A Different View on Group Analysis: (Eye-) Tracking Social Influence

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ABSTRACT

Individual satisfaction is essential in group decision scenarios in which people share their tastes and actively participate in group decisions. We designed and ran an experiment with the purpose of measuring and tracking group influence in our GroupFun music recommender system. More specifically we were interested in analyzing the extent to which people change their opinions when facing various individual preferences coming from their friends. In our study we first asked participants to give individual ratings to songs uploaded to their group and then to perform an eye-tracking task in which they saw their friends' names and ratings and were asked to make a rating decision again. Our results focus on measuring group conformity, or the degree to which a person changed his/her own rating. Furthermore, the stronger social relationships through familiarity and trust are, the more individuals adapt to the group decision and are more inclined to change their preferences. Also, the correspondences users make between friends' names and their ratings represent a good indicator for understanding self-evaluation of a given song. Eye-tracking outputs present clear associations between various areas of the interests while fixation times are useful to understand group influence relative to closest friends in the group. These results have implications for psychology and personality research as well as decision making strategies.

Author Keywords

Group Influence, Familiarity, Trust, Music, Interfaces, Recommender System, Eye Gaze, Ratings, Efficiency.

ACM Classification Keywords

H.5.2 [Information Interfaces and Presentation]: User Interfaces - Evaluation/methodology, User-centered design.

General Terms

Design, Experimentation, Human Factors.

INTRODUCTION

Imagine you and your friends have to decide on the location your holiday together or new activities that you would like to plan together, or even the songs for a party you are all going to attend. How would you participate? Would your preferences be strict or will you adapt to the group decision? Which members in your group do you trust most and for which of them are you most familiar with their music tastes you would like to discover? A group recommender system help your group make a qualitative decision together.

Traditionally, group recommender systems (GRS) have evolved by building on individual preference specification models which correspond to users interests [6, 7]. However, these preferences change significantly over time and are context dependent: e.g. my friends and I would like to listen to one type of music for Saturday night's party and while carpooling to work together. Thus GRS propose new algorithmic approaches by: using user-item similarity measures [2], incorporating social relationship interactions [7] and combining user and item information together [3]. Personalized recommendation has the great advantage of removing popular, uninteresting, recommendations and favoring the discovery of new items [5, 9] even within the same group. However, the development of algorithms with increased accuracy in knowing users' tastes is not necessarily the key direction to improve recommendation since these algorithms demand for an extensive user effort and produces only a small increase in user acceptance. Other studies focused on the "pursuit of satisfaction" in GRS proving the role of an affective state [8].

Eye-tracking devices represent a precise and reliable technology measuring users' eye movements facing an interface. However, such technology was not previously used in the study of group influence before but only in online marketing related studies for which mainly retailers assessed website features capturing the visitors' interest for a specific item [4].

Finally, social influence analysis was addressed in large-scale online networks with the purpose of identifying the most influential persons and understanding the influent-follower role [10]. Other studies focused on technology adoption via social influence – how people tend to adopt new technology given a social pressure [11]. People indeed switch their preference differently when receiving recommendation from friends or other users and, rather than having a fixed preference they conform to the group choice.

To investigate how much friends' ratings influence one's decision we designed an experiment to identify which factors are most influential for individual decision making: is it the "average" group ratings, some members of the group or closest friends? We used GroupFun to display an individual rating interface for participants listening to group songs and give ratings. Then they were asked to restate their preferences through an eye-tracking experiment aimed at collecting users' gaze and fixation times. Our results show that social conformity is dependent on group connectivity and peer pressure thus proving social conformity theory. The influence is stronger groups where participants were most familiar and trusted their friends' tastes. Eye-gaze data confirms that individuals follow other members that they trust most and are most familiar with their preferences.

The rest of the paper is organized as follows. We describe the experiment setup in detail and present the participant's background information. The paper continues by presenting our main research goal before reporting the results of the study. We then discuss the results and their implications and present certain advantages and limitations. Finally, we present our conclusions and ideas for future work.

EXPERIMENT DESIGN

Participants

The study was carried out over a period of 3 weeks and proposed a music incentive. In the first week the two groups used GroupFun to create a group, upload music and give ratings individually, without any group interface and influence. During weeks 2 and 3 eye-tracking experiments were carried out with the purpose of recording users' eye-gaze and analyze their new ratings by comparing them with previous ones. The reward that all users received at the end of the study was a collection of all group songs uploaded by all group members. We created an archive for each group and sent the music library to all members of the same group. A total of **19 volunteers** were recruited as participants. **9** users formed the "Cool Party" group while the other **10** friends the "Legendary Party" one. In the first group there were only male participants whereas in the second there were 4 female and 6 male members. Users had 12 different national backgrounds: Switzerland, France, China, India, Russia, Romania, Italy, Turkey, Iran, Germany, Greece, USA and 3 different educational backgrounds: Master, PhD and Post-Doc students.

User Tasks

Participants were asked to perform the 3 following tasks supposing they would prepare a group party:

1. Complete an **online questionnaire** for subjective evaluation of individual familiarity and trust towards other group members;
2. Use **GroupFun** to create a group, upload music and give individual ratings to group songs;
3. Listen and give ratings to 24 group songs while seeing group interfaces containing group members' names and their ratings while being recorded by an **eye-tracking** device.

Tasks 1 and 2 represented Phase I (Figure 1, in green) and were done by each group during the first week. Task 3 represented Phase 2 (Figure 1, in red) and was done by each group subsequently during weeks 2 and 3.

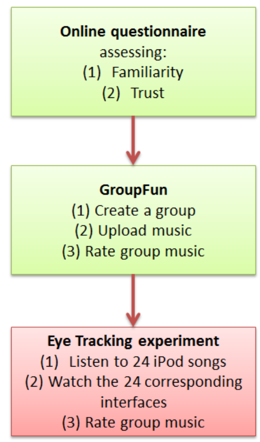

Figure 1. Experiment setup

Objectives

In a social context people adapt their decision to that of the group. We expect that our volunteers will adapt their decision given their group orientation rather that maintaining their strict preferences through ratings. Our main aim is to analyze this group influence, define metrics for analysis and compare different types of users in order to understand which factors produce social alignment and which others push users towards reconfirmation of their preferences. Furthermore we draw correlations between the implicit familiarity and trust network information and explicit eye-tracking data.

