding* of a recommendation is what makes it effective. Consequently, they propose that recommender characteristics and the recommendation context (e.g. romantic date vs. business lunch) need to be considered for the recommendation strategy and as explanation aids in order make the whole process more transparent [3].

Situating recommendations in their social context in an online environment warrants the examination of how people use tools to socialise online. Social networking applications provide a platform for their users to connect with their friends through their profiles. Seeking recommendations from friends is a naturally occurring social process, which has so far been under-explored in this context. The following section therefore briefly examines social networking applications.

2.2 Social Networking Systems

Social networking applications have grown significantly over the past few years, with *Friendster*[5] claiming 27 millions users[6], *Facebook* 7.7 millions users [18], *hi5* over 50 million users[7], and *mySpace* with more than 100 million users[8]. First generation systems like *sixdegrees.com* initially saw an enthusiastic uptake, this was followed by an equally quick decline, mainly due to a lack clearly defined usage goals. Once signed up, users simply did not know what to do with the applications. Donath & Boyd [6] point out that these networking sites had the three following basic underlying assumptions:

(1) there is a need for people to create connections,

(2) using a network of existing connections is the best way of doing this,

(3) making the above easy is a great benefit.

Social networks are a new form of self-representation and communication, and as such subject to social behaviour different to the real world. For instance, while for some users the main purpose of social networking sites has been to amass social currency through a huge network of friends (a large number of whom they do not actually know in person), for others there is a more goal-driven approach (e.g. business in *LinkedIn*[9]), where accountability is valued more highly, albeit at the cost of reduced privacy because people use their real names [6].

As the main point of social networking sites is making new connections, the underlying assumption is that having a mutual acquaintance or being connected via a chain of acquaintances provides context for connecting. People need a focus or common ground to turn a connection into genuine benefit. Finding a mutual acquaintance can provide common ground in the form of shared experiences, beliefs and areas of interest [6].

Apart from mutual acquaintances, however, finding like-minded people in current systems is still a very laborious search process in which the user has to browse different networks, communities and profiles and judge individually whether another person is actually of any interest.

Additionally, social networking applications have extended their traditional goals of creating connections among its users, to becoming a hub for producing and sharing digital content. Bands post their demo tracks on mySpace, people share their photos in galleries; political activists organise rallies or petitions through special interest groups.

It is the intersection of RS and social systems that introduce a new type of system: Social Matching Systems, as suggested by Terveen & McDonald [17]. These will be explored in the following section.

2.3 Social Matching Systems

Social networking systems are based on people joining and providing information about themselves, such as demographic data, hobbies and interests and connecting with their friends. RS, on the other hand, almost exclusively use item ratings to define the user profile for the system. Item ratings however come from real people, which are indicative of their tastes and preferences. Decoupling the two deprives an RS and its resulting recommendations of a lot of potentially useful

[5] www.friendster.com

[6] www.friendster.com/info/tour/1_0.htm

[7] www.hi5networks.com/press.html

[8] according mySpace primary network stats after log in

[9] www.linkedin.com

information. The connection between items and recommender is one that needs to be capitalised on for more effective recommendations and system transparency.

The simplest definition of a social matching system - according to Terveen & McDonald [17] - would be a RS that recommends people instead of items. We believe that item and people recommendations do not have to be mutually exclusive. On the contrary, they actually benefit from each other because they are so interrelated [2,4]. Good recommendations are usually tied to people we are familiar with and trust.

2.4 New approaches to RS design

Since the growing popularity of social networking applications is a fairly recent phenomenon, the research community is only beginning to examine the interactions in that particular context. RS research has longer track record, but user-centred approaches are very recent [3,4,17]. There is more to advice-seeking and decision-making than merely being presented with options. The information needs to be qualified on different levels, such as how the recommendation was computed, if done by matching, who it is based on and of course information about the recommended item itself. Thus, the usefulness of such systems needs to extend that of mere information retrieval or has to be embedded into another structure that complements the uses of it.

Advice/recommendation-seeking is a fundamentally social process, and researchers are beginning to recognise the potential use of information and profile characteristics contained in social networking applications. Users already specify trusted networks through their connections as well as information rich interest / taste profiles.

Recommender characteristics such as *familiarity*, *profile similarity* and *rating overlap* are collateral influences to the decision-making process because they allow a person to judge the appropriateness of a recommendation. In their RS simulation, Bonhard et al. [3] found that *profile similarity* in combination with high *rating overlap* had a significant impact on participants' choices. They argued that revealing recommender profile information and visualisations of similarity and rating overlap should be used as explanation aids to RS. They did not find an effect of *familiarity* on participants' choice, arguing that this was due to the fact that it was simulated through repeated exposure and not real.

Mapping out people's tastes is a complicated endeavour, because taste is complex and multifaceted, and descriptions of taste can vary wildly from person to person (e.g. one music fan's definition of 'Indy Rock' might include bands that another one would only sneer at). Liu et al. use user profile information such as interests, films and music to feed a *taste fabric* [10]. In this, people are grouped in various spheres defined through an ontology that was defined through keywords in user profiles. This taste fabric can be used to generate and navigate recommendations based on related items.

