An investigation of the suitability of heterogeneous social network data for use in mobile tourist guides

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ABSTRACT
Social Networking Sites (SNS) are used daily by billions of people worldwide to keep them informed about the latest news, to help them interact with other people as well as to provide them with Points of Interest (POIs) to visit. In this paper we examine to what extent the information from SNSs such as likes, tags, check-ins can influence the visitors or locals of a city in choosing venues to visit. Next, we implement an Android application, Social City, for mobile devices, which collects and evaluates the information from Facebook and Foursquare in order to recommend to users venues to visit in the city of Patras, Greece. Finally, we discuss an evaluation of Social City. Our results indicate that the combination of SNS data from multiple social networking sites into a single rating, appears to lead to more efficient recommendations for the users, helping them choose faster and easier and with more confidence about the quality of their choice.

Categories and Subject Descriptors
H.1.2 [**Information Systems**]: Human Information Processing

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *Information Filtering*

General Terms
Human Factors; Design; Measurement.

Keywords
Tourist guide; Recommendation Algorithm; Android; Social Networks

1. INTRODUCTION
Nowadays an increasing number of new social networking sites (SNS) are created, in order to promote the communication and the interaction between their users. Most of them vanish as time goes by and only some of them manage to achieve popularity. The success of a SNS is mainly determined by the unique services that distinguish it from others and by the frequency of use by their members [1]. However, a number of SNSs that are still popular today are Facebook, Foursquare, Twitter, Instagram, Google+ etc. Most of them provide location-based services with some overlap and the majority allows cross-posting to other SNSs. In order to benefit the most from all these SNSs, a user needs to install a variety of applications on her smartphone. To obtain a complete impression of a POI, and finally select one or more to visit, the user needs to interact with several SNS applications, as each one contains different kind of information for the same POI. Users typically make choices from list, or map-based interfaces. In POI lists, most SNSs provide a rating mechanism for POIs to instantly show users their popularity. However there is no consistency amongst these and it is not always clear to the user how this rating was derived. The purpose of our paper is twofold: firstly to examine how various types of SNS data influence users' decisions in choosing venues. Secondly, to examine how data from heterogeneous SNS can be combined into a cumulative rating for POIs and whether such a cumulative rating can yield better recommendations than the ratings presented in singular SNS, using POI lists. Our work is based on the combination of social data from three SNSs (i.e. Facebook, Foursquare, Google+ Local) in order to propose to the user venues to visit in a city.

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2. RELATED WORK
Searching and browsing results on mobile devices has been a subject of study for several years. Church et al. [3] emphasize the importance of the position in which search results from mobile devices are displayed, where space is limited due to the physical dimensions of the screen. After research they found that the position of a choice-result in web searching was on average in 6^{th} place with users having browsed on average 1.3 result pages before selecting. Furthermore, they concluded that over 60% of the users choices were found in the first three positions in the list. In their research, Jones et al. [5] mention that most of the search systems, present the results of a user's query as a ranked list. Such approaches show that even on large screens, search interfaces are not widely used, as they complicate the search process and prevent the user from using it. Thus, it is important for the user to find quickly the search results and for the search systems to be dynamic and flexible enough to respond to user changes. After studies, they concluded that the users of mobile devices completed 14% fewer procedures when searching for web content than the large screen users, compared to the results of the previous study showing a failure rate of 50% for users of mobile devices. They also show that the success is related to the size of the mobile screen, as users are more satisfied with the existence of more elements such as title, description, image in search results, which is difficult to do on mobile devices with small screens. Pantel et al. [8] extend previous studies by adding the factor of social networking data to the factors that influence a user's selection

such as accuracy, experience, presentation, detail, recency etc. More specifically, they consider the type of social data (e.g., likes, shares) that can affect the user's choice. It was found that the user can benefit from such information in different ways such as a) discovery of the proposed options, b) personalized search results, c) participation in the activities of friends, d) selection results and e) emotional connection with impersonal search engines. Finally, Haas et al. [4] note that search results that include multimedia such as images, videos, etc. are preferred by a large percentage of users over the simple search results, as they lead to more relevant results. In relation to geotagged results, there has been considerable research in the visualization of these as icons on maps, particularly dealing with the problem of off-screen visualization (Chittaro et al. [2]). A fair amount of literature can be found on venue recommendation algorithms based on data from social networks, although these are limited to data from either a single social network, mostly Twitter or Foursquare [6][7][9][10]. The problem hence of determining which SNS is the best source for recommending venues and, additionally, in cases where multiple heterogeneous SNS data are used, which type of data carries most weight for calculating recommendation rankings, remains unanswered.

