Recommendation of Yelp's Reviewers: Who Should You Listen to?

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Abstract. *Online ratings are nowadays one of the most trusted sources of consumer confidence when they need to decide which business to choose. As a matter of fact, reviews have become so abundant that many times the task of deciding upon whether or not to elect a business is getting increasingly difficult – each person has their own values and intrinsic characteristics that contribute to forming an opinion. In this work, we discriminate relevant users from a review website considering the perspective of a second user. This way, we are able to infer what would be the individuals that think alike certain user and recommend their reviews amongst a plethora of diverse opinions.*

1. Introduction

Consumer reviews have revolutionized the way that people choose which businesses to attend. It is now very common to turn to the web in order to make everyday decisions, such as where to eat or where to get a haircut. Yelp[1] is an opinion and experience sharing system about businesses of several kinds. In this platform, a user is able to write their impressions about certain place and rate it with a score from one to five stars. Therefore, before choosing where to go, someone can investigate what others think about different places and make a decision with a wider knowledge basis.

To illustrate the importance of such platforms, a survey recently discovered that 64% of all consumers scan reviews before choosing a service [Cone Communications Inc. 2011]. Businesses' owners, on the other hand, are being forced to direct their attention to such platforms, since it was found that an extra half star on average rating increase sales on 19% [Anderson and Magruder 2012].

However, users differ in values and taste. Thus, an opinion might be useful for someone and not so much for somebody else. Knowing the profile of an individual is helpful to understand the viewpoint behind a review and decide if its adequate considering the reader's angle.

The purpose of this work is to identify important reviewers on Yelp for determined user in order to recommend reviews aligned with the readers' preferences and style. Different features might be helpful in this process, including the friendship network of reviewers. In this work, we analyze the relevance of the friendship network in users profiling as well as of a hidden friendship network — defined by users who are similar but are not connected on the social network. By encountering individuals with similar opinions, validated by the homophilly on the network, we recommend the reviews of those to the reader and reduce the burden of manually searching for relevant viewpoints.

[1]www.yelp.com

2. Dataset

The data used consists of a set of reviews, business, users and related content of Yelp's website regarding the metropolitan area of Phoenix released for a challenge[2]. There are $15,585$ businesses, $70,817$ users and $335,022$ reviews, which covers a period from $2005-02-01$ until $2014-01-28$.

Yelp also contains an online social network (OSN), thus users are able to be friends of each other. This network, however, is not the main purpose of the platform and does not entirely represent the true interaction between individuals — sometimes the motivation of connection is not really a friendship, but similar businesses preferences and reviewing behavior. A great part of the users, however, does not even have any friends: only $30,255$ of them are socially connected. This proves that this network is not enough for discovering reference reviewers, demanding an extrapolation with unobserved edges.

3. Network Analysis

As previously mentioned, the friendship network of Yelp is rather incomplete: the majority of users does not have any connections. The users that participate on the social network, however, are highly connected, since 40.92% of them are in the large connected component, which means that only 1.80% of the OSN participants are absent. The average degree of the whole network is 4.68 and the clustering coefficient is 0.06. Figure 1 depicts a plot of the network. In this plot, nodes who are friends tend to be closer than nodes who are not friends. We can note a central core of users which are more highly connected, as well as a cloud of disconnected users.

Yelp provides an option for users to vote in reviews that they found useful. Figure 2 relates the closeness centrality to the total useful votes received by a user. We observe that there are roughly three situations: users with low centrality and low usefulness; users with high centrality and low usefulness; and users with high centrality and high usefulness. There is not such a configuration in which users with high usefulness have low centrality. This is a motivation to consider the network structure as an evidence for profile of reviewers.