Materials

During Phase I volunteers used an online form to fill in their responses. Then they proceeded to use the GroupFun system[1].

We used the Tobii 1750 eye-tracking device[2] consisting of a monitor with embedded cameras using infrared light to

[1] http://grpupc1.epfl.ch/~george/GroupFun/

[2] http://grpupc1.epfl.ch/~george/Tobii1750.gif

capture pupil movement. We attached a desktop computer running Windows XP and the predefined ClearView 2.7.1 software capable of capturing users' eye gaze, display fixation points and generate heat-maps. After an initial calibration for each participant, we asked our users to look at the screen in a natural and comfortable way with the help of a head mount object.

The second device for our experiment was an Apple iPod Shuffle[3] on which we recorded 24 songs played for each group participant in the interface order displayed on the eye tracker.

The two main conditions being investigated are individual preference specification and group influence preference specification.

QUESTIONNAIRE

Before the experiment we asked our participants to fill out an assessment questionnaire. Its completion lasted around 2 minutes per participant. Two variables were analyzed: familiarity and trust. First we asked users: "How much do you know your friends' musical tastes?" and then "How much do you trust your friends (music-wise)?" We hypothesized that people are more inclined to trust others' even though they do not know much of their friends' music tastes in advance. Thus, the music discovery process would allow them to enhance group familiarity and trust.

When analyzing familiarity we noticed two categories of users in both groups: one includes friends which are more isolated and another in which people connect with others and familiarity distribution covers most group members (Figure 2). An alternative visualization graph (Figure 4) uses edge weights and positioning to identify the persons who are more influential in each group. We designed an oriented graph in which the higher the weight given by Pi to Pj the thicker the directed line connecting them.

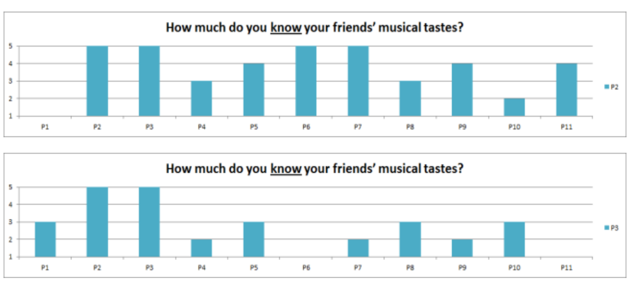

Figure 2. Familiarity distribution across group members.

The second variable we analyzed is trust. The responses submitted by first group members demonstrate that people who know their friends' music tastes trust them more for music recommendation: P1 and P4 trust themselves more than others and trust others' tastes even though they don't know them (Figure 2 – in red). However, members who do not know their friends' tastes are tempted to trust them given their tight social relationships and openness to discover new music: P2 and P3 trust other members' preferences. The trust distribution covers most group members (Figure 3 – in blue). Similar results yield for the second group.

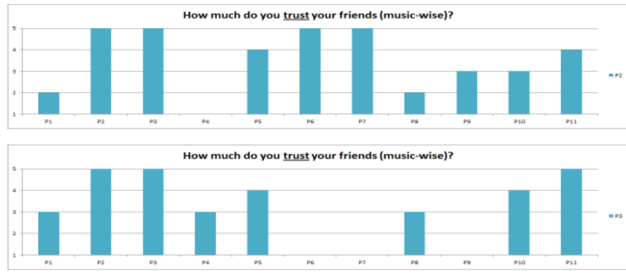

Figure 3. Trust distribution across group members.

The directed graphs included in Figure 4 present familiarity (up) and trust (down) networks of the "Cool party" to the left (P1 to P9) and "Legendary party" to the right (P10 to P19). The two graphs show that friends positioned at the center of the graphs are mostly influenced by those who are at the exterior. They take into account their friends' music tastes most. Reciprocally, the participants positioned at the exterior of the trust graph are mostly trusted by others given a large number of weighted edges oriented towards them. We note from the upper-left graph that participants P1 and P4 are only familiar with P3 and P2's music preferences. Conversely, P2 stated that s/he is most familiar with most of his/her friends' tastes.

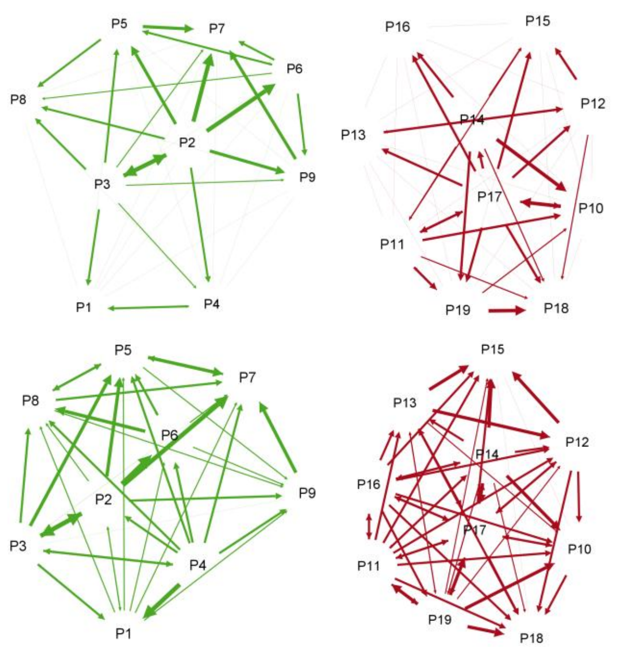

Figure 4. Familiarity and trust networks for the 2 groups

Comparing music familiarity among groups (upper graphs) we note tighter relationships in the second group. Similarly,

3 http://grpupc1.epfl.ch/~george/iPod%20shuffle.jpg

trust relationships are stronger given the higher edge-weight density. By looking from up-to-down we remark that trust is determined familiarity since the two upper graphs have sparser relationships that the bottom ones. We interpret this as users are more inclined to trust their friends' music tastes in their group even though they are not necessary familiar with such tastes.

