Can Social Network Be Used for Location-aware Recommendation?

Pasi Fränti, Karol Waga and Chaitanya Khurana
School of Computing, University of Eastern Finland, Joensuu, Finland

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Abstract: Our goal is to give recommendations for mobile users about interesting places around his current location. The only input is the user, location and time. In this work, we study whether the social network of the user can be utilized for improving recommendations. We will answer the following two questions: (1) can we measure user similarity based on their Facebook profile and location history, (2) do these imply usefulness for the recommendations.

1 INTRODUCTION

Location-based services have become widely used due to the fast development of positioning systems in multimedia phones. We study recommendation system for a mobile user who wants information about nearby services such as shops and restaurants. User can make a query specified by keyword(s), or he can just ask general recommendation without any keywords as input (see Fig. 1). In the latter case, the relevance of a service must be determined merely by other factors such as user location, time and personal preferences. In (Fränti et al., 2011), relevance of a recommendation was considered to consist of four aspects:

- Location
- Time
- Content
- User and his/her network

Location is the key aspect but not the only one, see Fig. 2. In (Waga et al., 2012), recommendations were influenced by the overall search history by giving higher rating for entries with popular keywords in their title or tags, see Fig. 3. Extra points were given to keywords that were used often, used recently, or search in the nearby location of the user. Keywords used by the user himself were also given higher score. Recommended items were taken both from Mopsi service directory, and from the photo collections of the users.

In this work, we study whether a network of the user can be used for improving recommendation. Social knowledge was explored in (Bao et al., 2012) by considering opinions of local experts in the given area. This can be useful for improving rating of the services by utilizing users whose opinions matter most. User network can also become useful when making recommendations, especially for the

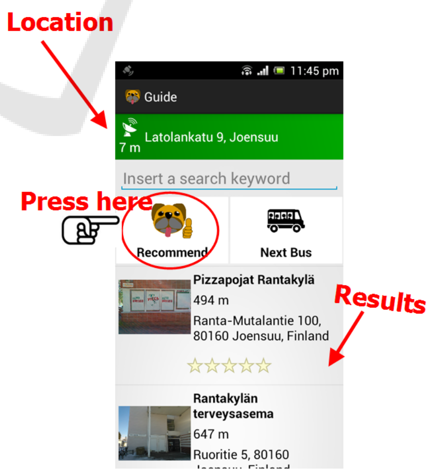

Figure 1: Recommendation in Mopsi (http://cs.uef.fi/mopsi).

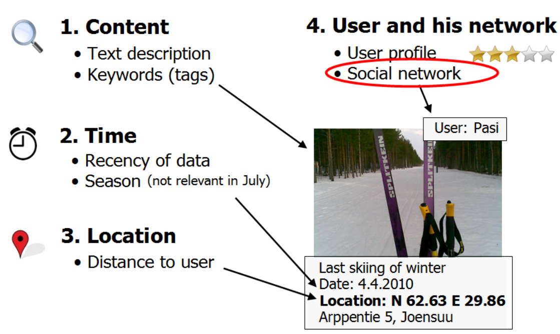

Figure 2: Four aspect of relevance in geo-tagged photo.