3. SOCIALCITY PROTOTYPE/APP

We developed the SocialCity prototype (Figure 1) in order to combine information from multiple SNSs (i.e. Facebook, Foursquare and Google+ Local) and to suggest to users venues to visit in the city of Patras, Greece, in a list format. Our system runs locally on the user's device and is based on an SQLite database that contains matched Facebook, Foursquare and Google+ venue IDs. As the problem of automatic venue matching across heterogeneous SNS is beyond the scope of our work, we have manually compiled a database of 200 venues, using our local knowledge of the area to resolve conflicts. The app initially uses the Fourquare API, in order to receive data (e.g. *name*, *total check-ins*, *coordinates*, *number of tips*, *here now*) for the venues in a specific category (e.g. *Nightlife* or *Arts*), that are in the user's locality. Data is retrieved in a JSON format. Subsequently, the proximal venue IDs are used to retrieve a subset from the device local database that contains those IDs found in the user's locality. For this subset, the corresponding Facebook and Google+ Local venue IDs are retrieved. For each one of the matching venue IDs, a request is send to Facebook or Google+ APIs in order to obtain data (e.g. *likes*, *were-here*, *check-ins*, *rating*) for each venue in JSON format. Combining all the previously mentioned data, we implemented an algorithm that ranks the venues based on their weighted attributes and presents them to users in a list format. Each list element contains an image of the venue, its name, its calculated rating, its category and its distance from the user (as calculated from the Foursquare venue coordinates). Upon clicking on a result, the user can see a detailed breakdown of the SNS data that contribute to the rating of the venue. The entire retrieval and calculation process takes a very short amount of time to complete (<4 seconds on a quad-core Nexus 4 device over a 3G network), negating the need for a remote server to carry out the necessary calculations.

4. DETERMINING THE IMPORTANCE OF SNS DATA FOR VENUE RANKING

4.1 Algorithm

In order for the venues to be evaluated and recommended to the user, we attempted to devise an algorithm that consists of the computation of the weighted mean and a formula based on the true Bayesian estimate. For the implementation of the algorithm we took under consideration the *historical interaction* data from Facebook (i.e. "likes" and "were here"), *real-time interaction data* from Foursquare ("here now"), *subjective venue ratings* from Google+ Local ("rating") and *spatial information* (i.e. the calculated venue's distance from the user). Since there is no past literature to hint at which element of the above is more influential for the user, our first goal was to find appropriate weights for each one of them. For this reason, we attempted to determine the weight importance empirically from the users and experimentally via machine-learning, using a feed-forward Neural Network, which we will discuss later.

