Toward Superior Searching System Design: An Empirical Study of Yelp Dataset

Abstract—**As one of the most popular online business searching systems, *Yelp*'s service scope has covered numerous domains, from restaurants to shopping malls. A great volume of data is being generated and stored, which is usually considered a potential treasure for facilitating businesses while effective data mining algorithms are applied. However, finding out an efficient approach that can reach a high performance information distribution and retrieval is a challenging issue for system designers due to the high complexity in algorithms, datasets, data storage. This paper aims to accomplish an empirical research of Yelp's dataset evaluations by analyzing the real world data offered by the *Yelp Data Challenge*. The purpose of this work is improving the design of the next generation system by acquiring users' major interests. Our evaluations have generated a lot of interesting findings. Elite user mechanism is especially effective in maintaining the healthy of the whole network. Users who write less than 100 business reviews dominate. Those insights are expected to be considered by Yelp to make intelligent business decisions in the future.**

Index Terms—**Searching system design, data mining, dataset evaluation, data storage**

I. Introduction

Recent rapid increasing growth of Internet-based technologies have driven a great change in social networking implementations [1], [2]. The propagation of cloud computing and big data have enabled numerous applications that have penetrated into various hemispheres of people's lives [3], [4]. *Yelp* is one of the popular social networking platforms that has a specific focus on the business evaluations and information sharing between customers. Moreover, a large volume of data has been created every day, since the platform is supported by both mobile and on-premise apps, which can reach a wide scope of users [5], [6]. Users can share or gain information via posting and reading comments or scoring the businesses in a ranking system. Despite many benefits of using current Yelp's services, a great challenge still exists in pushing effective information to users in order to enhance the efficiency of the information delivery.

One solution to this issue is finding out which information is valuable to a certain user group, such that the information can be pushed to users. Contemporary approach is adding labels to each user who will receive the pushed message based on the attached labels. Nevertheless, this method is restricted by many conditions and implementations, such as usage scenarios and accuracy. Addressing the issue of attractive information identifications, this paper concentrates on the perspective of Yelp's dataset and presents an evaluation work by using a variety of data mining techniques. The analyses address a few distributions and hops in order to understand the rules hidden by the phenomena.

Moreover, focusing on the dataset evaluations, we design an empirical study implementing a group of analysis methods. Fig. 1 represents the structure of our study that illustrates the main research activities in this work. First, we examine the data distributions from different dimensions, such as the number of friends, connected components, and user properties. Next, the relationship of the friends' friend has been evaluated in our research. The dimensions used in the evaluations are activities occurred between an individual and his/her friend's friend. Finally, we also accomplish a deep data analysis by using a few data analytic techniques, such as clustering coefficients and maximal K-core.

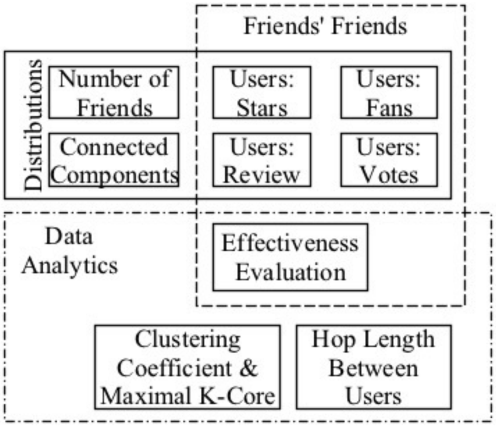


Fig. 1: Structural mapping of our evaluation research.

The main contributions of this paper are twofold:

1) We design an empirical research that focuses on evaluating Yelp's dataset in a real world operation environment. The findings of this work are valuable for both researchers and practitioners to design a superior next generation social networking system.
2) We apply and evaluate the *Six Degree of Separation* (SDS) theory in Yelp's social networking systems with real world dataset.

The remainder of this paper is organized by the follows: First, we present a brief review about the recent academic achievements in Section II. Next, the preliminaries and main evaluation methods are given in Section III. Furthermore, Section IV illustrates our evaluation results, as well as main findings. Finally, Section V provides the conclusions of this paper.