Svensson et al. [15] present a similar approach through social navigation of the food recipe domain. This includes RS functionality, information on other users' activity, and communication features. They found that some social aspects of their system were more popular for self-expression than to see what other people did.

Golbeck & Hendler explore how connection data of social networks can be used to generate recommendations in their "FilmTrust" systems [7]. They use explicit trust rating between users and their respective film ratings as a basis for making calculations about similarity.

While Liu et al. concentrate solely on profile information to connect and categorise users, we believe the existing connections among users need to be leveraged as well. Svensson et al.'s study demonstrates that social functions have a significant impact on users' perceptions and behaviour in such systems. And the familiarity between the advice-seeker and recommender can also act as a trust builder [4]. Golbeck et al. incorporate this idea through using explicit trust ratings among users. Firstly, such ratings require additional input (which users might be reluctant to make), and secondly they are tied to a particular domain (in this case the 'trustworthiness' of their film recommendation). Profiles in SN applications already contain information about members' taste, which could be used for matching and generating recommendations, but the combination of connection and profile similarity data is currently not exploited.

When meeting new people, part of 'getting to know each other' is establishing some form of common ground in our likes and dislikes. This is a trust-building exercise as it helps evaluate our counterpart's personality. Indeed, social psychology has shown that people like others who are, among other things, familiar, similar to themselves, and with whom they have a history of interaction [2].

Friends from whom we seek recommendations are not just a source of information for us: we know their tastes, views and they provide not only recommendations, but also justification and explanations for them. If in doubt, we can always question their recommendations by simply asking about their reasoning and referring back to previous recommendations we might have received from them.

Seeking and receiving a recommendation is a social activity that often involves the discussion of a particular item. Why did the recommender like it? Would she want to experience/buy it again? Will the experience change after a while? Social networking systems already contain vast amounts of information about their users' likes and dislikes, interests and hobbies. This information essentially encapsulates common questions that are asked in social encounters. To date however, this information is neither used for generating recommendations nor for matching like-minded users.

The aim of our research was to explore this avenue of integrating RS and social networking systems in order to leverage the advantages of both. We wanted to explore in greater detail the effect of *familiarity* on users' choices and how that can be applied to RS design. Since familiarity was previously unsuccessfully operationalised [3] we examined actual, *real familiarity* between the advice seeker and the recommender. Being friends with a given recommender gives the advice seeker additional knowledge that can be factored into the decision-making.

We further tested our results in creating a novel interface of a popular social system that incorporates this new user centric view of RS design.

Figure 1 - recommendation choice

3. Experimental Study

While Bonhard et al.'s [3] study *simulated* recommender profile characteristics such as *familiarity*, *profile similarity* and *rating/taste overlap*, we were interested in how participants' choices would be affected if they actually know some recommenders and judge them individually on similarity and rating overlap. In short, the familiar recommenders would be actual friends, rather than system-generated.

3.1 Participants & Procedure

3.1.1 Participants

During recruitment, we asked every interested participant to recruit four additional friends, who would participate with them as a group. Thus the final participants were all part of groups of five friends who all knew each other. 12 groups of 5 participants were recruited. The majority of participants knew their friends more than six months and a significant number knowing them longer than a year. Thus, familiarity among group members was real. The age range varied from 18-31 with a variety of backgrounds including students and professionals. Participants were paid £7 on completion of the study.

3.1.2 Scenario

The scenario was a film festival where there were more films scheduled than any person could see in the time available. Participants were asked to use a film recommender system that would match them with similar people, based on their rating profile. They were told that as well as being matched with similar people, some of their friends

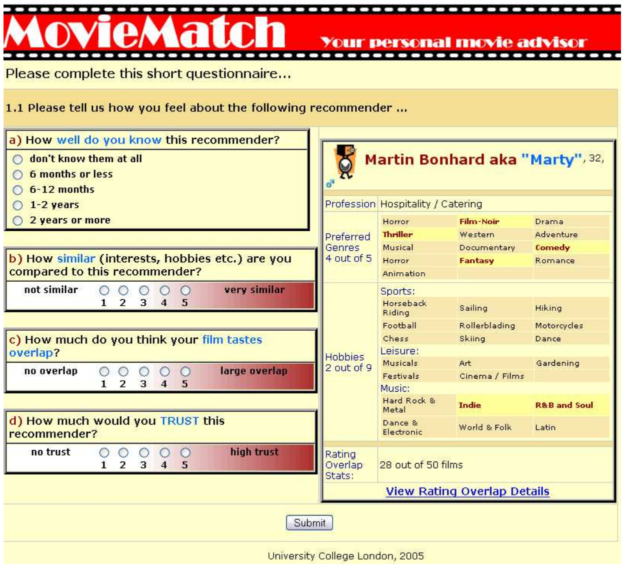

Figure 2 - post hoc questionnaire

had seen trailers, read synopses and had thus been able to recommend some films to particular people in their group.