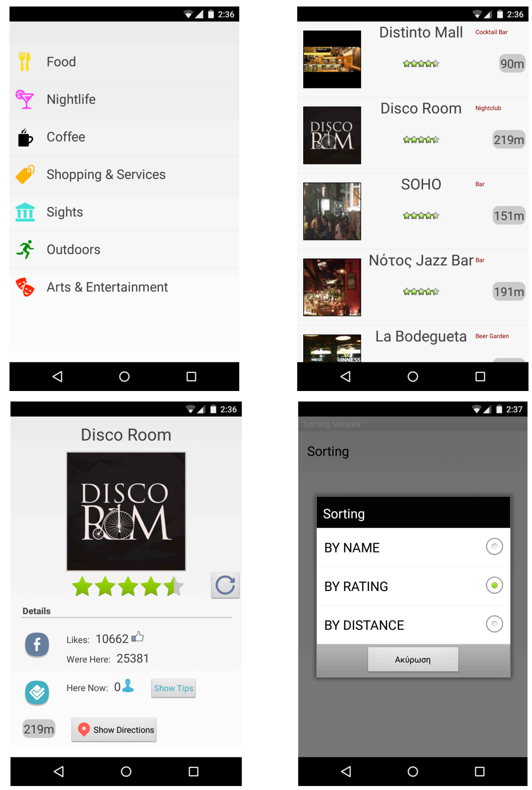

Figure 1: User interface of the SocialCity prototype app

4.2 Empirical Estimation of SNS Data Type Weighting

We carried out an experiment to evaluate which social data type, i.e. historical (H), real-time (RT), subjective (SUB) and venue distance from the user (SPT), affects users the most, when making a decision. We designed a series of screen mock-ups (Figure 2) that presented a list of three venues per screen along with SNS stats for each venue, and asked users to indicate their venue choice based on the venue attributes for each screen. The venue attributes were randomly generated so as to reflect, for each data type, a value belonging to a high, medium and low category, whose ranges we defined based on actual SNS data. We deliberately did not use meaningful venues names as we did not want to influence the users' choice based on possible personal prejudices. As a result, we provided users with a total of 16 screens. In each screen, we modified one of the three venue attributes to represent all possible category combinations, while keeping the other two venue attributes in the "high" category. The number of users who took part were 32 (11 female), aged 17-42. The screens were presented randomly to each user and we noted the selected venue and also the time taken to reach a decision in each screen.

The results of the first experiment failed to indicate clearly which data type affects users the most. Users typically selected the number of screens where the data value was high (M_H=14.97, SD_H=1.09, M_{RT}=14.13, SD_{RT}=1.26, M_{SUB}=13.91, SD_{SUB}=1.40, M_{SPT}=13.81, SD_{SPT}=1.33). We did not find a statistically significant difference for these, or for the cases where the selected screens had medium or low values.

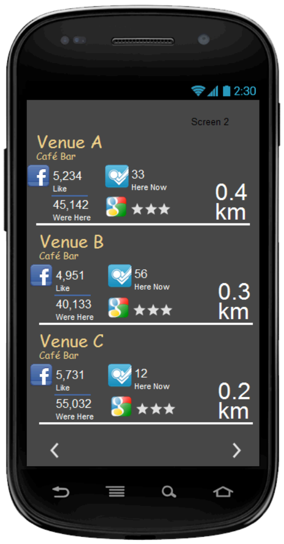

Figure 2. Venue stats mock-up example

As the results of the first experiment failed to reveal clear differences between SNS data types, we carried out a follow-up survey of our original users and added a few more, for a total of 45 users (18 female) aged between 17-45. In this survey we asked them to list in order of preference (1-5) the data type that they consider most significant for forming an opinion on a venue, and to comment on their most and least significant choices by free text. Our results (Figure 3) indicate that users rely more on the historical interaction data as an indicator of venue importance, but their decision is also affected strongly by spatial distance. Subjective venue ratings seemed to play little role for our users.

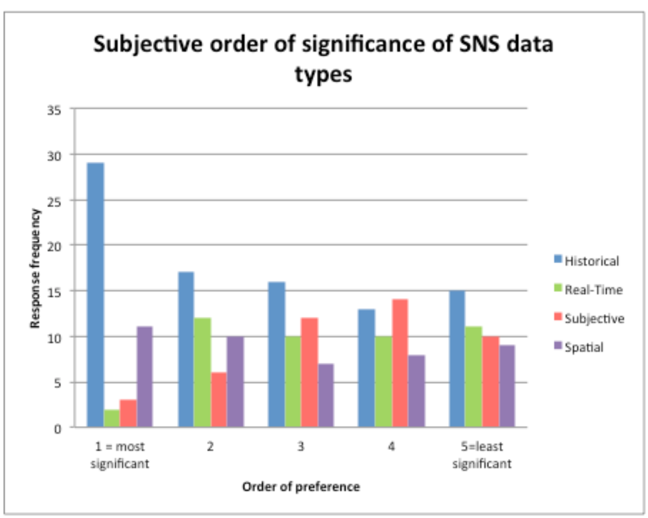

Figure 3. Self-reported data type significance for informing venue choices

4.3 Automatic Determination of SNS Data Type Weighting

Even though our analysis of subjective importance could be a basis on which to calculate weights for a recommendation algorithm, we chose to investigate if these could be reliably deduced with automatic means. For this purpose, we constructed a 12-4-4 feed-forward Neural Network and trained it on the results of our first experiment (venue choices), so that we could observe the NN's synaptic weights, given to output nodes that represented the SNS data types. As such our NN consisted of 12 nodes in the input layer (3 venues x 4 data types), 4 nodes in the hidden layer (1 node per venue attribute) and 4 nodes in the output layer (the computed weights for each attribute).