II. Related Work

During the several rounds of Yelp challenge, a lot of interesting works are done to make use of the dataset. For instance, Bakhshi *et al.* use the dataset to understand the difference of review feedbacks including *useful*, *cool* and *funny* [7]. Lee *et al.* targets for a multidimensional model, which are used to find expert (elite users) on Yelp [8]. The model uses review text, network structure, and user metadata to find elite users. Their conclusion was the model needs to consider all information together to improve the accuracy of the model. In this paper, we also find several efficient indicators for elite users, which are complementary to their work. Crain *et al.* analyzed the elite users in terms of the network structure, where they found elite users are *super-connectors* in Yelp [9]. The results are consistent with ours. Besides, a lot more analysis are provided in our work. Tanvi Jindal proposed to find local experts by the use of machine learning [10], while our focus in this paper is to analyze the dataset, find useful insights and be helpful to the design of next generation online review system.

III. Concepts and Evaluation Methodologies

A. Preliminaries

1) Dataset: The dataset is collected from real Yelp business and is released for academic purpose [11]. It contains 366K user profiles for a total of 2.9M edges; 1.6M reviews and 500K tips for 61K businesses and aggregated check-ins over time for each of the 61K businesses. To make the dataset diversity, the data of four countries are included (U.S., UK, Germany and Canada). All data are divided into 5 *JavaScript Object Notation* (JSON) files, which are business, review, user, checkin and tip. The content of these files are straightforward to understand.

Specifically, business file presents the attributes of each business, like the internal unique id of the business, name, geolocation, categories, et al. The checkin file is a complementary attributes for each business. It presents the aggregated checkin time for each business in the grain of each hour in a week. User file contains the basic information for each user, such as yelping time, name, fans and social relationship with other users. Tip and review files are the review of a particular user to a business. The difference of tip and review is that tip is always short to represent a user's opinion, like "Don't waste your time" or "Great drink specials!", while review is long enough to allow users express their feedback.

2) Data Storage: Due to the size of dataset, it is both time consuming and inconvenient to analyze the statistics without the help of data storage system. At the same time, it is rather natural to model the network of Yelp using graphs, because users and businesses can be abstracted as nodes with different properties; review to a business and user friendships can be modeled as the relationships between nodes. Thus, the graph database is a great fit for this purpose. For this project, we select Neo4j [12] as the database as it has a great web UI which makes graph visualization possible and a SQL-like query language (Cypher), which is easy to learn and use. In our graph, there are two kinds of nodes, *User* and *Business*. The information used to describe users and businesses are stored as attributes in the node. Three relations exist in the graph, which are *knows*, used for user friend relationship, *tip* and *review* for user and business relationships, respectively.

Importing the dataset into Neo4j is all about creating nodes or relationships. However, it is worth to mention two tricks we made. The first one is used when importing user friendship data into Neo4j. Each user has zero to many friends. To build up the friendship, what we can do is a straightforward twice scan algorithm. We create each user node without adding the friendship at the first scan, and build up relationship at the second time. To improve the performance of data importing, we adopt a scan-once method. The basic idea is when creating a user node, we build up the friend relationship directly. Specifically, for each friend of a user, a look up is performed in the current graph.

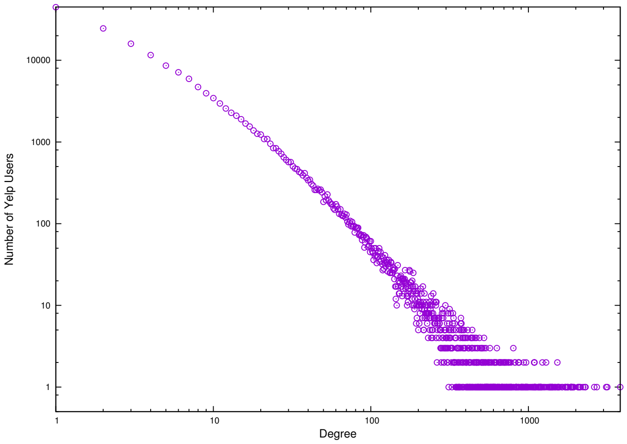
If a node is found, the user node being established and the found node is connected using *knows* relationship, otherwise, we create a node with label *Person*, which means it will become a user in future, but right now its full set of properties are not filled. When trying to create a new user, a look up is also necessary. If there is not such a node, we create a new user, otherwise, the user node exists as a *Person*, and the full information should be filled into the node. exist as a *Person* node. Another trick that we used to speedup the dataset importing is to create unique index for both users and businesses because we noticed that the internal user id and business id are unique and there are a lot of queries made based on their ids.