3.1.3 Procedure

Participants completed the experiment over the Internet. The experiment consisted of four main phases. In the *first phase* participants were asked to provide a basic profile with demographic data, hobbies, interests and music tastes. In that phase participants were also required to rate 50 popular films, which was subsequently used for showing rating overlap statistics.

In the *second phase*, participants chose from a series of 32 pairs of recommendations from different recommenders (see Figure 1). In the *third phase* they rated the familiar and unfamiliar recommenders in terms of *familiarity, profile similarity, rating overlap* and *trust*. This was followed by *phase 4*, which was a post-hoc questionnaire (see Figure 2) where users could elaborate on their decision reasoning.

3.2 Recommenders & Independent Variables

As participants were recruited in groups of five, for each participant there were four familiar recommenders. Each of those four would be subsequently used to generate an unfamiliar counterpart with a similar interest / rating overlap profile (based on the number of items in common see

Figure 3).

3.2.1 Familiarity (fam)

Bonhard et al.'s [3] study did not show an effect of familiarity on participants' choices. They concluded that because their familiarity was not real, but only simulated through repeated exposure their experimental operationalisation of the variable had failed and that only interactions over a longer period can establish familiarity. In this study, we therefore wanted to compare participants' choices when the recommender was an *actual* friend. This was the main independent variable that was controlled.

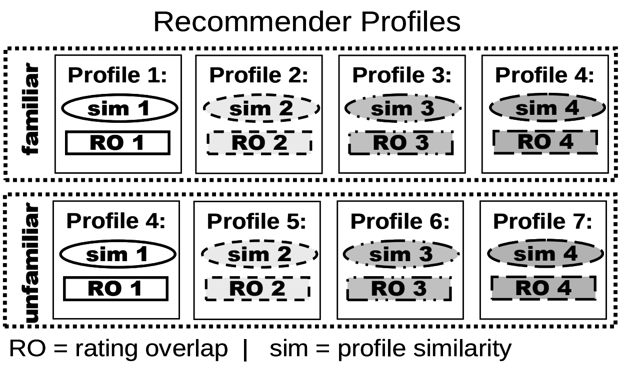

Figure 3 – Familiar & unfamiliar recommender profiles – unfamiliar profiles were modelled on familiar ones

3.2.2 Profile similarity (sim) & Rating Overlap (rate)

Since all the familiar recommenders were real people, we could not control for *profile similarity*, *rating overlap* and *trust*. However since the participants rated the recommender profiles on these dimensions (as well as *familiarity*) in phase 4, we used them as *subjective measures* and thus independent variables.

3.3 Conditions

Each condition in phase 2 was a forced choice between two films recommended by two different recommenders (see Figure 1).

The recommenders could be any combination of familiar (i.e. friends in their group) or unfamiliar recommenders (computer generated). Thus, there were three different conditions types:

1) **F-UF:** familiar vs. unfamiliar recommenders
2) **F-F:** familiar vs. familiar recommenders
3) **UF-UF:** unfamiliar vs. unfamiliar recommenders

This resulted in a total of 32 choices to be made.

3.4 Dependent variable

Choosing from the recommendations they received in essence translated into choosing to trust a particular recommender. This choice was therefore our dependent variable. In addition to that, we also recorded a confidence rating for each choice.

No reviews or synopses were provided in order to avoid choice bias based on preferences for textual descriptions we could not control for.

3.5 Hypothesis & Analysis

3.5.1 Hypothesis 1 – Recommendations from actual friends will be preferred

We wanted to test the previous prediction of [4] that recommendations from familiar recommenders would be preferred.

3.5.2 Hypothesis 2 – Recommendations from similar recommenders will be preferred

Previous social psychology research states that we like people more if they are similar to us [2]. Thus we predicted that participants prefer recommendations from people they consider more similar to them.

3.5.3 Hypothesis 3 – Recommendations from people with high rating overlap will be preferred

The basic assumption of any CF-based RS is that users want to be matched with others who like the same films as them. While this was tested in [3], the variable there was simulated, while in our experiment, high or low rating overlap was real. We predicted that participants would prefer recommendations from recommenders with a high rating overlap.

3.5.4 Hypothesis 4 – Recommenders with higher familiarity, profile similarity and rating overlap ratings will be trusted more

Each choice in phase 2 of the experiment effectively translated into choosing to trust a particular recommender. We believed the recommenders chosen more often would also be rated higher in terms of trust (*explicit trust*). *Implicit trust* (recommenders chosen) would therefore match *explicit trust* (trust rating).

3.5.5 Analysis

We analyzed the data from the recommendation phase in the following ways:

1. **Familiarity Analysis (H1)**

   For the F-UF conditions we examined across and within subjects whether participants consistently chose the familiar recommender. This was tested by comparing the percentage of familiar advisors chosen over unfamiliar advisors.