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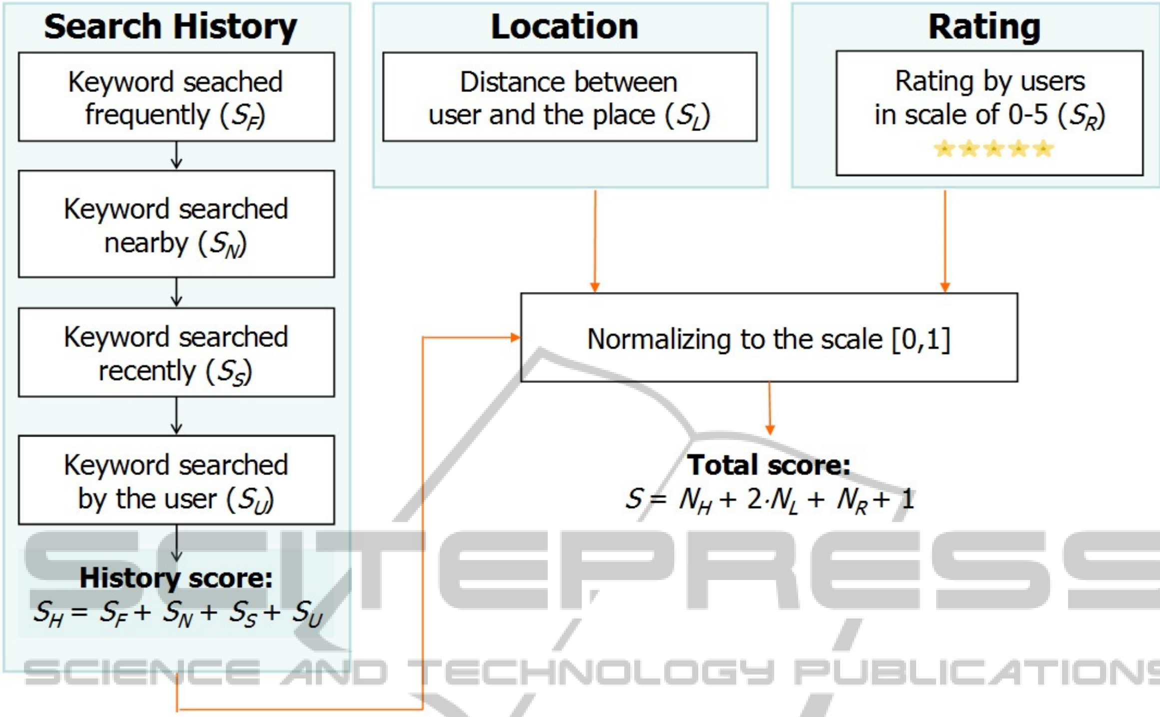

Figure 3: Scoring recommendations based on relevance to user.

so-called *cold start users*, from whom we have very little or no previous history data. Profiles and parameters used for their friends and similar users can provide good initial guess for personalizing the recommendations (Yang et al., 2012).

For utilizing the network, it is not clear what type of network should be used, and how much a given user should influence the recommendation for another user. For this task, we study how similar two users are when measured by the following features:

1. Friendship in Facebook
2. Pages liked in Facebook
3. Places visited in Mopsi

We perform qualitative experiment with a small set of nine Mopsi users. We study the facebook pages the users like, and the frequency of the places they have visited in Joensuu. We study how much the user similarity according to these features correlate to the subjective opinions of the user themselves, and also how they useful they rank the recommendations of the other users in the location-aware recommendation context.

The main findings are that the user similarity correlates with all the features studied but not very strongly. There is mild correlation with the user locations (0.28) and the pages liked (0.47) but the strongest correlation is with the facebook friendship. In most cases, users ranked their facebook friends as more similar than the others. However, when asked how useful they would expect the data (photos in Mopsi) of the other users, all the correlations decreases and indicate that these features are not easy to utilize on location-aware recommendation system.

2 UTILIZING USER NETWORKS

So far, user networks have been the least utilized aspect in Mopsi recommendations. The service is public to entire world and there are no friend-to-friend connections. Currently the only user network implemented is the one suggested by clustering the users according to their location, see Fig. 4. This can be used to inform people who else is in the same area. We next discuss possible types of network from the following perspectives:

- Social network vs. information sharing network
- Buddy network vs. stranger network
- Selected friends vs. automatic ad hoc network
- On-line vs. offline network

For a more extensive taxonomy of social web sites, see (Kima et al., 2010).

2.1 Effectiveness of the Network

By far the most widely used networks nowadays are the social networks implemented by Facebook, Twitter, Google+, Instagram and other similar platforms where users explicitly specify with whom they share their data. Social network has indeed very strong influence whose data is more relevant to the user but it is not the only possible network.

Users in general are more interested what their friends are doing than other people in general. However, in recommendation system, the relevance of the information is more important than the social aspect. In location-aware recommendation system, users are seeking for information around his current location. A user visiting the place often is therefore more likely to have more relevant information than a friend. In this view, we have more pragmatically driven information sharing platform rather than merely a social network.

Another aspect of social network is that how well the people connected actually know each other. According to the *small-world* phenomenon (Watts and Strogatz, 1998), we can reach anyone in the world by six steps, on average.