Although the use of these tricks, the whole importing process is also quite slow. Roughly speaking, it costs us 2 weeks to import all 366K user basic information and their relationships. Although one can optimize the graph establish using REST API instead of Cypher, it is left as future work. In order to establish graph quickly and reproduce our experiments results easily, our database is open sourced using Dropbox, along with the graph establish and analysis codes used in this paper (https://github.com/ycui1984/yelp-data-challenge). Readers who are interested to use our database just need to download the database, extract in the proper folder and restart the service.

B. Evaluation Methods

The benefits of using Neo4j is that it simplifies our analysis process by writing simple Cypher queries. For complex tasks, we created python scripts and used *py2neo* library to manipulate Neo4j.

Fig. 2: Number of Yelp Users against Degree



1) Number of Friends Distribution: From the high level, we found that there are 2576179 *knows* directed friend relationships among 366715 users. So, on average, each user has roughly 7 friends. To investigate into the number of friends distribution for each user, we looked at the number of Yelp users for different degrees, which is shown in Figure 2. In this figure, we ignore 192621 users with no friends. One thing worth to point out is that x and y axises use the log scale. As shown in this figure, the degree distribution exhibits the power law phenomenon, which is expected. In the dataset, the largest degree among all users is 3830. Although there is a hard limit for the largest number of friends for a user on Yelp (5000) [13], we did not see any user who hits the limit.

2) Hop Length between Users: The number of hops between users are investigated in this subsection. A classical conclusion about social network is *six degrees of separation* [14], which means that the average number of hops between every two nodes is no more than 6. To verify this, we randomly selected 10000 node pairs among all nodes and measured length of shortest path.

One natural reasoning is that two nodes are selected from two separate connected components when there is no path; otherwise, nodes come from the same connected component. Also, there should be a lot of connected components such that there is no path between two nodes in a high probability. Note that the average path length is even smaller than most of social networks including Facebook [15], YouTube [16], and LiveJournal [16], which implies that the information in Yelp network spreads faster than other networks.

3) Connected Components Distribution: To verify our reasoning about the structure of Yelp network, this subsection investigates the distribution of connected components. To find all components and the number of nodes in each component, we recorded each subgraph encountered so far. Then, each user node is iterated one by one. For each subgraph, the path existence between the subgraph and the target node was tested. If there exists a path, the user node is included into the subgraph, otherwise, a new subgraph iscreated.

4) Clustering Coefficient and Maximal K-Core: After understanding the network structure in the high level, the next investigation is how Yelp friends of a particular user interact with each other. We try to answer interesting questions such as how many of your friends are also friends? To this end, we measure the average clustering coefficient for users with different degrees. The clustering coefficient for a graph is calculated by dividing the existing number of *knows* relationships by the total possible number of relationships. For example, assume there are 4 nodes in a graph, and there are 2 *knows* relationships. So, the clustering coefficient is $2/(4 * 3/2) = 0.33$. If one has 100 friends, the average maximal k-core is roughly 13, which means there are at least 14 users who knows the other 13 friends of this user. One exception of the curve is the data point when the degree is 1000. It is larger than that when degree is 3830. After examining the results, we found that there is only one user who has degree 1000 and 3830. The exception is considered as statistical errors. If enough users with high degrees exist, the curve is believed to increase continuously.

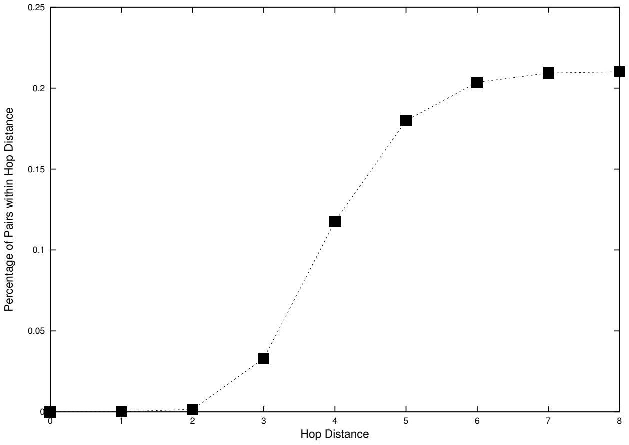
5) Friends of Friends: One important property of social networks is friends of friends. For example, LinkedIn recommends people you may know if two users share the same friend. Yelp can also benefit from recommending to a user the businesses that liked by his friends of friends. To this end, the number of unique friends of friends and non-unique friends of friends with increasing number of degrees are counted. Note that unique friends of friends are a distinct set of user nodes one can reach by two hops from a user, while non-unique friends of friends are all user nodes that are reachable by two hops.