For the input we constructed a 12x16 matrix which consisted of 16 columns which represent an encoding of the 3 combinations made in our previous experiment. For this we used a value of 1 for "high" data values, 0 for "medium" data values and -1 for "low" data values. Table 1 below depicts an example of this encoding.

Table 1. Sample encoding of venue attributes for NN input

Data type	Data Label	Venue A		
		Value	**Category**	**Encoding**
Historical	FB Likes	5.234	H	1
	FB Were-Here	45.142		
Real-time	4SQ Here now	33	H	1
Subjective	Google+ rating	2 stars	M	0
Spatial	Distance	1400m	L	-1

For the target outputs we constructed a 4x16 matrix which consists of the answers which were chosen by a participant in our first experiment in all the 16 screens, i.e. if the participant chose the Venue A in screen 1, then the first column of this matrix is h,h,m,h and after the setting of the variables, it is 1,1,0,1. We created 32 such matrices, one for each participant.

We trained the feed-forward network 32 times using the Matlab's nntraintool, and stored the resulting weights on the synapses between the hidden nodes and the output nodes. To measure the network's training performance, we checked the value of regression. We concluded that the value was between 0.94 and 1, which means that the network was efficiently trained. Since we have 4 hidden nodes and 4 output nodes each weight set consisted of a 4x4 matrix with 16 values, and we ended up with 32 such matrices. For each one of these matrices we calculated the absolute weight values and then placed the sum of each row (as it represents the weights from the same hidden node to any output node) and into a 4x1 vector. From the resulting 32 vectors we found the average of each vector at each position *i* and we stored them in a final 4x1 vector, which ultimately provides our final calculated rounded weights i.e. Historical=9, Real-time=2, Subjective=1, Spatial=22. Interestingly, these results do not fully agree with our users' self-reported weighting of the data types. While historical data still seems to carry more weight than real-time data, leaving subjective data last, the most important weight derived from our NN, seems to be the distance.

4.4 A Recommendation Algorithm Based on SNS Data Types

Based on our investigation, we devised an algorithm for recommending venues based on SNS data. The algorithm takes a two-step approach. In step 1, our algorithm uses the weighted mean *R* for a venue, using the weights output by the NN, as follows:

$$R = \frac{w_H x_H + w_{RT} x_{RT} + w_{SUB} x_{SUB} + w_{SPT} x_{SPT}}{w_H + w_{RT} + w_{SUB} + w_{SPT}}$$

where:

$\{x_H, x_{RT}, x_{SUB}, x_{SPT}\}$ represent the value category (h, m, l) of each data type (historical, real-time, subjective, spatial) using an appropriate numerical value mapping (we use the following mapping: h=5, m=2.5, l=1), and;

$\{w_H, w_{RT}, w_{SUB}, w_{SPT}\}$ represent the NN-extracted weights for each data type (we use the values respectively 9, 2, 1 & 22 as mentioned in subsection 4.3 above).

In step 2 the algorithm extracts the final ranking for each venue using the formula:

$$\mathrm{WR} = \frac{\mathrm{R} * \mathrm{L} + \mathrm{C} * \mathrm{m}}{\mathrm{L} + \mathrm{m}}$$

where *R* is the computed weighted mean of step 1, *L* is the number of a venue's likes crawled from the Facebook's API, *m* is the upper bound of the minimum number of likes (set to 2000) and *C* is the average number of likes in a specific category for a particular geographical area of interest (for example for category 'Food' we crawled 48 venues from the Facebook API and took the average number of "likes"). The rationale behind this algorithm is to take into consideration the "Like" attribute of venues, as our participants previously identified this as being most trustworthy but also to include the context of the user's locality, by adapting the *C* metric to the user's current area.

5. EXPERIMENTS

To determine the performance of the venue recommendation algorithm, we constructed an experiment to compare its output against the results provided from two popular services, i.e. Facebook and Foursquare. We based our experiment on a dataset of venues retrieved from Foursquare, Facebook and Google+, which were collected from the SNSs' APIs, by requesting them to return all the available venues within 200 meters from one of the most central squares of Patras, in its popular city centre area. We then divided the venues into five categories (Food, Nightlife, Coffee, Shopping and Services, Arts and Entertainment). For each category we collected 37, 21, 47, 48 and 12 venues respectively (165 venues). Upon examining the dataset, we found that Google+ Local returned very few results, probably due to its low use in the area of interest. Hence we decided not to include the Google+ Local data in our experiment and hence set the relevant weights in the algorithm from 1, to zero. The 165 venue IDs were matched between the two SNS sets manually by the researchers.