The 4 graphs also allow deriving friendship bounds which are useful for the study of reciprocal relationships among participants. For instance, the edge between P2 and P3 in the upper-left graph corresponds to the same score (5) given by both friends reciprocally as a measure of their familiarity one to another. Similarly the edge between P17 and P18 corresponds to scores of 4 and, respectively 3, between the 2 members. The influential participants are those positioned at the exterior of the graph: most thick arrows are pointed towards them. Their music tastes are best known by others in the group.

Furthermore, in Figure 5 we report that average familiarity per user is less than average trust. This trend can be noticed for most users. For the first group we note an average familiarity of 1.97 (out of 5) for all 9 users compared with an average trust of 2.41. For the second group average familiarity for the 10 users is similar, 1.95 (out of 5) while average trust is higher: 2.64. We observe some individual users for whom trust distinguishes more notably compared with familiarity: the distance between the two is highest such as P4 and P16. Thus, participants are open to discover their friends' music tastes, even though they are less familiar with these tastes which they trust a priori. The correlation between familiarity and trust is 0.600.

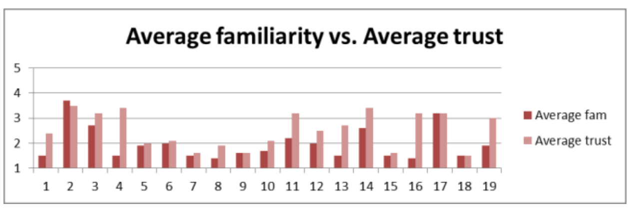

Figure 5. Openness to music discovery

These results prove to be very useful for the study of human personality and group influence by comparing subjective evaluations, such as the current one, with objective factors, such as the ones that will follow for the eye-tracking experiment.

GROUPFUN

The GroupFun experiment took approximately 2 hour per group. As mentioned before, users connected to the system to create 2 groups: "Cool party" and "Legendary party". The members of the first group contributed with 39 songs while those of the second group with 47 songs: an average of more than 4 songs per user. Given the fact that users did not join and upload songs to GroupFun in the same order, each of them saw a different number of songs available for rating. Thus, the users-ratings matrix follows a pseudo-triangular form with the first user rating his/her own songs, the second one his/her and the previous user's songs and the last user seeing all group songs and rating as many as s/he wanted.

Each user submitted a rating from 1 to 5 - 0 meaning that the current user did not submit any rating - to as many songs as s/he wanted. In the first group the 9 users submitted a total of 203 ratings for all 39 songs yielding a group satisfaction index of 3.27 computed as the average amongst all individual preference ratings. Average individual satisfaction shows that most satisfied members are P1, P2, P3, P5 and P6 (in green) in Table I whereas least satisfied are P7 and P8 in Group1 (average rating: 3.27 and 0.437 standard deviation).

Table I. "Cool party" statistics

P1	P2	P3	P4	P5	P6	P7	P8	P9	
20	9	19	39	26	9	37	29	16	203
3.3	3.9	3.6	3.2	3.7	3.4	2.5	2.7	3.1	3.27

In the second group the **10 participants** submitted a total of **189 ratings** for all **47 songs** yielding a higher **group satisfaction** index of **3.57**. The average individual satisfaction shows that most satisfied members are P10, P12 and P13 (in green) in Table II whereas least satisfied are P17 and P19 (average rating: 3.57 and 0.473 standard deviation).

Table II. "Legendary party" statistics

P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	
9	12	21	16	9	12	13	23	33	41	189
4.1	3.6	4.2	4.4	3.6	3.3	3.2	3	3.3	3	3.57

EYE TRACKING EXPERIMENT

We designed our eye-tracking experiment aiming at understanding how people look at their friends' ratings and which type of correspondences they mentally make. During the eye-tracking study (15-20 minutes) each participant went through the following steps:

Step1. The experiment's admin first debriefs each participant on the nature of the experiment explaining the main process flow presented in Figure 1 (red box).

Step2. The admin assists each participant during the calibration process of the eye tracking system. He then saves the precise calibration data for each user.

Step3. The user puts on the iPod headsets and fixates him/her-self in a comfortable position in front of the tracking device. S/he also uses his/her right hand to locate the "forward" and "pause" buttons" on the iPod which are useful to shift to the next song (one button press), fast-forward the current one (button pressed) or pause the song when ready.

Step4. Each user listens to one song and sees a corresponding interface at a time. In each interface are presented the title and artist information (at the top), a list of friends' names (to the left) and a list of their ratings (to the right). There are 24 songs on the iPod corresponding to 24 interfaces customized for each user in the sense that each participant sees only the ratings of others and not those of him/her-self. When ready with the song evaluation the participant presses the pause button and verbally transmits a rating from 1 to 5 to the admin. The admin saves the rating and the participant proceeds to the next song by clicking on the "forward" button and any keyboard key on the computer controlling the eye-tracker.

Step5. To conclude the study, the admin collects general comments through open discussions with each participant in order to assess the user's overall perception of the experiment.

Interfaces

There are few observations we need to make about our experiment. First, it is tailored for each user considering personalized interfaces for each participant. Thus, we had to eliminate the current participant's name from the list and update all other interfaces with his/her friends' names. Furthermore, we consider 8 interfaces corresponding to all remaining group members, 8 with closest 5 friends and the last 8 interfaces with 2 closest friends. Each of the last 16 interfaces was adjusted by the trust values extracted from the online questionnaire.

The interface from Figure 6 contains a random list of first names and family names replacing real participants' names and generated with the purpose of showing the reader a clear display of information which our participants saw on their screens. Thus each participant in the first group saw first 8 interfaces of 8 friends remaining in the group whereas each participant in the second group saw 8 interfaces with 9 remaining friends and their ratings.