- *User Distribution in Stars, Reviews, Fans and Votes:* The distribution of users in terms of four important attributes (stars, reviews, fans and votes) are evaluated in this subsection. Before going into the details of the results, we introduce how these attributes are generated in Yelp. Stars are used to evaluate the quality of a business after a visit. One can give stars from 1 to 5. The more the better; Reviews are comments from a user to a business, users usually write reviews to express their opinions; Fans are used when an user likes reviews or comments from another user (probability because they have similar taste) and wants to receive more recommendations from him; Votes are comments to a review from a user. Specifically, user can submit a vote of *useful* or *cool* or *funny* to a review.

- *Effectiveness of Elite User Mechanism* A famous mechanism used to encourage review writing on Yelp is elite members [17]. If one becomes elite user successfully, he or she will be invited to many epic parties for free, which are not available for common users. Any Yelp user can apply for a elite user, but there is a community to decide whether the application passes or not. Without doubt, elite users should be very active in many aspects such as review writing, commenting reviews from others and making friends on Yelp, although the internal algorithm to decide elite users are not available to the public. This subsection measures the effectiveness of elite user mechanism, which we believe important to Yelp because if elite users are not much more important than common users, Yelp should stop the investment to elite users as soon as possible to save cost.

IV. Experiment and the Results

Fig. 3: CDF for Number of Hops between Two Nodes



Based on the measurement, the cumulative distribution function (CDF) against the number of hops is calculated. Figure 3 presents the experimental results. As we can see, the CDF curve increases with the number of hops, and stabilizes at 8 hops. The probability of two users within 8 hops is 21%. Actually, most of the time (79%), there is no path between selected user nodes. Based on these conclusions, we can see the largest number of hops between any two nodes in the same connected component is 8, which is the diameter of the connected component. The average distance of two nodes in the same connected component is calculated to be 4.5, which verifies the six degree separation theory.

Fig. 4: Connected Components Distribution

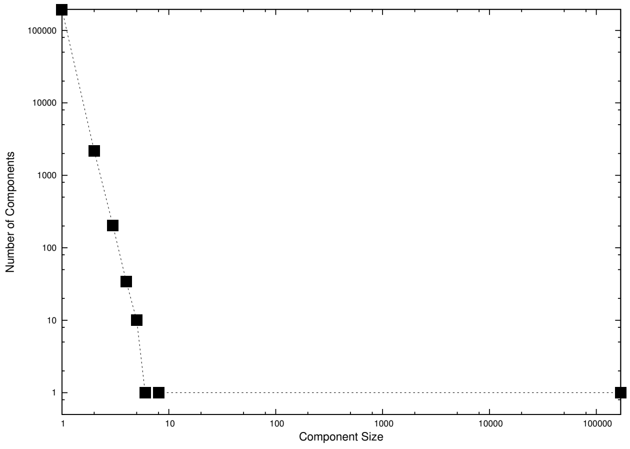


Figure 4 presents the experimental results. As expected, there is 192621 connected components wheresingle user exists. Except that, most of users belongs to a single large connected component, which includes 168917 users. If we calculate the probability of two user nodes in the same connected component, it is roughly 0.21, which matchesthe results in the last subsection.