[2]www.yelp.com/dataset_challenge

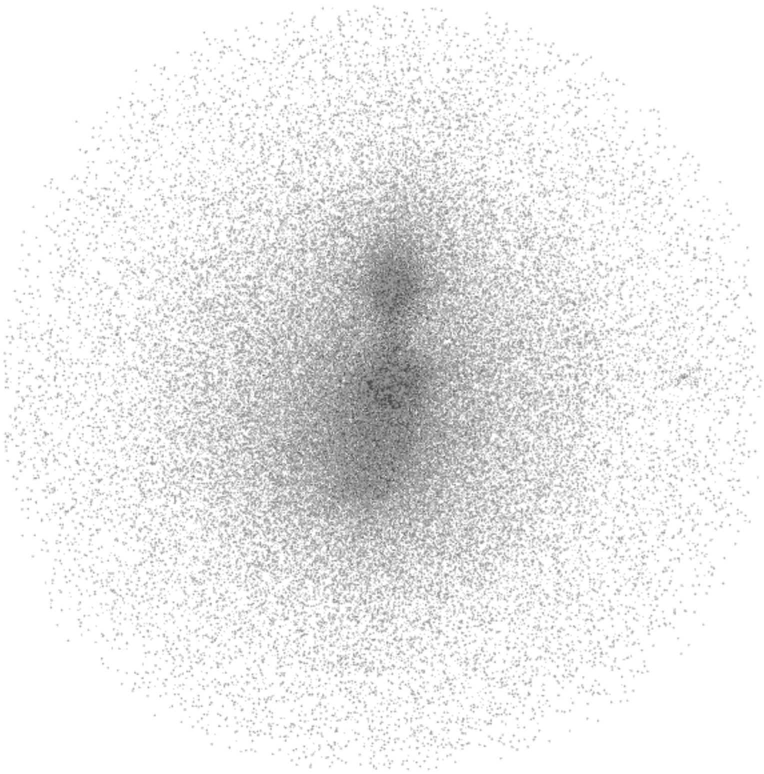


Figure 1. The visualization of the friendship network.

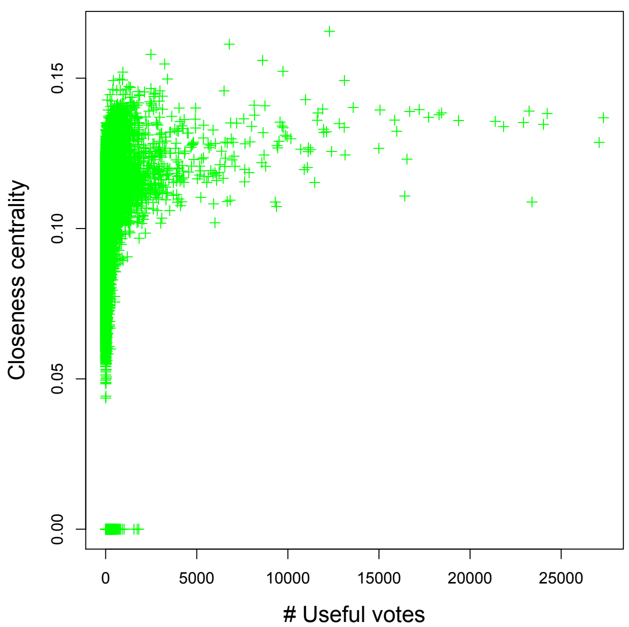


Figure 2. Correlation between closeness centrality and the number of useful votes for a reviewer.

The third set of users cited, a minority, corresponds to reviewers that influence a lot of people. However, few useful votes might indicate that those reviewers provide important experiences for only certain kind of people. Thus, it is necessary to investigate further those reviewers in order to present the information they provide to the ones interested.

3.1. Homophilly Investigation

Aiming to validate the presence of homophilly in the network, it was conducted the following experiment: for each edge on the network, the business overlap was computed considering the jaccard similarity of reviewed establishments; a similar process was perfomed for a modified graph with the same nodes and number of edges, which were randomly assigned to pairs. The empirical cumulative distribution of the overlap values are depicted on figure 3. We observe a clear difference between the real and the random graphs — the second practically do not contain positive overlaps, while the first present some.