The 24 interfaces were conceptualized as follows:

1. First group of 8: all remaining group members
2. Second group of 8: 5 closest friends
3. Third group of 8: 2 closest friends

Furthermore, we split each of the 8 into:

1. Controversial: highest standard deviation of ratings
2. Non-controversial: lowest standard deviation of ratings

We also arrange each next 2 interfaces by trust, displaying the most trusted friends in order, from highest trust to lowest, in the left column with names, and by familiarity, sorting users by their rating and display them from highest to lowest rating.

We divide all interfaces into 3 areas of interest (AOIs):

1. AOI Song: the grey rectangle at the top
2. AOI Users: the left part containing user names
3. AOI Ratings: the right part containing user ratings

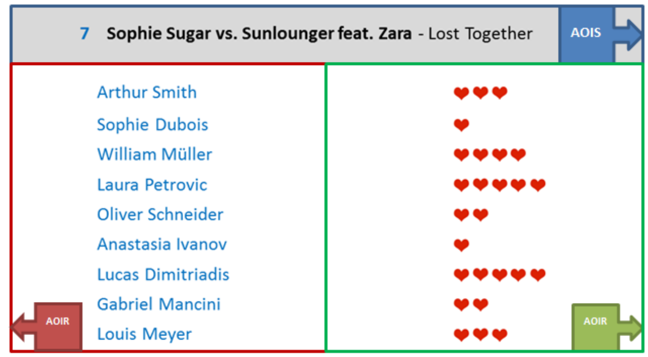

Figure 6. Examples of eye-tracking type interfaces

For each interface the eye-tracking system provides as output the fixation-point representation in Figure 7 - we erased participants' names from AOI Users in the left hand-side of the image. The blue circles represent the main fixation points that the eye-tracker detected, the blue lines represent the eye's movements from one element to the next and the numbers inside the circles represent milliseconds of each fixation. Thus this graphic schema is a powerful representation for: (1) extracting both fixation times for each of the areas of interest through which we detect users that are most influential for each participant and (2) study fixation directions: parallel lines (between AOIs) correspond to the fact that participants associate their friends with their ratings whereas vertical lines (within AOIs) denote the fact that users are in search of either user or rating information which is not coupled: user-rating.

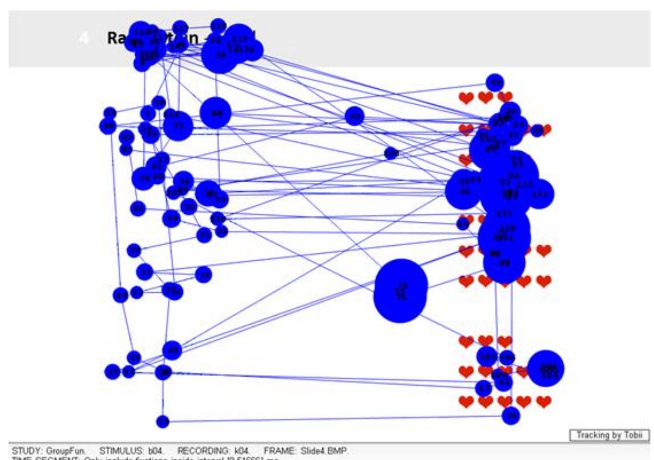

Figure 7. Fixation-point map as eye-tracking output

An extensive dataset containing fixation points (measured in seconds) was collected from the study of the 19 participants x 24 interfaces = **456 images**. We collected the total time corresponding to each user-name and rating for each of the three AOIs and for each participant. A summary is presented in Table III with the following abbreviations:

- TTI = Total Time Indicated
- TTC = Total Time Computed
- AOIS = Area Of Interest Songs
- AOIU = Area Of Interest Users
- AOIR = Area Of Interest Ratings

The proportion between TTC and TTI gives the eye-tracker's efficiency for each group: 84% for Group1 and 83% for Group2. Each song received a different sight attention from all members – respective watching times for Group1 for the last 8 songs are listed in Table III below. We report that some songs, such as S18 and S22, have as much as 3 times more watching time than others, such as S17. Given that the number of displayed users for all 8 songs was 2, we formulate the following possible explanations: either the users did not know the respective songs and discovered it while listening or they enjoyed it more than others and wanted to continue listening.

Table III. Time view-statistics expressed in seconds per Group, AOI and number of users

Group	TTI	TTC	AOIS	AOIU	AOIR
Group1	4867.5	4080.7	1536.7	1382	1161.8
	8/9	1642.1	386.6	640	615.5
	5	1284.7	543.8	406.9	334
	2	1153.9	606.3	335.3	212.3
Group2	6436.8	5336.4	1517.4	2188.9	1630.1
	8/9	1793.5	274.6	891.7	627.2
	5	1872.4	464.7	786.5	621.2
	2	1670.5	778.1	510.7	381.7

Several preliminary conclusions yield from the table:

1. Overall, for all interfaces, participants spent about the same amount of time on all 3 AOIs;
2. For all friends, users of both groups looked mostly at the AOIU, then at their ratings and finally at the songs name;
3. For 5 closest friends the situation is different per group. The first group looked mostly at AOIS and least at AOIR, thus users being least influenced, while for the second group users looked mostly at AOIU, then their ratings and finally AOIS being mostly influenced.
4. For 2 closest friends, participants from both groups looked most at the song's name and artist, then at their friends and finally at their ratings. This suggests that they were least influenced. However, since the interface area was reduced in size it is somehow natural that they looked less than before at these last two AOIs.

We use the Chi-Square statistical test whether actual data differ from a random distribution and compares the counts of categorical responses for the "8/9", "5" and "2" closest friends groups between the 3 independent groups: AOIS, AOIU and AOIR. We obtain very low p-values for all both groups and 3 conditions: p_AOIS_1 = 1.365E-11, p_AOIU_1 = 1.181E-24, p_AOIR_1 = 1.085E-48, p_AOIS_2 = 2.667E-34 and p_AOIR_2 = 0.001. Thus, the probability that participants rated randomly is almost 0.

RESULTS

By comparing the two groups we note that the network structure is strongly correlated with eye-tracking parameters.