5.1 Phase 1 – User Preferences

We invited 20 participants (7 female) aged between 20-28 years old, all of which claimed to have good local knowledge of the area of interest that we collected data from, to participate in our experiment. Starting our experiment, we handed participants a questionnaire with 5 questions, one for each venue's category and asked them to provide a venue recommendation based on their local knowledge. The questions contained contextual information that involved social activity and temporal context aspects. This was a deliberate choice, in order to reflect typical tourist needs, which have been shown to relate to context and not just general opinion [11]. The questions were:

Q1. Which place would you recommend to a friend for dinner at 9.30pm?

Q2. Which place would you recommend to a friend for a drink at 11.00pm?

Q3. You want to go for a coffee with a friend around 7.00pm. Which place would you recommend?

Q4. It's Tuesday afternoon and the shops are open. Which shop would you recommend to a friend who wants to get another friend a present for her 25th birthday?

Q5. It's Friday evening and you want to go to an Arts or Culture place with a friend (e.g. live music, theater, cinema etc.). Where would you recommend?

We collected each user's responses and used them as their individual "targets" for the next phase of the experiment.

5.2 Phase 2 – Evaluation of Venue Recommendation Interfaces

In order to keep the user experience the same and to prevent SNS mobile app presentation and formatting from influencing the users' opinions, we developed an interactive mobile prototype (in mobile HTML5) that presented the result sets from each SNS using a similar format (Figure 4). This format is adapted to show for each venue the SNS data available from each SNS. We presented to users the search results from both APIs, counterbalancing so that half participants started with the Facebook results while the other half started with the Foursquare results. For each venue category, we presented the returned default sorting, and asked participants to select their chosen venue as indicated by them in Phase 1 (or to click the "does not exist" button at the bottom of the list). After having selected a venue, we logged the selected venue's position on the list and also the time it took participants to locate it. Additionally, after each venue selection, the participant was asked to respond to two questions as follows:

Q1. How satisfied are you from venue's position in the list?

Q2. How easy was for you to find your choice within the list?

After having finished with the information seeking process with all the categories for each SNS, the user was prompted to respond to the following two questions:

Q3. How useful did you think the presented venue info was?

Q4. How much do you trust the venue sorting?

Finally, users were asked to complete a NASA TLX questionnaire for each of the two interfaces.

Following on from this step, we introduced participants to our own application, which was presented to the users with the venues ranked via our algorithm and showed for each venue a star rating (out of 5) as well as the distance from the venue to the user. The process was identical to the previous stage of the experiment that involved the Facebook and Foursquare interfaces, involving the same logged data, questions and NASA TLX questionnaires as before. After participants had finished working with the three interfaces (Facebook, Foursquare, SocialCity), we asked them a final set of three additional questions:

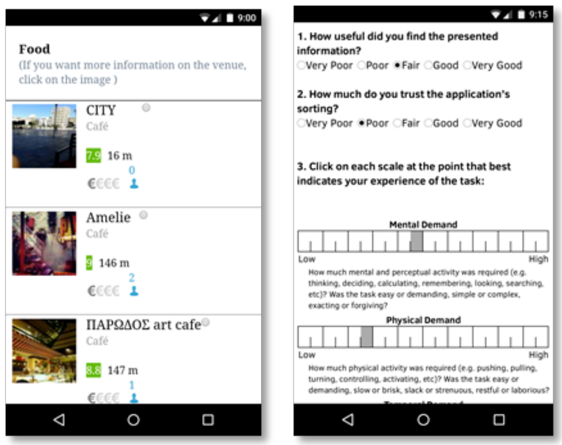

Figure 4. Screenshots from the MobileHTML5 interface for Foursquare results & NASA TLX questionnaires

Q5. Which interface did you like the most?

Q6. Which interface did you find more trustworthy?

Q7. If SocialCity was available to you, how often would you use it?

5.3 Results

For our experiments, we carried out Wilcoxon signed rank and paired-sample T-tests according to the distributions of variables.