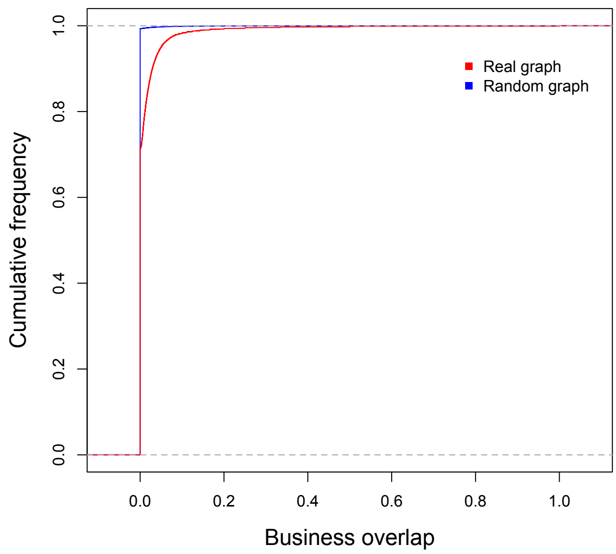
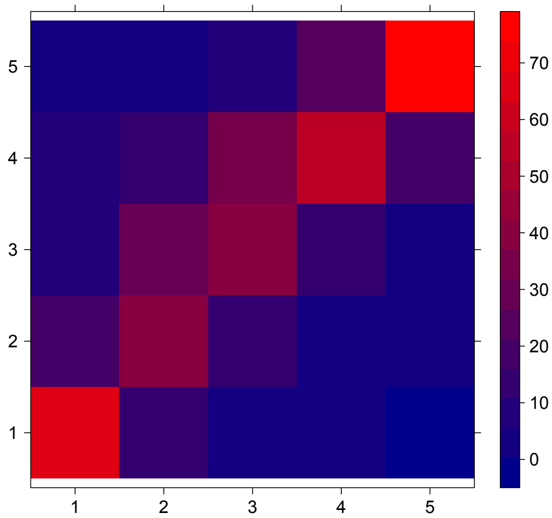


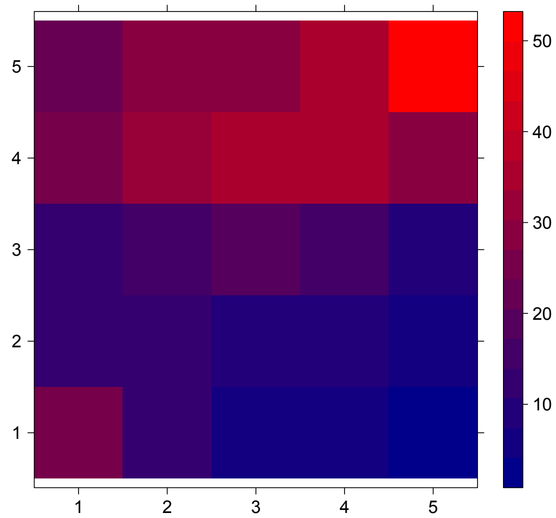
Figure 3. Empirial cumulative distribution of business overlap on real and random graphs.

3.2. Temporal Effect

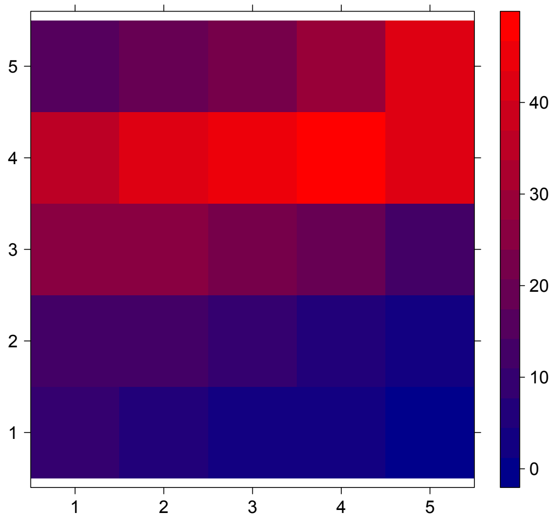
Another important aspect when considering similarity of opinions is the date of the review. People that visit a place in the same day are more likely to experience the same events and to have approximate opinions. The figure 4 contains the correlation reviews given to the same establishment by friends in the same day 4a, not friends in the same day 4b, friends in different days 4c and not friends in different days 4d. The results are normalized — each cell represents the percentage of co-occurences for the given column. For example, in figure 4a, if one individual rates 1, there is a proportion of 70% of their friends who rated 1, nearly 30% who rated 2 and practically 0% who rated 3, 4 or 5.