Time in AOIs

We observe that members in Group2 are more connected than members in Group1: familiarity and trust network are denser as it is inferred from Figure 4. For all interfaces and any number of friends, users in Group2 looked less at AOI Songs and spent more time by looking at AOI Users and AOI Ratings: 38% vs. 28% for all interfaces, 24% vs. 15% for all friends, 42% vs. 25% for closest 5 friends and 53% vs. 47% for closest 2 friends. This implies that they were more interested in seeing and analyzing their friends' ratings than members in the first group. So, this observation can be summarized as follows: the more connected a group is (through familiarity and trust) the more interested its members are to discover other friends' music preferences.

The results also show that, within group, participants looked less at AOI Songs for the first 8 interfaces, i.e. when all other members and their ratings where displayed. This is an expected behavior since the most information was included in the first part of the experiment and users needed more time to scan through the names and ratings.

Another important result is that for the interfaces containing 2 closest friends, participants in both groups split approximately at half the time they looked at song's name and artist (grey rectangle in Figure 6) vs. all other information: 53% for Group1 and 47% for Group2 for AOI Songs.

Eye Gaze

Now, we compare the time in AOI Users with the time in AOI Ratings within group. Over all interfaces time in AOI Users is longer than time in AOI Ratings as follows: 34% vs. 28% overall, 39% vs. 37% for all friends, 32% vs. 26% for closest 5 friends and 29% vs. 18% for closest 3 friends.

The relative percentage difference between AOI Users and AOI Ratings is less for all 8 friends in Group1 and for 2 closest friends in Group2. Turning back to the network structure we find this result very encouraging. We explain it by the fact that the more distant the relationship between users is (Group1) the more they are inclined to look at the whole list of friends rather than drawing correspondences between friends and ratings.

To understand this group phenomenon in more detail we searched into more details about the eye gaze of each member (Figure 8). We observe that in the first group the total time in AOI Users and AOI Ratings is, on average, equally distributed between the two for all 8 users with correspondences between some users and their ratings. The same phenomenon is observed in the second group for the 2 closest friends.

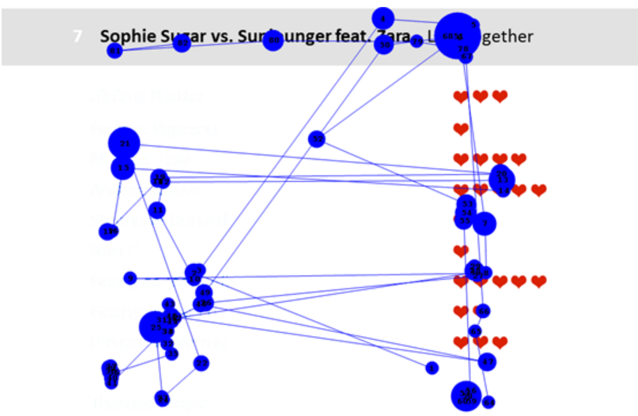

Figure 8. Participant eye-gaze

As it can be inferred from both figures there are two types of correspondences or saccades which help understand the importance of information displayed to each participant through an objective measurement: horizontal lines – between users (left) and their ratings (right) – and vertical lines – within AOI Users or AOI Ratings.

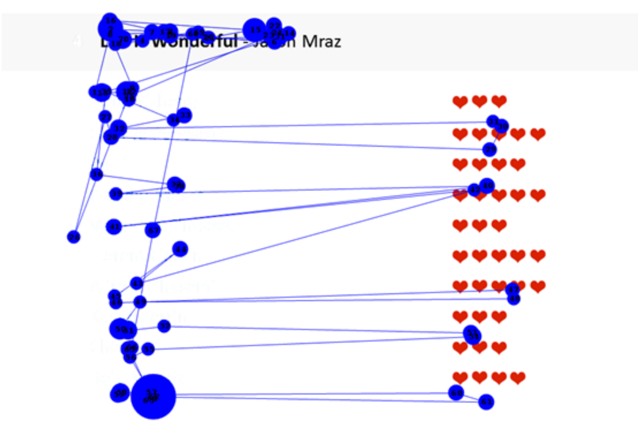

Figure 9. Clear eye-gaze patterns

In Figure 9 are presented clear horizontal correspondences between users and their ratings. Out of the entire number of users displayed to the left the current participant looked at only 5 and draw associations with their ratings in evaluating his/her own rating. Another result noted from the figure is that participants skipped some rating information more than they skipped name information: vertical lines are denser in the left side than in the right side but the focus corresponds to the horizontal lines which are clearly marked.

Not only that we obtained a very good eye-tracking movement recognition and fixation times but also most of the outputs were similar to those from Figure 9. However, not all eye gaze patterns were very clear. We noticed some outputs in which users looked: (1) mostly (90% of the time or more) at the song's name, (2) from top to bottom on both users and ratings columns and draw few associations and (3) had a non-uniform, even chaotic, gaze skimming from one corner of the interface to the next (Figure 10).

We notice that fixation times do not correspond well to the names on the left and corresponding lines are non-horizontal but skewed. Furthermore, in this case we state that the participant combined the 3 AOIs drawing associations from AOI Song to AOI Users (top names) and from AOI Song to AOI Ratings (middle and bottom hearts) which is undesired for a clear evaluation. Here we cannot conclude anything about group influence for any of the members on the left but can only use the fixation times for each of the 3 AOIs.

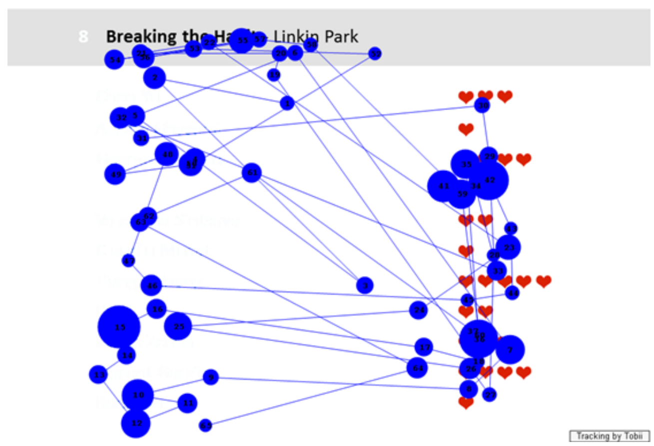

Figure 10. Unclear eye-gaze patterns

Group vs. Individual Interface

Not only that the "group" interfaces that we designed helped us record fixation times and understand the meaningful information per participant but they also proved to increase group satisfaction for both groups.