5.3.1 *Performance of SNS Ranking Algorithms*

In several cases, our participants were unable to find the venue of their choice in the result sets of the three interfaces. The best results in terms of occasions where the desired venue was not found, were provided by Foursquare (M=1.10, stdev=0.85), followed by SocialCity (M=1.55, stdev=0.76) and Facebook fared worst (M=3.95, sd=0.76). Wilcoxon signed-rank tests reveal that the differences are statistically significant between Facebook and the other two interfaces ($p<0.01$ in both cases) and that the difference between SocialCity and Foursquare is not statistically significant. The Facebook result is particularly bad, considering the total of 5 venues that each participant selected.

A more interesting result arises from the analysis of the position in the list where venues where found. For this analysis, we considered only cases where at least three of the venues were found. This excluded the Facebook results from the analysis, since there were no instances where our participants could find at least three of their chosen venues in Facebook. Additionally, there were 16 cases where our participants found at least three of their chosen venues in both SocialCity and the Foursquare interface. The results show that venues were found nearer the top of the list in SocialCity (M=8.16, stdev=3.45) than Foursquare (M=10.86, stdev=4.18). A paired-sample T-test showed that this difference is statistically significant ($p<0.05$).

Finally, in terms of the time participants spent searching for their desired venue, our participants were fastest with SocialCity (M=14.73s, stdev=8.52s), followed by Facebook (M=30.22s, stdev=12.57s) and finally Foursquare (M=41.14s, stdev=18.37s). The differences between SocialCity and the other two interfaces are statistically significant (Wilcoxon signed-rank tests, $p<0.01$ in both cases). The difference between the Facebook and Foursquare interfaces is also statistically significant (Wilcoxon signed-rank tests, $p<0.05$), which is an intriguing result, since we would have expected participants to take longer with Facebook, given the very low rate of success with this interface.

5.3.2 *Subjective Feedback*

Based on our participants' feedback in the NASA TLX questionnaire, we note that the participants indicated an overall dissatisfaction with the Facebook interface (Figure 5). The following results derive from paired-sample T-tests. Through these, in terms of mental demand we note that a statistically significant difference exists between Social City and the other two interfaces (SC-FB $p<0.05$, SC-4SQ $p<0.01$) but not between Facebook and Foursquare. Physical demand exhibits a statistically significant difference between Facebook and SocialCity ($p<0.01$) and Foursquare and SocialCity ($p<0.05$), but not Facebook and Foursquare. In terms of temporal demand, Facebook fared worse than both Foursquare and SocialCity with a statistically significant difference in both cases ($p<0.01$), while no statistically significant difference was observed between Foursquare and SocialCity. Performance was deemed high with both Foursquare and SocialCity (no statistically significant difference), while Facebook was worse ($p<0.01$ against both Foursquare and SocialCity). However, in terms of the effort required to obtain this performance, SocialCity has a statistically significant difference against Facebook ($p<0.01$) but not against Foursquare. The latter two also do not exhibit a statistically significant difference between them. Finally, it was clear that participants were mostly frustrated with Facebook, which has a statistically significant difference in this metric against the other two interfaces ($p<0.01$ in both cases). Also, the frustration exhibited with Foursquare and SocialCity did not reach a statistically significant difference.