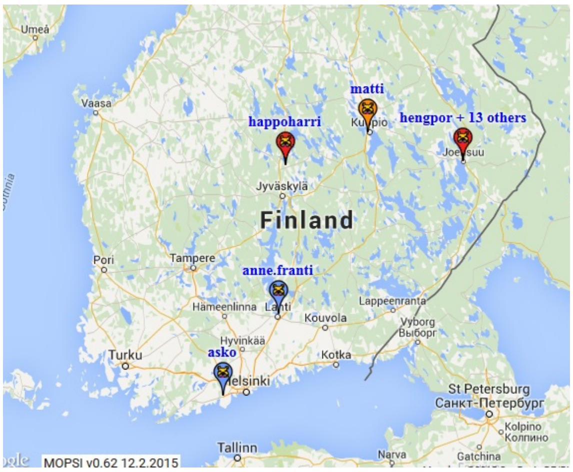

Figure 4: Example of clustering users according to their location.

It was shown in (Barrat and Weigt, 2000) that even a small amount of disorder (randomness) in the network is able to trigger the small-world behaviour even if the network was otherwise strongly clustered. Therefore, the connectivity of the network is not the bottleneck but the quality of the links is.

Network like Facebook is not really friend network, but a term like *buddy network* would be more appropriate. Due to social pressure, people often try to be as connected as possible, which does not really make sense from the efficiency point of view. Having 400 Facebook friends does not imply that the person has 400 real friends; a more likely number would be about 10 or less. Nevertheless, the people who are linked together know each other, and the small-world phenomenon applies.

From information distribution point of view, the relevance of the information sent via network is affected by how many people we are connected to, and how often we use these links. Instead of sharing information via a large number of links, few strong connections are likely to be more effective than a large number of weaker links. The strength of the connection is therefore more important than the connection itself.

Contrary to social networks, strangers may also be linked together because of sharing the same interest. In *cough surfing*, people offer accommodation to others without financial compensation (Bolici, 2009). The key aspects in such *stranger network* are the reputation and trust between the users. In Mopsi, only information is traded but in the same way, the reputation of the author influences how trustworthy we consider his/her data. Recommendations can be used to build up the trust, and improve the quality of the information.

2.2 Automatically Created Networks

For computer scientists, anything that can be automated is always worth to consider. Users can be linked based on their behaviour how they use the service (Gratz and Botev, 2009), or simply according to their location. In Mopsi, the location is taken into account in the recommendation system already, but the similarity of the users is not yet utilized. In (Bacon and Dewan, 2009), similar users are recommended to each other. Once there will be enough users in the service, similarity can be used to offer personalized search result.

A more ambitious ad hoc network is considered in (Wu et al., 2009) using face analysis technique to identify people in photos, and use this information to create more complex social network automatically. If more thorough content analysis could be successfully done, people with the same hobbies could be connected automatically.

Another approach is to combine location-based service and social network from two independent components as done in (Simon et al., 2009). One can then focus on developing the location-based media collection and service directory, and utilize existing network for user identity and all the social networking functionalities that come along. In Mopsi, we implemented login using Facebook credentials, which allows users to share their Mopsi data in Facebook: the system generates (optional) status update to inform their network buddies as shown in Fig. 5. Data is still stored also in Mopsi but all the discussion happens in Facebook.

2.3 Behaviour in a Public Network

The nature of being an on-line or offline network affects how people use it. In our case, the data collection itself has online nature but since there is no online conversation forum in Mopsi, the system is more like offline by its nature.

Personality also affects how people use social networks. Extravert personalities are more likely to engage social activities but according to (Ross et al., 2009), personality has much smaller effect than expected on how they use Facebook. For example, social person is likely to join more groups but it does not reflect much on the size of the network, or how extensively the communicative functions are used. This can be partly explained by the fact that Facebook is less widely used for on-line chatting than other forums for live communication.

Figure 5: Facebook status update via Mopsi photo upload.

The level of neuroticism in personality, however, affects on how much people preferred text (writing on the wall) or sharing photos in Facebook. People with higher sensitivity to threat use more textual expression and less photo sharing because it was more controllable due to its off-line nature Ross et al., 2009). Another study showed that the identity people present in their social network can differ a lot from their real personalities. It was observed that the image people gave was more real in off-line chatting environment than in offline social network (Zhao et al., 2008).