Preference Correlation

We used the Pearson correlation index to determine the users who are closest to each other preference-wise, where r represents the individual rating for each of the 24 songs. Largest correlation values are marked in bold in Table IV for each participant. We mapped this with the familiarity and trust network to observe if subjective familiarity corresponds with objective ratings.

In the first group, P1 thinks is closest to P4 but the ratings show him/her closest to P8. Reciprocally, P4 thinks to be closest to P1 but rating correlations prove him/her to have closest tastes to P9. Another case shows P7 to know most P5 and P9's music tastes. Once again the correlation coefficient shows that s/he likes music similar to P8.

In the second group P19 is the "standard" rating reference for all other members. P11, P13, P14, P16, P17 and P18 all have highest rating correlation with P19. Furthermore, P18 and P19 stated to have known each-others' preferences the most. Another interesting result is that P12 knows P15's tastes and these tastes are also highly correlated (0.6).

Table IV. Pearson correlation index

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**
P1	1	-0.4	0.3	0.3	-0.5	-0.1	0.2	**0.7**	0.4
P2		1	0.2	-0.1	**0.7**	0.3	0.1	-0.5	-0.7
P3			1	0.1	0.2	**0.5**	0	0.1	0
P4				1	-0.2	-0.3	0	0.2	**0.4**
P5					1	**0.2**	**0.2**	-0.6	-0.5
P6						1	**0**	-0.2	-0.2
P7							1	**0.2**	0
P8								1	**0.6**
P9									1

	P10	**P11**	**P12**	**P13**	**P14**	**P15**	**P16**	**P17**	**P18**	**P19**
P10	1	0.2	0.4	0.3	0.2	-0.2	-0.2	0.3	**0.5**	0.2
P11		1	0	0.4	0.5	0.2	0.1	0.2	0.4	**0.6**
P12			1	0	0.1	**0.6**	-0.3	0.1	0.4	0.4
P13				1	0.4	0	0	0.1	0.4	**0.7**
P14					1	0.2	0.1	-0.2	0.4	**0.5**
P15						1	-0.2	-0.2	**0.4**	0.3
P16							1	0	-0.3	**0.6**
P17								1	0	**0.7**
P18									1	**0.7**
P19										1

Group Influence Index

We computed a normalized group influence index per participant measuring the difference in ratings s/he submitted while being exposed to the individual interface vs. the group interface.

For each group member we compute an average rating for the GroupFun experiment in Phase I as a measure of individual satisfaction (Equation 2). We normalize this by the number of rated songs (j) since this number is different among users.

$$satisfaction_i = \frac{\sum_{1..j} r_{ij}}{j(i)}, \forall i \in U, j(i) \in R \qquad (1)$$

We compute the signed difference and absolute difference between the two arrays of ratings to determine the number of positive: "+" (increase), negative: "-" (decrease) and neutral: "0" (same), where the first ratings are for the individual condition and the stared ratings are for the group.

$$\Delta_i = \sum_{1..j} \left| r_{ij} - r_{ij}^* \right|, \forall i \in U, j(i) \in R \qquad (2)$$

$$\varepsilon_i = \sum_{1..j} r_{ij} - r_{ij}^*, \forall i \in U, j(i) \in R \qquad (3)$$

Table V. Rating change statistics

	j	**+**	**-**	**0**	**Δ**	**ε**	**c**
P1	17	8	6	3	21	7	**82.35**
P2	7	0	0	7	0	0	0
P3	16	5	2	9	9	3	43.75
P4	24	10	7	7	29	5	**70.83**
P5	23	0	2	21	2	-2	8.69
P6	8	1	1	6	2	0	25.00
P7	21	8	3	10	16	10	**52.38**
P8	21	5	2	14	7	3	33.33
P9	14	4	2	8	7	3	42.86
P10	7	2	1	4	6	0	42.86
P11	9	1	3	5	4	-2	44.44
P12	14	1	4	9	5	-3	35.71
P13	11	5	0	6	8	8	45.45
P14	7	1	2	4	4	-2	42.86
P15	9	3	2	4	6	2	**55.56**
P16	11	2	6	3	11	-5	**72.73**
P17	13	2	7	4	20	-14	**69.23**
P18	17	2	3	12	5	-1	29.41
P19	22	3	11	8	16	-8	**63.64**

In Table IV we denote the following:

- Avg_i: average rating for the individual interface;
- Avg_g: average rating for the group, eye-tracking interface;
- j: number of songs in both interfaces divided into 3 categories: “+”, “-“ and “0”;
- +: number of positive changes – increase of ratings;
- -: number of negative changes – decrease of ratings;
- 0: number of neutral changes – ratings are kept the same;
- Δ: absolute rating difference;
- ε: signed rating difference;
- c: change rate percentage.

One first observation is that participants did indeed change their ratings at a very high rate. If we sum the “+” and “-” columns it yields a higher number of changed ratings than non-changed ratings from column “0”.

Both Δ and ε help understand the variations of ratings. The minus sign correspond to a decrease of ratings compared with the individual interface used as baseline. However, this decrease corresponds to a small variation in rating difference whereas the increase corresponds to a large variation.

Another result is that members in the first group have achieved about the same satisfaction in both conditions whereas in the second group 8 out 10 members have improved their ratings overall.

Across all participants we measure an average group influence rate of 45.32% - average of all 19 c-values. Overall, the more songs people rate the higher the group influence and social alignment - the bold percentages from the right column mark group influence higher than 50%.