2. **Influence of FAM / SIM / RATE (H2, H3)**

   To analyze individual the influence of *familiarity*, *profile similarity* and *rating overlap* we used a binary logistic regression for which we transformed the resulting data in order to create a dummy dependent variable. We examined all the profiles that were presented on the left/right side of the recommendation pairs (they were counter balanced). Each profile was rated in terms of familiarity, profile similarity and rating overlap. For each pair we used the rating difference between the profile chosen and its counterpart that was not chosen as independent variables.

3. **Paired t-tests (H4)**

   We also examined the fam/sim/rate/trust ratings of each choice and compared it to the ratings of those recommender profiles not chosen. Additionally we compared the confidence ratings of participants' choices among the three condition types.

4. **Trust and confidence ratings (H4)**

   We examined the trust ratings for the chosen recommender profiles for each condition type and confidence ratings for each choice with one sample t-tests.

4. Results

4.1 Advice from familiar recommenders

In the *familiar vs. unfamiliar condition*, participants overwhelmingly preferred recommendations from familiar recommenders (73% vs. 27%, consistent within subjects $p<0.01$). Thus hypothesis 1 was supported.

4.2 Individual influence of fam, sim & rate

4.2.1 All conditions

When examining all 3 conditions together, all 3 factors (fam, sim, rate) turned out to have a significant influence on participants choices.

Factor	B	S.E.	Wald	df	Exp(B)	95.0% C.I.for EXP(B)	
						Lower	Upper
RATE *	0.4364	0.0549	63.1822	1	1.5472	1.3893	1.7229
SIM *	0.2894	0.0503	33.1429	1	1.3357	1.2103	1.4740
FAM *	0.1487	0.0334	19.7737	1	1.1603	1.0867	1.2389
Constant**	-0.0255	0.0532	0.2294	1	0.9748		

* $p < 0.001$ ** $p = 0.6319$

Table 1 - All conditions – regression data

Across the condition types rating overlap turned out to be the most significant choice predictor, followed by profile similarity and familiarity (see Table 1). The choice behavior was slightly different when examining the individual condition types by themselves.

4.2.2 Familiar vs Unfamiliar conditions (F-UF)

When one recommender was familiar and the other was not, the strongest choice predictor was rating overlap, followed by familiarity. Profile similarity turned out not to be statistically significant (see Table 2).

Factor	B	S.E.	Wald	df	Exp(B)	95.0% C.I.for EXP(B)	
						Lower	Upper
RATE *	0.2966	0.1205	6.0625	1	1.3453	1.0624	1.7035
FAM **	0.2169	0.0418	26.8683	1	1.2422	1.1444	1.3483
SIM ***	0.0883	0.1167	0.5731	1	1.0924	0.8690	1.3731
Constant***	-0.0710	0.1088	0.4253	1	0.9315		

* $p < 0.05$ ** $p < 0.01$ *** $p > 0.05$

Table 2 – F vs. UF regression data

4.2.3 Unfamiliar vs. Unfamiliar conditions (UF-UF)

When both recommenders were unfamiliar, the most significant choice predictor was profile similarity. This was followed by rating overlap and familiarity (see Table 3).

Factor	B	S.E.	Wald	df	Exp(B)	95.0% C.I.for EXP(B)	
						Lower	Upper
SIM **	0.3553	0.0734	23.4179	1	1.4265	1.2354	1.6473
RATE **	0.3141	0.0810	15.0414	1	1.3690	1.1681	1.6045
FAM *	-0.5059	0.2144	5.5679	1	0.6030	0.3961	0.9179
Constant***	-0.0143	0.0847	0.0287	1	0.9858		

* $p < 0.05$ ** $p < 0.01$ *** $p = 0.8656$

Table 3 – UF vs. UF regression data

4.2.4 Familiar vs.Familiar conditions (F-F)

When both recommenders were familiar, the most significant choice predictor was rating overlap, followed by profile similarity and familiarity (see Table 4).

Factor	B	S.E.	Wald	df	Exp(B)	95.0% C.I.for EXP(B)	
						Lower	Upper
RATE **	0.713	0.1016	49.2313	1	2.0401	1.671677	2.489687
SIM **	0.2611	0.0892	8.57952	1	1.2984	1.090246	1.546344
FAM *	0.1816	0.0812	5.0048	1	1.1991	1.022751	1.405843
Constant***	-0.0082	0.0907	0.00823	1	0.9918		

* $p < 0.05$ ** $p < 0.01$ *** $p = 0.9277$

Table 4 – F vs. F regression data

4.3 Paired t-tests

4.3.1 FAM / SIM / RATE

We examined the ratings for *familiarity*, *profile similarity* and *rating overlap* for all profiles provided in the post-study questionnaire. Specifically we compared the ratings for the recommender profiles chosen to those not chosen. In all cases the recommender profiles chosen were rated higher in terms of *fam, sim* & *rate* than those not chosen (see Figure 4).