Fig. 5: Cluster Coefficient and Maximal K-Core

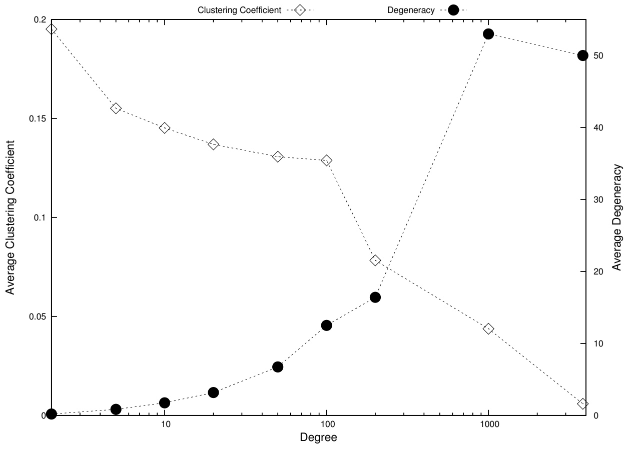


Figure 5 (labeled as clustering coefficient) shows the results for users with different degrees. As indicated, the coefficient keeps decreasing with the increasing degree, which suggests that the more friends one has, the more possible ways one's friends are also friends. Specifically, the total number of relationships is a number of $O(n * n)$, where n is the number of friends for a user, while the actual graph is not dense enough to keep up with the total number. To shed light on the structure of the subgraph formed by all friends of a user, we also measured the average maximal k-core for users with increasing degrees. The k-core of a graph is defined as the maximal subgraph where each node has k degrees at least. The maximal k-core is to look for a k-core which maximizes k. The curve labeled as degeneracy in Figure 5 plots the experimental results. Overall, the trend is the more friends one has, the larger the maximal k-core.

Fig. 6: Number of Friends of Friends

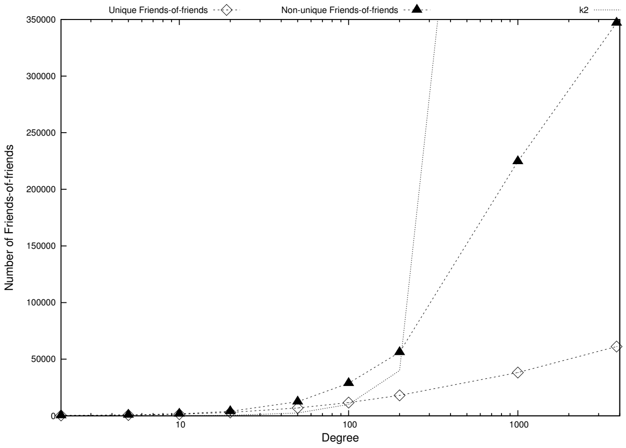
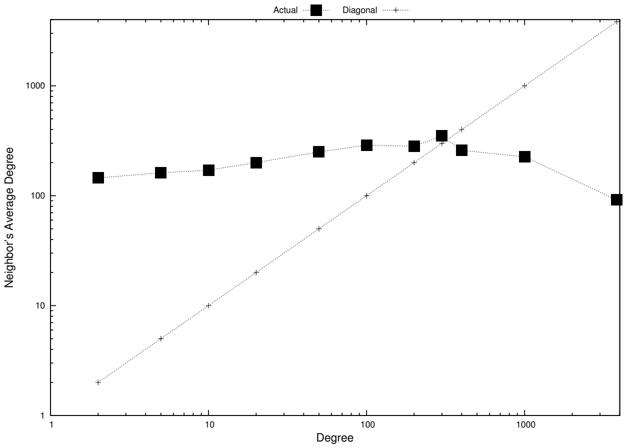


Figure 6 plots the results. Besides, the $k*k$ curve is also presented for comparison, where k is degree. The common sense is that if one has k friends, then $k*k$ is an estimation of the number of total friends of friends, assuming that each of his friends has k friends. By adding the $k*k$ curve, one can compare with our estimation. From this figure, we can see that the number of unique friends of friends and non-unique friends of friends is larger than our estimation when the degree is smaller than 100 and 200, respectively. Note that the percentage of users whose degree is smaller than 100 is over 90%, which suggests that, for most of users in Yelp network, your friends have more friends than you.

Fig. 7: Average Neighbor's Degree



To further prove this conclusion, the average neighbor's degree against degree is presented in Figure 7. Note that the figure is drawn in log scale for both x and y axises. As can be seen, the average neighbor's degree keeps increasing when the degree of a user is relatively small, which verifies that your friends has more friends than you. Once the degree is large enough, the average neighbor's degree becomes smaller. However, this only happens to a small portion of users.