We consider the following 2 functions:

$$\bar{r}_i = \frac{\Delta_i}{j(i)}, \forall i \in U, j(i) \in R \qquad (4)$$

$$\eta_i = \frac{\sum_{1..j}\left(\# r_{ij}^{+} + \# r_{ij}^{-}\right)}{\sum_{1..j}\left(r_{ij}^{+} + r_{ij}^{-} + r_{ij}^{0}\right)}, \forall i \in U, j(i) \in R \qquad (5)$$

The first one computes the average rating difference (on a 1 to 5 scale) for the absolute rating difference whereas the second one is an index measuring the number of rating changes vs. the total number of ratings. The variable from Equation 5 is our normalized group influence index.

The results from Figure 11 show the difference for the group interfaces compared with the ratings recorded in GroupFun (Equation 4). This chart allows us to recognize, on one side, participants who changed their ratings the most: P1, P2 in the first group and P17, P16 and P10 in the second (higher than a score of 0.8 of 5 on average, per song) and, on the second one, participants who did not change almost at all their preferences: P2, P5, P6 and P8 in Group1 and P18, P12 in Group2 (lower than a score of 0.4 of 5 on average). Noticeably, participant 2 didn’t change any of his ratings for the 7 songs he previously rated! To understand this change we correlate the group influence index with eye-tracking data in the following section.

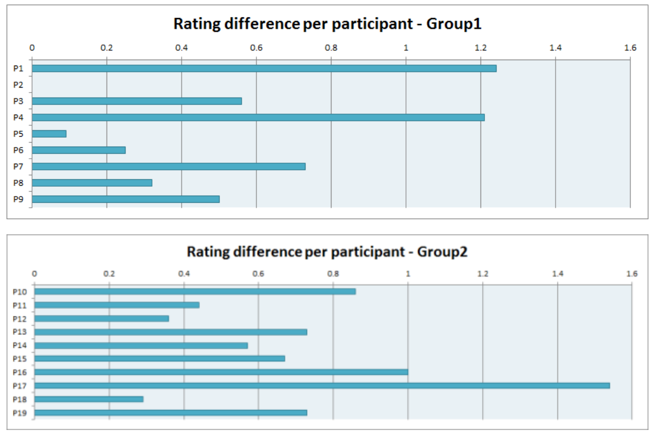

Figure 11. Rating difference per participant for both groups

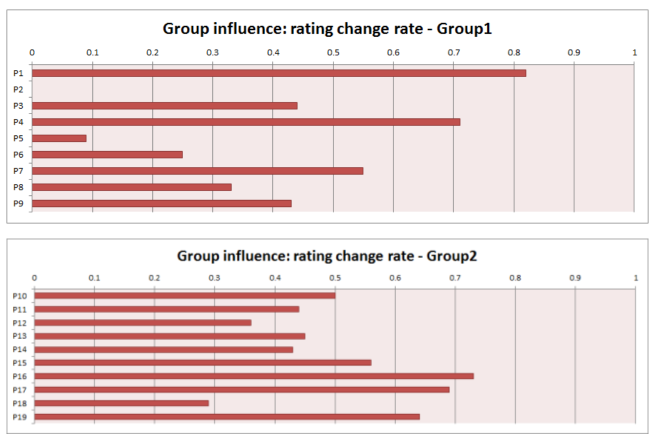

Figure 12. Group influence index for each participant

As it can be inferred from Figure 12 the change rate for both groups is very high suggesting that individuals were strongly influenced by their friends’ ratings. An average η for Group1 is **0.4** and for Group2 **0.5**. Indeed social influence in the second group is more homogenous given the groups higher connectivity compared with the first group (Figure 4) in which some participants tended to have a strong preference which they care about and would not adapt to the group decision. In the next section we compare this explicit group influence with the objective eye-tracking correspondences measuring the other members which participants paid most attention to. Our data suggests that individuals do not have fixed preference values that they stick to but they adapt to group suggestions.

Group Distance and Eye-gaze Correlation

In order to have a deeper understanding of group influence we correlate subjective results from familiarity and trust measurements with eye-tracking data. First, we compute an average between familiarity and trust for each participant with respect to other group members and then we normalize this into a value between 0 and 1 based on the total familiarity and trust one submitted. Secondly, we extract horizontal correspondences from each interface and count the number of times one participant looked at all other members. We obtain 0 or 1 values for each interface and for each other member which we aggregate into a total score per participant: some members have a clearer eye-gaze than others thus we normalize again these values into a 0 to 1 number. Next, we draw correlations between the normalized combined familiarity and trust group distance and the eye-tracking social distance. We obtain very high correlation scores for the following participants: P1 (c1=0.668), P5 (c5=0.622), P6 (c6=0.842), P8 (c8=0.682), P9 (c9=0.847), P11 (c11=0.79), P12 (c12=0.69), P14 (c14=0.769), P18 (c18=0.802) and P19 (c=0.936). These results prove that the implicit social relationships in the group are well reflected by the eye-tracking gaze: participants look more at the people they trust and are more familiar with their tastes.

However, when computing the correlation between the normalized group influence index (Figure 12) and the eye-gaze social distance we obtained no significant value: 0.008. Even when we normalized the social distance for each group taking into account the precision of the eye-tracker we get a negative correlation of -0.153.

Nevertheless, despite the fact that this quantitative analysis does is not very useful in evaluating the overall correspondence between the implicit group characteristics and the explicit ones, we focus on more detailed, quantitative view by correlating familiarity and trust networks with the eye-gaze horizontal associations per participant. Indeed, we report a mediation effect between the gaze data and the group influence index: the more tighter the familiarity and trust relationships between a participants and other members are the more s/he follows those other members' preferences. High familiarity and trust values correspond to high eye-gaze values per participant, e.g. P1 (P4 – maximum familiarity index of 2 and 13 eye-gaze out of 24, P2 (P5 – maximum familiarity index of 4 and 11 eye-gaze correspondences), P5 (8/4), P6 (12/3), P7 (12/2), P9 (15/4), P10 (11/4), P11 (23/3), P12 (17/3), P14 (9/4), P18 (9/2), P19 (15/4).