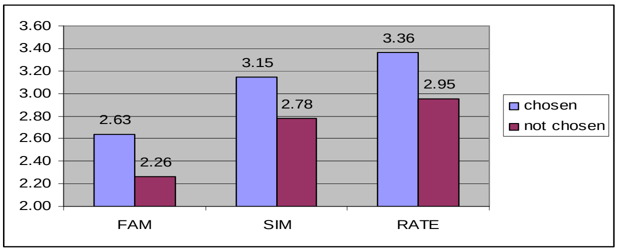

Figure 4 – FAM / SIM / RATE comparisons across all conditions (chosen = recommender chosen)

This matched our predictions that participants would prefer recommenders who are more familiar, similar and have a higher rating overlap with the participants (hypotheses 2 & 3).

4.3.2 Trust

Participants rated the recommender profiles in the profile rating section in terms of trust. We compared the trust ratings of the profiles chosen and the ratings of the ones not chosen. Since these ratings were made *after* participants had received their recommendations, we could compare *implicit trust* (based on choices) to *explicit trust* (trust perceptions based on ratings). This showed that overall participants rated the recommender profiles they chose higher in terms of trust than those they did not choose (see Figure 5). *Implicit trust* (recommender choice) and *explicit trust* (trust rating) matched. Hypothesis 4 was therefore supported.

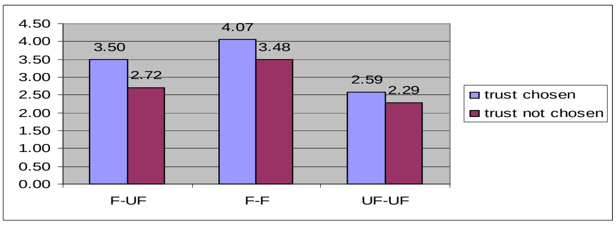

Figure 5 – Trust ratings in all condition types (chosen = recommender profile chosen)

4.4 Confidence

Examining the confidence ratings participants provided with each choice, we found that they were most confident in their choices when both recommenders were familiar and least confident when both recommenders were unfamiliar. All means significantly differed from the median rating (3, $p < 0.01$, see Figure 6).

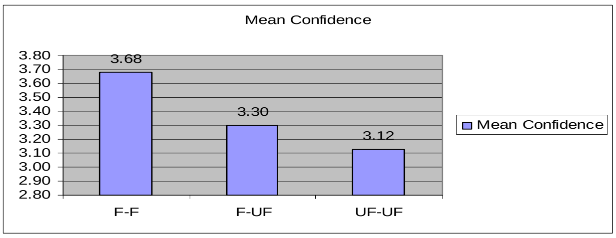

Figure 6 – Confidence ratings across all condition types

4.5 Post-study questionnaire

In the post-study questionnaire, participants were able to elaborate their reasons for choosing a recommendation. A total of 82 comments were recorded and examined.

The degree of familiarity with the recommender was seen as important in both a real life and an online context. It is important how long they have known a particular recommender and if they had had a positive / negative recommendation history (*"How well I think they know me is important for me to trust their recommendation. That comes with the amount of time I have known them and the amount of overlap in taste I have with them."*)

The comments suggest that for participants in an online context, profile similarity as well as rating overlap was important.

Next to recommender characteristics, in real world situations accompanying film information such as trailers is important to people.

5. Discussion

Our results demonstrate the impact of recommender characteristics on participants' recommendation choices in online environments.

But first let us revisit our original hypotheses:

1. **Familiar recommenders will be preferred**

   This hypothesis was supported. Participants overwhelmingly preferred recommendations from their friends. This showed that knowing the recommender does indeed have a significant influence on the decision-maker's considerations.

2. **Recommendations from similar people will be preferred**

   This hypothesis was supported. The paired t-tests of similarity ratings of the recommender profiles showed that participants preferred recommendations from those rated higher in terms of similarity.

3. **Recommendations from people with high rating overlap will be preferred**

   This hypothesis was supported. As above the chosen recommender profiles were generally rated higher in terms of rating overlap than those not chosen.

4. **Recommenders rated higher in terms of familiarity, profile similarity and rating overlap will be trusted more**

   This hypothesis was supported. Participants' implicit trust (i.e. their choices) matched their explicit trust (i.e. their trust ratings for those profiles) because these were higher for the chosen recommenders than those not chosen.

5.1 Do I know you?

The findings on hypothesis 1 are in contrast to those in [3], whose authors hypothesised after the experiment that that their simulation of *familiarity* was not successful, and that it had to be real to have an effect. It also supports the prediction of [4], which is the first time this has been shown from a quantitative perspective.

Our results show that participants clearly prefer recommendations from recommenders they actually know. The decision and evaluation process is different when the recommender is known simply because there is a lot of contextual information such as an interaction history that makes it easier for her to trust the recommender and be confident in her choice.