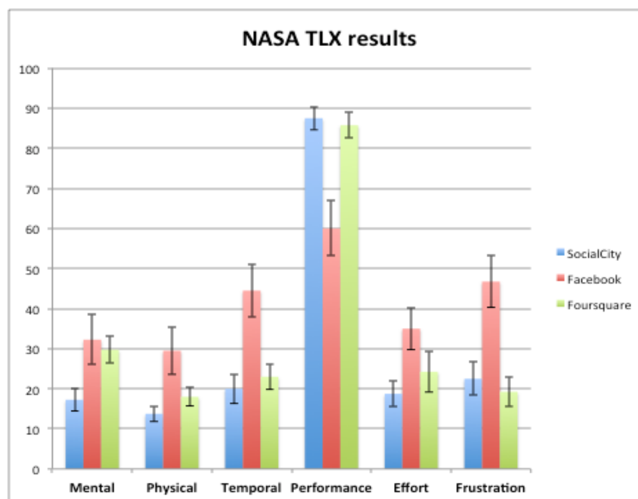

Figure 5. Subjective evaluation of result retrieval process

We asked our participants to report their satisfaction with regard to their chosen venue's position in the list for each interface, on a Likert scale (1=not satisfied at all, 5=very satisfied). The responses showed that Foursquare satisfaction was greatest (M=3.35, stdev=0.74), followed by SocialCity (M=3.22, stdev=0.72), although the difference between the two is not statistically significant (paired sample T-test). The least satisfaction was with Facebook (M=1.66, stdev=0.49) and the difference with the means for Fousquare and SocialCity is statistically significant ($p<0.01$ in both cases, Wilcoxon signed rank tests). Although we previously found that SocialCity performed better in terms of venue position in the list by two places, it seems that this performance advantage is not considered important to the users (both Foursquare and Social city bring results within the top 15 places, hence searching is quite limited). Our second question related to the ease with which participants found their chosen venues on a Likert scale (1=not easy at all, 5=very easy). Here, participants reported that it was easier for them to find their venue within the Foursquare interface (M=3.46, stdev=0.49), followed by the SocialCity (M=3.30, stdev=0.68), although the difference between the two is not statistically significant (paired sample T-test). However a statistically significant difference exists between the latter two interfaces and Facebook (M=1.68, stdev=0.54), in both cases $p<0.01$ (paired sample T-test). The third question related to the participants' perception of the usefulness of information presented in each interface on a Likert scale (1=not useful at all, 5=very useful). Here, participants felt that the most useful information was presented in SocialCity (M=4.20, stdev=0.77), followed by Foursquare (M=3.85, stdev=0.67) and Facebook (M=2.15, stdev=1.09). The differences in pairwise comparisons for all three interfaces are statistically significant at the $p<0.01$ level for Facebook vs SocialCity and Facebook vs. Foursquare, and at the $p<0.05$ level for SocialCity vs. Facebook (Wilcoxon signed rank tests). Our fourth question asked participants to indicate their level of trust in the sorting algorithm provided by the interfaces, indicating their appraisal of how good suggestions were, regardless of their own personal venue choices. Here, participants reported a Likert scale (1=not trustworty at all, 5=very trustworthy) and showed their preference towards the SocialCity recommendations (M=4.05, stdev=0.95), followed by Foursquare (M=3.35, stdev=0.75) and finally Facebook (M=2.00, stdev=1.026). The differences in pairwise comparisons for all three interfaces are statistically significant at the $p<0.01$ level for Facebook vs SocialCity and Facebook vs. Foursquare, and at the $p<0.05$ level for SocialCity vs. Facebook (Wilcoxon signed rank tests).When asked which interface they liked most, 19 participants selected SocialCity and one selected Foursquare. In terms of their overall trust in the recommendations, 17 participants stated they trust SocialCity most, two selected Foursquare and one person selected Facebook, in line with the results of our fourth question. Finally, when asked how often they would use SocialCity if it was available to them, the majority indicated that they would use it very often (9), often (7) and sometimes (4).

6. CONCLUSION

We developed an Android application, SocialCity, which gathers information from social networks and attempts to recommend venues to visit, using a ranking algorithm that fuses data of various types from multiple SNSs. To help us understand which information from those found in social networking sites plays the most important role for the users, we designed and performed two experiments involving potential users.

While subjective user feedback indicated that users reported to rely more on the historical interaction data as an indicator of venue importance, however, our automated analysis of attribute weighting showed that spatial distance played a more significant role in their actual venue choices. Compared to the results of ranking algorithms used by Facebook and Foursquare, our algorithm showed a performance improvement in ranking users' targets higher and hence improved retrieval speed.

Our participants also found the aggregated "star" rating and distance information to be more helpful at appraising the eligibility of venues than simply presenting factual data. Finally, our recommendations were perceived to be more trustworthy, regardless of participants' individual preferences.

Our study was not without limitations: we asked participants to perform our experiments in carefully controlled environments, acting out the role of a local expert and comparing their recommendations to those generated automatically by three systems. We would like, in the future, to run a field-based longitudinal experiment with visitors in a city, in order to gain a better understanding of our application's ability to recommend venues through fusing SNS data. Although our participants were within the same age range as the typical social network user, and classified themselves as having adequate local expertise in the area where we focused our experiment, the question remains as to how our system might fare against the recommendations of objectively appointed experts in each venue category (although such persons would be arguably hard to recruit). Finally, our approach is limited by the need to have a set of matching SNS venue ids, which we compiled manually. A scalable implementation would require an automated method to build this set for users, possibly based on machine learning techniques. Despite these limitations, we conclude that the incorporation of social data to the results of multiple SNS seems to lead to better recommendations, helping them chose faster and easier, and with more confidence in the quality of their choice.

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