When computing symmetry relationships, i.e if participant Pi often looks at Pj, does also Pj also looks at Pi?, we notice that familiarity and trust symmetry guarantees to a certain extent the eye-tracking correspondences. For instance: P1 is most familiar with and trust P4 most. P4 also is most familiar and trust P1's tastes. The eye-tracking data comes in support of this: P1 identified P4 13 times out of 24 interfaces. However, P4's eye gaze was very poor and we could not detect any correspondence made with P1.

In the second group P18 and P19 are familiar and trust each-other more than other group members. P18 looked at P19 ratings 9 times out of 24 (most compared with other members) while P19 followed P18's preferences 15 times. This analysis is very useful for the study of explicit group influence. One important challenge is that group relationships involve more than 2 individuals and computing symmetry among a larger number of participants is hard problem involving other factors such as attention, precision and interest.

An extension of this type of analysis is transitivity: if participant A has a strong social relationship with B and B is most familiar and trusts C then does the social graphs and eye-tracking data support the relationship between A and C?

ADVANTAGES AND LIMITATIONS

This study represents a new approach to the study of group influence by incorporating objective eye-tracking data rather than users' subjective perceptions. It stands out with respect to other advancements in the study of group influence through the following key strengths:

1. It compares subjective evaluation with objective data measurements;
2. It uses an extensive dataset of eye-tracking fixation points;
3. It is based on group selected preference instead of external data;
4. It defines a group influence index based on group alignment useful for understanding individual preference variations and alignment.

Main limitations are due to the relatively small number of participants, the interfaces presented to them and the eye-tracker's precision. For example, for some songs, users did not spend enough time to analyze the interface but they proceeded to state a rating immediately after hearing the song. In other cases users simply liked the songs played to them on the iPod and browsed only for curiosity their friends' ratings explicitly mentioning that they were not influenced at all by them but by the quality of music.

We considered each songs uploaded by our participants to be equally important whereas some of the songs might be liked by an overwhelming majority of people whereas others might be totally inappropriate for a party. We minimized this effect through our selection of the 24 songs out of the 39 and, respectively 47.

CONCLUSIONS AND FUTURE RESEARCH

In this paper we presented our experiment design and results for understanding group influence in a music context. With the use of GroupFun, our music recommender system, we logged participants' individual ratings and compared them with individual preferences in a group setting. Users were asked about their new ratings given the scores of their friends in the same group.

We analyzed both rating and eye-tracking data. By comparing the subjective values from the familiarity and trust networks with the objective ones recorded with our tracking device we identified that the more connected or social a group is, the more correspondences there exists between users names and their ratings. Users create these associations visually in order to make decisions.

We identified clear visual types by clustering our interfaces into 3 AOIs and identifying inter and intra AOI horizontal and vertical correspondences. Our results show that participants which felt more familiar with their friends' music tastes and trusted them more looked for longer time and drew eye-tracking associations for all members in the sparse group (Group1) and for 2 closest members in the dense group (Group2). Furthermore, the eye-tracking data confirms the social relationships among participants: individuals followed their closest friends' preferences during the eye-tracking experiment as subjectively evaluated through familiarity and trust questionnaires.

Fur our future work we plan to:

1. Produce an in-depth qualitative analysis of rating changes by computing correlation values for all 4 conditions: controversial vs. non-controversial and familiarity vs. rating ordering;
2. Compare intra vs. inter AOI correspondences and interpret horizontal and vertical lines per user to study group influence and identify personality traits at an individual level rather than at a group level. We will further compute image histogram and overlay multiple interfaces from connected users to understand in more detail the extent to which users adapt to their friends' ratings;
3. Draw correlations between group influence, participation and involvement identifying isolated users who are most "distant" from group decision. Further analysis is needed to compute eye-tracking-based metrics and interpret individual alignment to group preference by comparing the ratings displayed in the interfaces with those selected by each participant.

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REFERENCES

1. Baskin, J., Krishnamurthi, S. *Preference Aggregation in Group Recommender Systems for Committee Decision-Making*. Proc. RecSys 2009, ACM Press (2009).
2. Bonhard, P., Harries, C., McCarthy, J., Sasse, M. A. *Accounting for Taste: Using Profile Similarity to Improve Recommender Systems*. Proc. SIGCHI 2006, ACM Press (2006).
3. Bu, J., Tan, S., Chen, C., Wang, C., Wu, H., Zhang, L., He, X. *Music Recommendation by Unified hypergraph: Combining Social Media Information and Music Content*. Proc. Multimedia 2010, ACM Press (2010).
4. Castagnos, S., Jones, N., Pu, P. *Recommenders' influence on buyers' decision process*. Proc. RecSys 2009, ACM Press (2009).
5. Celma, O., Cano, P. *From Hits to Niches?: or how Popular Artists can Bias Music Recommendation and Discovery*. Proc. KDD & Netflix prize competition. ACM Press (2008).
6. Chen, H.-C., Chen, L. P. *A Music Recommendation System Based on Music Data Grouping and User Interests*. Proc. CIKM 2011. ACM Press (2001).
7. Gartrell, M., Xing, X., Lv, Q., Beach, A., Han, R., Mishra, S., Saeda, K. *Enhancing Group Recommendation by Incorporating Social Relationship Interactions*. Proc. Group 2010, ACM Press (2010).
8. Masthoff, J. *The Pursuit of Satisfaction: Affective State in Group Recommender Systems*. Computer Science (2005), Vol. 3538, 297-306.
9. Popescu, G., Pu, P. *Probabilistic Game Theoretic Algorithms for Group Recommender Systems*. ACM RecSys 2011, ACM Press (2011).
10. Tang, J., Sun, J., Wang, C., Yang, Z. *Social Influence Analysis in Large-Scale Networks*. Proc. SIGKDD, ACM Press (2009).
11. Vannoy, S. A., Palvia, P. *The Social Influence Model of Technology Adoption*. Communications of the ACM, ACM Press (2010).
12. Zhu, H., Huberman, B. A., Luon, Y. *To Switch or Not To Switch: Understand Social Influence in Recommender Systems*. Computer Science, Computers and Society. arXiv: 1108:5147 (2011).