Our study confirmed the importance of rating overlap and profile similarity as shown in [3]. Below we explore how this information can be effectively visualized to make it easier for users to find like minded people.

5.2 Context matters

The confidence levels and the relative weight of *familiarity*, *profile similarity* and *rating overlap* changed depending on the condition types (F-UF, F-F and UF-UF).

When the choice was between a *familiar* and an *unfamiliar* recommender (F-UF), *rating overlap* was still the strongest choice predictor followed by *familiarity*.

When both recommenders were friends (F-F), *rating overlap* was most important, followed by *profile similarity*. Participants were most confident in their choices in those conditions.

When both recommenders were unknown (UF-UF) to the participant, the situation was reversed, so *profile similarity* was a stronger predictor than *rating overlap*.

This indicates that, when recommendations are based on *familiar* recommenders, it is more helpful for the user to see how many items they have in common. In that context *profile similarity* is not as important because the advice seeker already knows about the recommender and therefore does not have to evaluate her as much.

When the recommender is *unfamiliar* it is the combination of *rating overlap* and *profile similarity* that is important for the user (advice seeker). *Profile similarity* helps the users to judge the recommender overall, whereas *rating overlap* tells them about their taste overlap.

5.3 Outlook

5.3.1 Research & Methods

Our study concentrated on particular elements of a recommender profile, while there are still other elements of a user profile that could be of interest. Different representations of users in online social spaces need to be examined in terms of appropriateness of representation, the associated usability and the amount of information provided.

With increasing amounts of information about users being available online, privacy concerns need to be addressed from a different perspective. Because users are the ones who are *providing* the information without being aware of the risks associated with it, there is a need to examine how users can be educated without losing faith in the technology.

Methodologically, current social spaces offer amazing opportunities to discover online social dynamics at work. Some social network providers such as Facebook even provide a developers' API, which makes it possible to develop new applications using their data (http://developers.facebook.com/). This provides immense opportunities to expand RS and social systems research.

5.3.2 Algorithm designers – let's be more flexible

When expressing our tastes, most of the time we do not specify it in terms of ratings. Of course there are nuances, gradations, but most of the time it is just a distinction between liking something or not.

In a social networking system context, there often is no real distinction between rating overlap data and profile similarity.

Users express their preferences in a binary fashion through keywords (e.g. film or book titles, artists) to indicate liking (or sometimes dislikes as well). While this makes it more difficult for classic recommender algorithms to compute recommendations; that is how users express themselves and we as RS designers need to take that into consideration. The interface could be extended to include the option to rate an item when the users click on it. If it is not rated the algorithm would have to consider the existence of the keywords as a degree of liking and incorporate that into its computation process.

5.3.3 System designers – leading by example

Our results support the idea of a new breed of social matching systems that combine the best of item recommendations with people matching. Showing users the degree of similarity between them and the rest of their network is helpful information for them to find like-minded users and judge the appropriateness of potential recommendations. System designers should therefore consider carefully the information needs of their users and incorporate them in the interface.

Using profile similarity information for matching, we created an altered interface for *Facebook*, which is an existing, popular social networking system.

As with many popular social networking systems, the original interface only lets the user click on certain profile elements as a search term, without any other additional information (see Figure 7).

This leads to a list of profiles that contain that particular keyword. This list included everyone in a particular geography (not just 1st degree contacts) and could thus be very long. It also did not indicate if there were any other similarities with the profiles shown.

We fed a person's profile data and that of all of their friends into our system, which extracted keywords and matched them against those of all the other people in their 1st degree network. As a result people were immediately able to see what they had in common with others in their 1st degree network.

Additionally, they were able to see which of their friends they had most in common with (see Figure 8). The aim was to reduce the effort users would have to go through to find like-minded people within their network and make it immediately visually obvious with who they shared common interests. This kind of visualisation would help people not only to spot potentially interesting people within their network, but could also be used as a basis for recommendations. If two users had a certain amount of items in common in an area it would be possible to recommend further items to them based on those matches.

To enhance the visibility of the keywords that users have in common with others they were highlighted and enlarged in proportion to their popularity. The bigger the term the more people have listed it in their profiles.

While our initial version limited the similarity feature to users within the primary network (i.e. directly connected), this could easily be extended to 2nd, 3rd degree or potentially to the entire network. Users could then specify how far the search should reach or they could completely turn it off.

Our enhanced similarity interface is a simple example of how similarity among users in one network (1st degree) can be efficiently used for people to be able to easily find like-minded people. It is intuitive for users to understand that if they had certain items in common with someone, they could be interested in other items that the matched user liked and the advice seeker did not know yet.

This makes the scanning process that users employ when browsing other people's profiles much simpler and efficient because the common items are obvious right from the start.