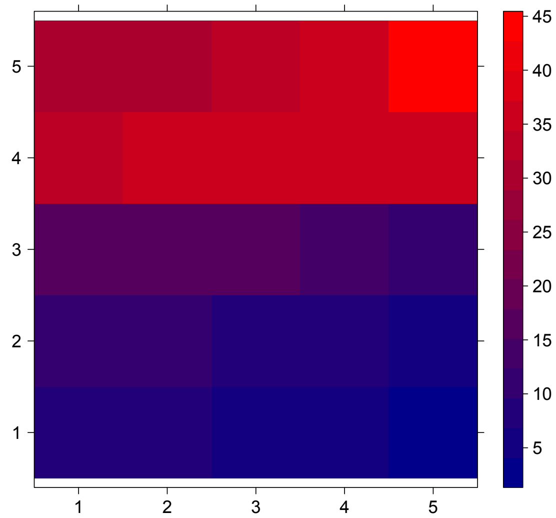
(a) Friends in same day.



(b) Not friends in same day.



(c) Friends in different days.



(d) Not friends in different days.

Figure 4. Correlation of votes between pair of users percentual by column.

We can observe a gradative pattern from a strong correlation of ratings to almost no correlation, in which the proportion of votes on each value rules the intensity.

An interesting observation is that there is much less agreement between people who visited a place in the same day and are not friends. If we infer that friends had the experience together, this is a very interesting fact: one might be affected by the mood and the way a friend is feeling about a mutual experience.

The heatmaps are very alike for different days, so the friendship plays no special role here.

3.3. Hidden Relationships

RECAST[Vaz de Melo et al. 2013] is an algorithm that identifies relationships in dataset of encounters of people and classifies the relationship between each pair of individuals as friend, bridge, acquaintance or random. Applying the method for reviews written in the same date, supposing that the day of the review is the same of the attendance, we obtain the result presented on table 1.

Relationship	# Friends	# Bridges	# Acquaintances	# Random
Friends on Yelp	69	21	689	634
Not Friends on Yelp	16	3	5876	13205

Table 1: Discovered relationships using RECAST.

We can observe a great value for acquaintances for Yelp users which are not friends. This indicates the potential of hidden relationships, which might be an indication of some similarity of opinions.

4. Recommendation of Reviewers

Collaborative filtering is an algorithm which combines the evaluation of users in a bunch of topics in order to predict users rating in unseen ones. In this process, the evaluated elements have a set of attributes that define them and are closely related to their scores. The users, on the other hand, have a representative vector which are coefficients for the attributes and informs the importance given for each one of them.

Considering this model, it is possible to discover people with similar interests, which does not necessarily have to be friends in Yelp, by filtering those with small euclidian distance.

The algorithm basically solves an optmization problem which consists of:

$$min_{x^1,...,x^{n_e},\theta^1,...\theta^{n_u}} \sum_{(i,j):r(i,j)=1} ((\theta^j)^T x^i - y^{(i,j)})^2 + \lambda \sum_{i=1}^{n_e} \sum_{k=1}^{n} (x_k^i)^2 + \lambda \sum_{j=1}^{n_u} \sum_{k=1}^{n} (\theta_k^j)^2$$

In this formula, x^i is the vector of attributes for the element i, θ^j is the coefficient vector for user j, $r(i,j)$ is 1 if user j rated element i and 0 otherwise, $y^{(i,j)}$ is the rating given by user j to element i, n_e is the number of evaluated elements, n_u is the number of users, n is the number of attributes, i.e., the dimension of x and θ and λ is a regularization factor. This expression tries to find the set of x^i, $i = 1, ..., n_e$, and θ^j, $j = 1, ..., n_u$ which dot product $\theta^j \cdot x^i$ approximates the existing ratings $y^{(i,j)}$. The last two terms simply avoids the increase of the calculated parameters in module.