The privacy issue can also be important for people who would want to use the service, but wish not to reveal their identity or even location. Methods have been developed specifically to prevent the system to combine user's identity and location (Takabi et al., 2009), which actually contradicts our goals of specifically sharing the user location. This reflects the privacy concern, which the social network and information sharing evidently weaken if not adequately solved.

In Mopsi, the motivation is to encourage people to share their information via their personal collection, and use their network for the same. We should encourage people to share as much information as possible so that it would have high coverage, but on the other hand, keep the quality of the information trustworthy so that it would be relevant and therefore useful to recommend to others. Division of the service to two different concepts – personal collection and service database – aims at reaching both of the goals at the same time. How to transfer data from the personal collection to the open database is a point of further development.

3 SIMILARITY OF USERS

We study next empirically the connections between users in Facebook and in Mopsi. We selected nine volunteers who work either in our lab or nearby (see Table 1). They all live in Joensuu use both Mopsi and Facebook, and know each other at some level. Most of them are linked in Facebook as well. We asked them to evaluate their relationship and rank the other people from 1 to 8 using the following two criteria:

Q1: *How similar you find the person is to you?*
Q2: *How useful you find his/her Mopsi photos?*

For the second question, context is that does he recommend, via his/her Mopsi postings, useful and interesting places to visit in future. The first question was to measure similarity whereas the second tries to explore whether the usefulness goes beyond similarity and friendship. The resulting rankings are shown in Tables 2 and 3. Pink background of a cell is used to indicate that the users are not linked in Facebook. As expected, if one considers the other similar, they are also connected in Facebook. In this regard, similarity and connection in social network seems to correlate.

3.1 Analysis of the User Evaluations

Detailed inspection of the data reveals that the similarity ranking is quite subjective. The sum values show that certain people tend to be more often "similar" than others. For example, Radu, Pasi and Andrei have average rankings of 1.5, 2.8 and 3.0. In specific, Radu is the most similar for five other users, and ranked 2nd or 3rd for the rest. By common sense, everyone cannot be just like Radu, but knowing him we conclude that most people would not mind being like him. Further analysis of the FB data (not included here) shows that the more the photos and status updates of a particular user are liked and commented, the more similar he/she is considered.

The two rankings have reasonable high correlation with each other (0.52) but there are few differences. In the usefulness evaluation Pasi becomes the highest ranked due to frequent publishing of travel photos. Also Julinka's photos are considered more useful for the same reason. Otherwise, the usefulness and similarity rankings are quite similar. However, we asked how useful users *expect* the data of their friends to be, but in fact, the expectation may not match the reality. Some low rankings might be biased towards low publication activity rather than the usefulness of these photos.

Table 1: Volunteers participating in the experiment.

	Mopsi			Facebook	
	photos	places	visits	friends	pages
Andrei	676	96	676	463	285
Julinka	3850	122	2116	229	154
Mikko	190	84	292	55	14
Oili	6467	164	1261	298	63
Pasi	9716	208	3847	88	67
Radu	1417	122	912	298	19
Rezaei	716	85	587	193	16
Chait	63	22	53	580	195
Jukka	991	126	682	142	120

Table 2: User similarity based on their own view.

	Andrei	Julinka	Mikko	Oili	Pasi	Radu	Rezaei	Chait	Jukka
Andrei	-	7	8	4	2	1	3	6	5
Julinka	2	-	4	3	6	1	5	7	8
Mikko	7	8	-	5	1	2	4	6	3
Oili	3	5	7	-	2	1	4	8	6
Pasi	3	8	5	4	-	2	6	7	1
Radu	1	8	4	5	2	-	3	7	6
Rezaei	4	7	2	6	1	3	-	8	5
Chait	2	8	4	7	5	1	3	-	6
Jukka	2	7	5	4	3	1	8	6	-
Average:	**3.0**	**7.3**	**4.9**	**4.8**	**2.8**	**1.5**	**4.5**	**6.9**	**5.0**

Table 3: Expected usefulness of friend's photos.