Figure 7 – original interface

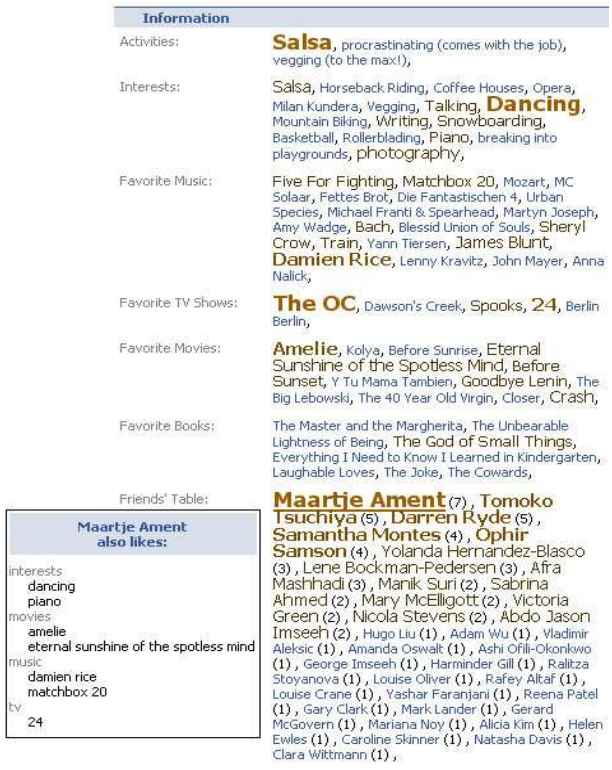

Figure 8 – enhanced similarity interface

6. Conclusions

6.1 Why contribute?

The results of our study illustrate why recommender systems to date have failed to meet user needs: seeking advice and giving recommendations is a social process which the focus of RS research on matching algorithms has failed to address. In the real world, it is not just the recommendation itself that is of interest to us, but also the process of seeking and acquiring it from particular people. It gives us an insight about their personalities, their interests and preferences and through this act of sharing information we bond a little. Friendships are often built on the discovery of shared interests.

Recommender systems suffer from a basic incentive problem: while it is easy to consume recommendations, users are often reluctant to provide ratings for a number of reasons:

1) Explicitly rating items or adding items to a database can be a cumbersome process.

2) Some users quickly need a recommendation as a one-off, and do not see any reason for interacting with such a system over a long period of time.

3) Having a RS merely for information retrieval when needed is not going to motivate users to either contribute to, or use the system in the long run.

There is more to advice-seeking and decision-making than merely being presented with options. This information needs to be qualified on different levels, such as how the recommendation was computed, if done by matching, who it is based on and of course information about the recommended item itself. Thus, the usefulness of such systems needs to extend that of mere information retrieval or has to be embedded into another structure that complements the uses of it.

6.2 Social systems for social creatures

Social systems are growing at an enormous rate and while they are not replacing "traditional" means of electronic communication like email, they are complementing them with additional elements and extending the scope of said communication. The ultimate goal is not mere information transmission anymore, but also the experience of sharing digital information as part of this communication. People share videos by embedding them in each others' notice walls, they tag each other in photos, notify friends of their different activities through status changes and include custom made radio players in their profiles that play songs from their favourite bands. All of this now counts as a form of communication, sometimes with a completely unknown audience (strangers who browse their profiles by accident), and sometimes it is known (explicit friends) or semi known (friends of friends) audience, to whom this information adds the knowledge about their friends.

Social matching systems, as proposed by this paper, aim to support this form of communication by making it easier to spot similarities and find like-minded people. This includes utilising the benefits of a RS approach to recommend items as well as people. In doing so the boundaries between RS and social systems are being blurred as one benefits from the other.

This type of system effectively exploits real world friendships in a virtual context. Of course friendships online are often different to real world ones. However, there is no standard definition of friendship in online social networks as people have different relationships with their respective online "friends" (e.g. Facebook friends).

We are particularly interested in real friends (from real world interactions), who often are also connected via online systems. Which social network people are drawn to, depends initially on where (or in which system) their real friends are.

Real friends are often not available to give advice and often we do not want to bother them. We also do not know every facet of their preferences or expertise (e.g. you might not know that your friend from your football team also likes *fado music*). If we can automate the access to that because their preferences or ratings are already stored in the system, we are helping the user in gaining useful recommendations and potentially helping them getting closer to their friends as they find out more about them.

Further, asking friends personally for a recommendation can create a sense of obligation to follow it, or the need to explain when a recommendation is not followed or additional advice sought (why did you ask me if you then don't listen to me?). Social matching systems allow us to explore recommendations without awkwardness, but might offer the chance for feedback and when a recommendations is successful, creating incentives to create and maintain recommendations

While it is obvious that an integration of RS and social systems is beneficial for both, the question remains of whether one should build an RS with social functions or a social system with RS functionality. We would argue for the latter, for a number of reasons.

Firstly, social systems have already established themselves and enjoy huge uptake, which makes adding RS features a more natural path to follow.

Secondly, existing social systems already contain a plethora of information rich user profile data, which should be used as a basis for generating recommendations.