In Figure 5, a clustering algorithm is performed on the set of obtained θ^j, $j = 1, ..., n_u$, for a small subset of Yelp database. The idea behind the process is using this clustering information to recommend *reviews*, and not *restaurants*. This way, a review system such as Yelp could benefit from the results of collaborative filtering and use the information to know which reviews to give more relevance to another particular user: the reviews could be ranked by the euclidian distance between the user and the author of each review. Note that even though we do include the restaurants on these plot, these information would not be delivered to the user.

Note that the attributes 1 and 2, shown in the plot, are not known, as they are obtained iteratively: as a future work, we intend to analyze the database to discover which characteristics tend to have such a high impact on the user experience.

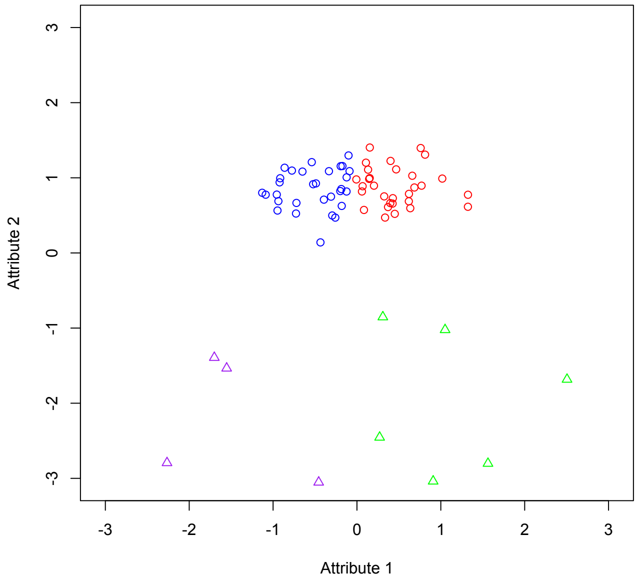


Figure 5. Clustering users (represented by circles) and restaurants (represented by triangles).

5. Related Work

The importance of recommending differently to each user has recently being addresed in the scientific community [Moghaddam et al. 2011, Tang et al. 2013]. They focus on review assesment, while our work is directed to reviewer recommendation. We believe users's opinion is the most important factor when finding a review useful.

Reviews, in general, are more volatile than reviewers. Recent studies found that review composition influence ranges from other's opinion to weather [Bakhshi et al. 2014, Sipos et al. 2014]. The aggregated pattern of a reviewer, then, is a more solid information to consider when performing recommendation.

6. Conclusions and Future Work

This work has two main contributions. First, we analyzed many aspects related to Yelp's friendship network, which yielded important observations such as the fact that Yelp's database contain a large number of hidden relationships, as defined in RE-CAST [Vaz de Melo et al. 2013].

We also proposed a novel way to take advantage of the results of collaborative filtering algorithms. These algorithms are classically used with the intent of recommending a final product. Nevertheless, the mechanism behind such algorithms imply on the construction of a matrix that indicates the preferences of each user. Here we propose that this matrix could be used to cluster similar users. Once a cluster is built, we believe that instead of recommending similar products, which frequently lead to failure, a system such as Yelp could choose to give more relevance (for example, showing first) the reviews of similar users. This approach is less affirmative than a recommendation and could be of great advantage for review systems, bringing more meaningful information and yet leveraging the personal analysis of the user.

As a future work, we intend to develop further this novel idea and discover how the friendship network could help to enhance it.

7. Acknowledgments

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