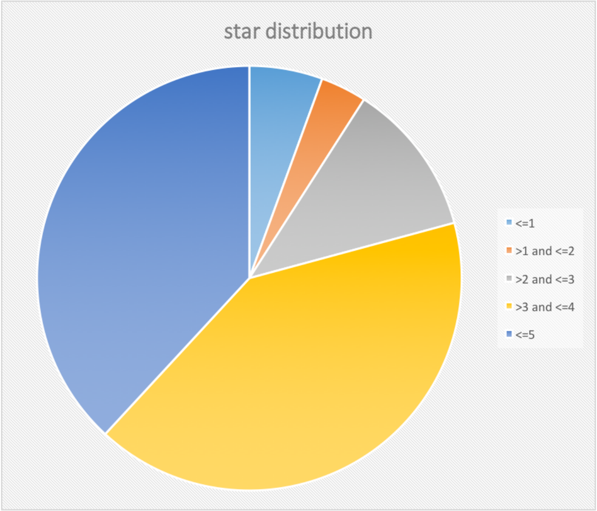


Fig. 8: Star Distribution

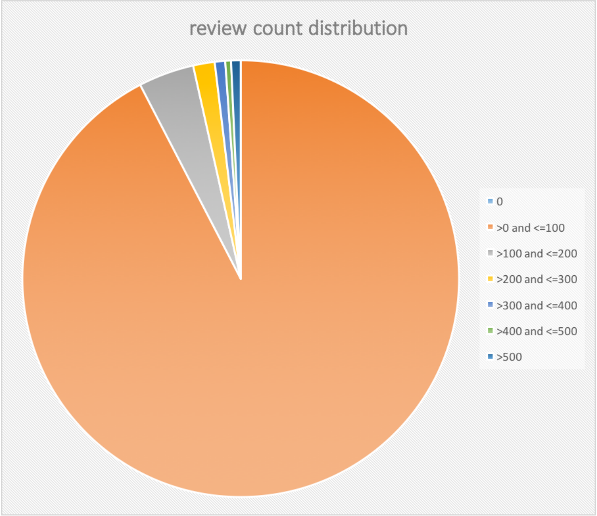


Fig. 9: Review Distribution

Figure 8-Figure 11 present the distributions of users for each attribute. The following details the analysis for each attribute. In terms of star distribution, businesses with 4 stars and 5 stars are the most (41% and 38% respectively),