Thirdly and most importantly, social systems do not have clearly defined usage goals and boundaries. Successful systems evolve with their users, adapt to their needs as well as providing them with new ways of communicating. Item recommendations and people matching only form a subset of these.

Our study has shown that familiar recommenders are preferred and more trusted, which is something current RS do not utilise sufficiently. Profile similarity and rating/taste overlap information helps users judge if a particular match is suitable or not. In combination this information is very valuable to users.

6.3 Future work

The exact nature of integrating RS and social systems still needs to be explored through new or existing systems. Existing systems offer exciting opportunities to test out new features with a massive user pool, as well as being a prime opportunity for observation of user behaviour.

User profiles in social systems are not limited to one domain of preferences such as films or music. Interests, as a category can include anything from cooking to photography. System designers therefore face the challenge of designing matching algorithms that consider different domains and how they relate to each other. Do the same rules apply for films as for music?

Finally, people have different relationships with different friends. How can a system mirror and effectively consider those differences without invading privacy?

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8. References

[1] Adomavicius, G. and Tuzhilin, A. Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. *IEEE Transactions on Knowledge and Data Engineering. 17,* 6 (2005), 734-749.

[2] Berscheid, E.and Reis, H. T. Chapter 22, *Attraction and close relationships* In The Handbook of Social Psychology Vol. 2. Oxford University Press. (1998). 193-281.

[3] Bonhard, P., Harries, C., McCarthy, J. D., and Sasse, M. A. Accounting for Taste: Using Profile Similarity to Improve Recommender Systems. In *Proceedings of CHI 2006, Montreal, Canada, 22-27 April 2006*. ACM Press. (2006), 1057-1066.

[4] Bonhard, P. and Sasse, M. A. "I thought it was terrible and everyone else loved it" - A New Perspective for Effective Recommender System Design. In *Proc. of the 19th British HCI Group Annual Conference, Napier University, Edinburgh, UK 5-9 September 2005*. Springer Verlag. (2005), 251-265.

[5] Breese, J. S., Heckerman, D., and Kadie, C. Empirical Analysis of Predictive Algorithms for Collaborative Filtering. In *Proc. of the Fourteenth Annual Conference on Uncertainty in Artificial Intelligence*. (1998), 43-52.

[6] Donath, J. and Boyd, D. Public Displays of Connection. *BT Technology Journal. 22,* 4 (2004), 71-82.

[7] Golbeck, J. and Hendler, J. FilmTrust: Movie recommendations using trust in web-based social networks. In *Proceedings of the IEEE Consumer Communications and Networking Conference*. IEEE. (2006), 1314-1315.

[8] Herlocker, J. L., Konstan, J. A., Borchers, A., and Riedl, J. An Algorithmic Framework for Performing Collaborative Filtering. In *Proc. of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*. ACM Press. (1999), 230-237.

[9] Herlocker, J. L., Konstan, J. A., Borchers, A., and Riedl, J. Explaining Collaborative Filtering Recommendations. In *Proc. of the ACM 2000 Conference on Computer Supported Cooperative Work*. ACM Press. (2000), 241-250.

[10] Liu, H., Maes, P., and Davenport, G. Unravelling the Taste Fabric of Social Networks. *International Journal on Semantic Web and Information Systems. 2,* 1 (2006), 42-71.

[11] Massa, P. and Avesani, P. Trust-aware Collaborative Filtering for Recommender Systems. In *Proc. of The International Conference on Cooperative Information Systems (CoopIS), 25 - 29 October 2004, Larnaca, Cyprus* . Springer. (2004), 492-508.

[12] McLaughlin, M. R. and Herlocker, J. L. A collaborative filtering algorithm and evaluation metric that accurately model the user experience. In *Proc. of the 27th annual international ACM SIGIR conference on research and development in information retrieval*. (2004), 329-336.

[13] O'Donovan, J. and Smyth, B. Trust in Recommender Systems. In *Proc. of The International Conference on Intelligent User Interfaces, San Diego, California, Jan 9-12, 2005*. (2005), 167-174.

[14] O'Reilly, Tim http://www.oreillynet.com/pub/a/oreilly/tim/news/2005/09/30/what-is-web-20.html

[15] Svensson, M., Höök, K., and Cöster, R. Designing and evaluating kalas: A social navigation system for food recipes. *ACM Transactions on Computer-Human Interaction. 12,* 3 (2005), 374-400.

[16] Swearingen, K. and Sinha, R. Beyond algorithms: An HCI perspective on recommender systems. In *Proc. of ACM SIGIR 2001 Workshop on Recommender Systems, New Orleans, Lousiana*. (2001), 24-33.

[17] Terveen, L. and McLaughlin, M. R. Social Matching: A Framework and Research Agenda. *ACM Transactions on Computer-Human Interaction. 12,* 3 (2005), 401-434.

[18] USA Today, Valerie Bauman, *Web generation preserves memories online, 25-6-2006, http://www.usatoday.com/tech/news/techinnovations/2006-06-25-yearbook-online_x.htm*