	Andrei	Julinka	Mikko	Oili	Pasi	Radu	Rezaei	Chait	Jukka
Andrei	-	5	8	4	1	2	6	7	3
Julinka	2	-	6	3	4	1	5	7	8
Mikko	4	1	-	8	2	6	7	5	3
Oili	4	5	7	-	1	2	6	8	3
Pasi	2	7	1	4	-	5	8	6	3
Radu	2	5	7	4	1	-	6	8	3
Rezaei	6	2	7	3	1	5	-	8	4
Chait	3	7	8	4	2	1	6	-	5
Jukka	3	6	5	4	1	2	8	7	-
Average:	**3.3**	**4.8**	**6.1**	**4.2**	**1.6**	**3.0**	**6.5**	**7.0**	**4.0**

3.2 Similarity in Page Liking

For testing the similarity of users, we compared how many same Facebook pages the users liked. For example, Mikko and Radu like four same pages (*Mopsi, Impit Finland, S+SSPR 2014 and East Finland Graduate School of Computer Science & Engineering*), out of total 29 pages that either both or one of them likes. Using these numbers, we define their similarity by Jaccard coefficient as the number of matches divided by the total number of pages: 4/29 = 14%, see Figure 6.

The similarity values for the page likes are shown in Table 3. As expected, lowest values are typically among users who are not linked in Facebook. The page liking correlates also reasonably well (0.47) with the user similarity values (Table 2) but the correlation with the usefulness values (Table 3) is much smaller (0.17). Therefore, even if user similarity could be estimated by their user profiles in facebook, using it for location-aware recommendation would still be questionable.

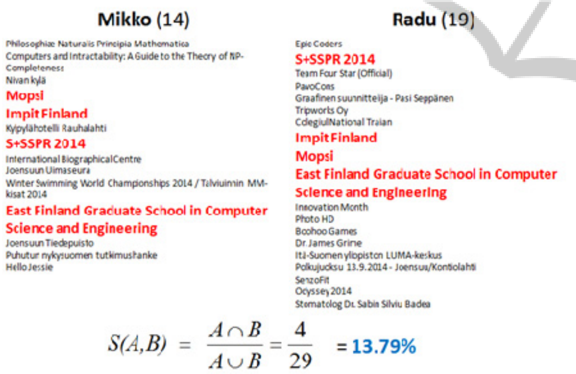

Figure 6: Sample similarity calculations of users based on their likes in Facebook.

Table 4: Similarity values for Facebook page likings (%).

	A	J	M	O	P	Ra	Re	C	JP
Andrei	-	3	2	3	5	2	2	3	2
Julinka	3	-	1	2	1	1	1	1	1
Mikko	2	1	-	7	6	25	16	3	5
Oili	3	2	7	-	8	6	6	3	4
Pasi	5	1	6	8	-	6	4	2	4
Radu	2	1	25	6	6	-	14	3	5
Rezaei	2	1	16	6	4	14	-	2	3
Chait	3	1	3	3	2	3	2	-	1
Jukka	2	1	5	4	4	5	3	1	-

Another issue is that liking exactly the same page is not likely to happen in larger scale. For example, if one person likes *McDonalds* and the other one a local brand *Hesburger*, they are still similar as they like fast food restaurants. We considered counting matches of the categories the pages belong to. Facebook has roughly 54 million pages, which all belong to 107 predefined categories. For example, McDonalds and Hesburger are both in *fast food* category. The same Jaccard measure can still be applied.

However, results using category matches show even lower correlation because the categories are too general. We therefore dropped this idea and use page liking as such. Fig. 7 shows part of the similarity graph for the set of test users.

3.3 Similarity in Location History

For studying location activity, we selected 293 places from Mopsi services as the visit places in Joensuu. We recorded user activities until 31.12.2014 as follows: (1) places where they took photos, (2) places where tracking a route was started or ended. Each activity is counted as a visit to the nearest place to the location of the activity. We used only locations within the bounding box (28.65E, 63.44N, 31.58E, 62.25N) that roughly covers Joensuu city and the rural areas of the municipality. There are 10,426 visits in total. The number of visits of each user is reported in Table 1.

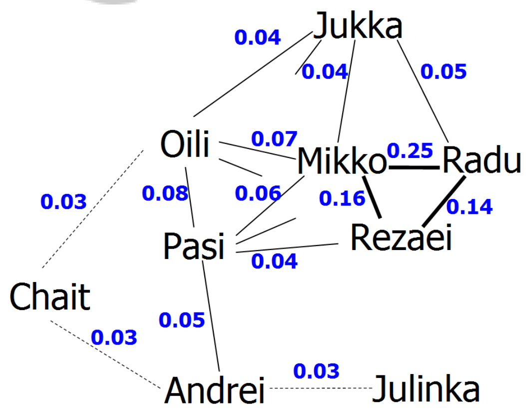

Figure 7: Similarity graph constructed from the biggest similarities in page likings.