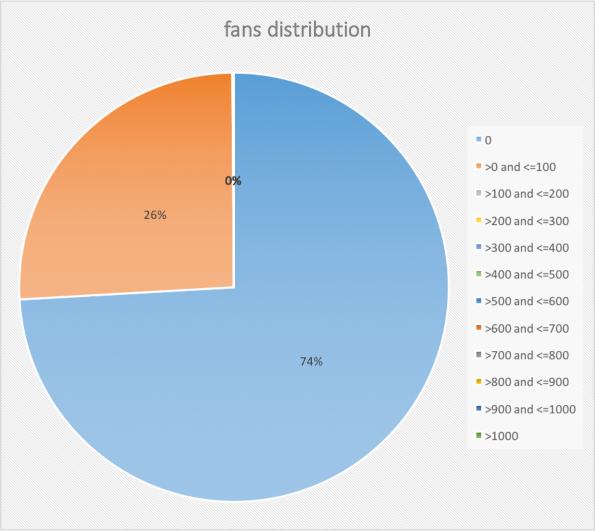


Fig. 10: Fans Distribution

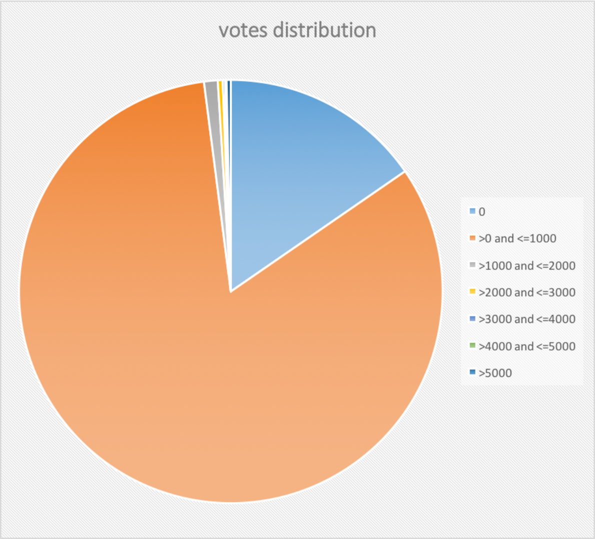


Fig. 11: Votes Distribution

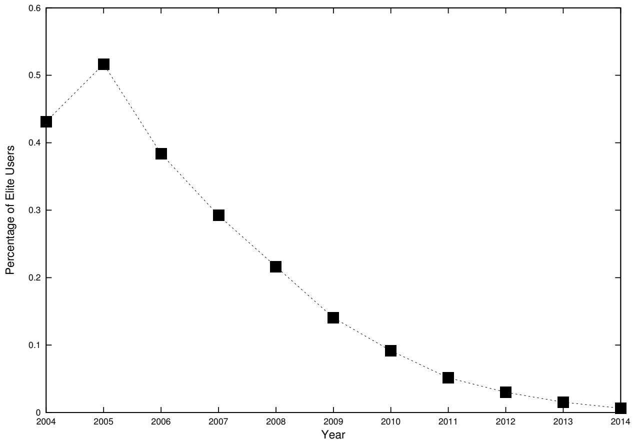
which means that businesses collaborated with Yelp are high quality and users have positive feedbacks to most of these businesses. Note that the results are highly consistent with the results released in the official website [18].

In terms of review distribution, besides the percentage of users who do not write any reviews, the percentage of users who write a particular number range of reviews (in the grain of 100) are also presented. As indicated in Figure 9, the percentage of users who do not write reviews are negligible, although 53% of all users do not have any friends on Yelp, which implies that review is a well-regarded feature on Yelp. If we look at the distribution of users who write reviews, it is easy to find that users who write no more than 100 reviews dominate (92%). This number tells us that although most of Yelp user do write reviews, most of them do not write a lot.

Figure 10 presents the results for fans. The interesting finding is that most of Yelp users (74%) do not have any fans, while users with 0 to 100 fans dominate the remaining percentage. From the results, we know that only a small portion of users actively comment a lot of businesses, which makes them followed by others. Most of users only care about the businesses that they have ever been experienced, which are limited.

Figure 11 shows the user breakdown in terms of votes. Similar to Figure 9, users who vote 0 to 1000 are the largest part (83%). The second largest part are users who do not vote (15%). The total number of votes is also breakdown according to *useful*, *cool* and *funny*. The percentage for each category is 48%, 27% and 25%, respectively. Among these three words, only *funny* is negative in tone. Thus, most of the time(75%), Yelp users satisfy with the quality of reviews.

Fig. 12: The Percentage of Elite Users against Years



Before introducing the details of measurement, let us look at the percentage change of elite users against years. Figure 12 presents the experimental results. As shown in the figure, there is an increase of the percentage in 2005, and the curve keeps decreasing since then. At 2005, the percentage is more than 50%, while it is even smaller than 1% in 2014. Note that Yelp is established in 2004. The curve suggests that at early stage of Yelp, the company uses this mechanism to engage users. Once the reputation is established, the increase of elite users is much slower than the increase of common users.

Next, we start to measure the effectiveness of elite user mechanism. Our methodology is to collect several metrics of elite users and compare them to average users. The first metric is the average number of fans for elite users, which is calculated to be 16. For all users, the average number of fans is 1.6, which is significantly smaller than 16. Next, we look at the average number of reviews written. The experimental results for elite users and all users are 245 and 32, respectively. Again, the metric for elite users is much better than the average of all users. The third metric we used is the average number of votes. The number is1336 for elite users and 122 for all users.

Finally, we compare the average degree for elite users. The result is 55, which is much larger than the average(7). From these four metrics, one can find elite users own significantly more fans (10×), write much more reviews (7.6×), comments more than others(10.9×), and has more friends (7.8×). In another word, elite users are much more active in the community. Next, we try to answer an interesting question. Do elite users give more or less stars for a business, compared to common users? Similar to metrics collected, the average of stars given by elite users is 3.78, while the average is 3.72, when considering all users as a whole. Although the value for elite users is higher, it is rather close to the average of all users. This result implies that elite users are famous for their activeness in the community(like the quality of reviews), instead of giving stars which are out of exceptions. Another insight of the measurement to elite users is that Yelp community can develop a machine learning model by the use of our metrics, which helps to decide whether an application for elite user passes or not, instead of evaluating it manually.

V. Conclusions

This paper presents analysis results for Yelp dataset. Our main focus is user related data, such as the social network formed by users and attributes in user nodes. We did not investigate the user behaviors of visiting a business and Yelp reviews, which are believed to be valuable. These parts are left in future work.

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