The location data of a user forms a frequency histogram consisting of 293 bins. The most popular places with the corresponding visit frequencies are listed in Fig. 8.

Location similarity of two users i and j are calculated using Bhattacharyya distance between their histograms:

$$D_B = -\ln \sum \sqrt{p_i \cdot p_j}$$

	AT	C	JP	Jul	M	O	P	Ra	Rez	
Joensuun kirkko	1	3	9	572	3	19	24	1	7	**639**
Science Park	20	8	6	62	9	245	102	45	28	**525**
Joen TV-huolto J,Simanainen	0	1	1	388	0	1	3	0	2	**396**
Salomökki 1	41	2	62	0	3	69	106	15	15	**313**
Niinivaara otto3	183	0	4	17	1	19	72	8	4	**308**
keskusta 1	0	1	2	0	5	1	280	1	0	**290**
Lounasravintola Louhi	31	6	8	149	1	8	11	25	15	**254**
Lounasravintola Puisto	9	6	2	12	2	30	18	112	41	**232**
Kiesa	5	0	77	1	0	1	2	142	1	**229**
Noljakan kirkko	2	4	0	10	5	6	83	106	9	**225**

Figure 8: Most popular places and their corresponding visit frequencies.

Table 5: Location similarities.

	A	J	M	O	P	Ra	Re	C	JP
Andrei	-	0,33	0,32	0,34	0,54	0,50	0,51	0,38	0,45
Julinka	0,33	-	0,29	0,45	0,52	0,40	0,40	0,46	0,35
Mikko	0,32	0,29	-	0,27	0,53	0,59	0,38	0,30	0,37
Oili	0,34	0,45	0,27	-	0,46	0,37	0,51	0,60	0,30
Pasi	0,54	0,52	0,53	0,46	-	0,68	0,68	0,52	0,54
Radu	0,50	0,40	0,59	0,37	0,68	-	0,58	0,45	0,65
Rezaei	0,51	0,40	0,38	0,51	0,68	0,58	-	0,53	0,56
Chait	0,38	0,46	0,30	0,60	0,52	0,45	0,53	-	0,42
Jukka	0,45	0,35	0,37	0,30	0,54	0,65	0,56	0,42	-

where the summation is done over all the 293 entries, and p_i, p_j are the relative frequencies of the given place. For example, Andrei has frequency 183/676 = 0.19 for the Niinivaara Otto 3, which is an ATM machine near to his home. Other similar visits happens near the users' homes (Julinka used to live opposite to Joensuu kirkko), or working place (everyone except JP works in Science Park).

The similarity results are summarized in Table 4. Only mild correlation (0.28) is recognized with the similarity of the users based on their personal views and their location history, and even smaller with the usefulness measure (0.17). Open question is how much the choice of the methodology influences the results, and if some choices made there could be changed. For example, the number of places and how they are chosen. High frequencies of the home and work places of the users had also a relative large effect: not living or visiting the same area might significantly decrease the similarity of such user.

Nevertheless, the results indicate that the location history has relatively small impact on user similarity and it is not clear how they could be used on improving recommendations.

4 CONCLUSIONS

Small-scale study was made with nine Mopsi and Facebook users to find out whether user similarity and their expected usefulness for recommendation could be predicted from Facebook profile and location history. Based on the results we observed that matching page likes in Facebook correlated with user similarity whereas the location history had only mild correlation. Neither of these statistics predicts which user's data is expected to be most useful.

However, we also noticed that if a user gives many likes and comments of the photos of another user, then he considers this user more similar than others; and what's more important, consider his data more useful for location-aware recommendation. We therefore conclude that, yes, social network can be used for improving recommendations, but not with the data (page likes and location history) in the way studied in this work.

Nevertheless, the results showed correlations and revealed potentially useful factors indicating user similarity. These findings should be confirmed by large-scale testing. We also plan to make similar study using likes and comments, which have been applied for recommending events and friends in (De Pessemier et al, 2013).

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