Proof of Concept for Comparison and Classification of Online Social Network Friends Based on Tie Strength Calculation Model

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***Abstract*— Facebook, the popular online social network, is used on daily basis by over 1 billion people each day. Its users use it for message exchange, sharing photos, publishing statuses etc. Recent research shows that a possibility exists of determining the connection level (or strength of their friendship, tie strength) between users based on analyzing their interaction on Facebook. The aim of this paper is to explore, as a proof of concept, the possibility of using a model for calculating strength of friendship to compare and classify ego-user's Facebook friends. A survey, which involved more than 2500 people and collected a significant amount of data, was conducted through a developed web application. Analysis of collected data revealed that the model can determine with a high level of accuracy the stronger connections of ego-user and classify ego-user's friends into several groups according to the estimated strength of their friendship. Conducted research is the base for creating an enriched social graph – graph which shows all kinds of relations between people and their intensity. Results of this research have plenty of potential uses, one of which is specifically improvement of the education process, especially in the segment of e-learning.**

I. INTRODUCTION

In today's era of rapid development of technology and information, the Internet has emerged as the largest global computer network. Facilitating everyday life for billions of people, Internet is used for easy discovery of information and performing various tasks, quickly becoming one of the main platforms for communication between people. Internet's ability to connect people in short time encouraged the emergence of a large number of online social networks (OSN), one of the most popular ones being Facebook. Facebook users share information about themselves and interact with other users in various ways. The assumption, which is confirmed by many recent researches, is that the data about the interaction on the online social network can be used to evaluate the level of connection between people in real life. On Facebook the complexity of real life relationships is reduced to only one type of relationship – "friendship". The nature of this relationship is merely binary in nature – ego-user is either connected with someone or not. There is no information about strength of friendship. The question which may arise is how to use the data published by the ego-user or their friends on online social networks to distinguish between strong and weak friendships and somehow evaluate the strength of connection between ego-user and his friends.

The aim of this paper is to verify the next hypothesis by using a model for calculating tie strength introduced in [1]:

1. Higher tie strength calculated by the model for two observed individuals is closely related with the strength of real-life relationship between said individuals.

This hypothesis will be explored in detail by investigating the next subhypothesis:

1. If the ego-user is asked to pick a better friend from selected pair of social network friends, he will select the one for whom the model calculate the higher tie strength.
2. Bigger gap in relationship intensity between two social network friends will result in a larger probability of model providing the correct output.
3. Model results will allow classification of ego-user's friends in 3 groups: *best friends*, *friends* and *acquaintances*. The ordering of these groups will be reflected by the decrease of calculated tie strength (*friends* will have lower tie strength than *best friends*, but higher than *acquaintances*).

To verify the hypothesis and its subhypotheses, we held a survey through a developed web application the purpose of which was to collect data about interaction of ego-user and his friends on Facebook, as well as to collect ego-user's answers on pertinent questions such as: select a better friend out of a selected pair, or distribute friends in one of the following groups – *best friends*, *friends* and *acquaintances*. Ego-users' answers are considered as ground truth. Friendship strength will then be calculated based on data about interaction between ego-user and his Facebook friends, and subsequent research will check for the overlap percentage between ground truth and model outputs, i.e. the level of model accuracy will be determined.

The paper is organized as follows: in section II related work is described; section III introduces a model for calculating tie strength and describes carried out research; in section IV the results of research are presented; section V provides a discussion of these results and in section VI a conclusion is given and ideas for future research are elaborated upon.

II. RELATED WORK

Social network (or social graph) is a social structure composed of entities connected by specific relations (friendship, common interests, belonging to the same group, etc.). By the network theory, social network is composed of nodes and ties. Nodes are entities and ties represent relations between them. An analysis of social networks is not based on entities, but on their interaction.

Nowadays, online social networks, such as Facebook and Twitter, are widely used by people for message exchange, sharing photos or publishing statuses. By using a more concise definition of what social network represents, online social networks can be considered as applications for social networks management.

Information about connections between online social network users is usually relatively poor, most commonly represented in a binary fashion– two users are either friends or not. Social graph that can be created from this information does not differentiate between strong and weak ties, i.e. there is no information about tie (friendship) strength [2].

In recent years, a lot of published papers are dealing with determining the strength of connection between two users on the basis of data about their interaction on online social networks. It is assumed that the interaction between strongly connected users will be more frequent then between those who are not mutually close.

Research being carried out in this area can be categorized by answering the next 3 questions: *What?*, *On what basis?* and *How?*. *What?* refers to what should be achieved by analysis, i.e. what are the analysis' objectives. These objectives can be different: identifying close friends [4][5], calculating trust between users [3][6], searching for the perpetrator and the victims [7], predicting health indicators [11] or recommending content [12][13]. Question *On what basis?* refers to data that are going to be analyzed. Example of parameters that can be analyzed on online social network Facebook are: private messages [3][10], personal interests (music, movies) [3], political views [3] or the frequency of interaction in general [3][4][5][6]. Question *How?* refers to mathematical algorithms and models used to correlate collected data and the objective of analysis. Commonly used are simple linear models, models based on machine learning, optimization algorithms such as genetic algorithms, etc.

A common characteristic of these researches is collecting two types of information: data from online social networks about users, their actions and interaction, and users' (subjective) assessment of observed relationship which is considered as ground truth. Based on those two types of data scientists are trying to construct a model which will be able to calculate the intensity of a connection between two people based on data about their interaction.

Recent research differs in a way how the researchers find ego-user's opinion about his friends, i.e. how they extract ground truth from ego-user. Generally it is done through surveys where users are asked about the type of relation which is the subject of analysis. There are some questions like: *Would you feel uncomfortable if you have to borrow 100$ from him?* [3] or *Would you believe to the information that this user shares with you?* [14]. Users are also asked to select their close friends [4][5] or a few of their best friends [6][8], new friends are recommended to them and a check is performed if the recommendation was accepted [9] or if the algorithm will successfully detect existing friends in a wider group of people [10][12].

The need for knowing the intensity of relations between users appears in different areas. Telecoms are trying, by analyzing social network where ties mean influence between users, to detect possible churners (users that are likely to change network) [15][16][17]. Usually information for building that kind of social network is fetched from call detail records (CDR). Enterprises would like to see a social network of their employees where tie strength means level of cooperation and communication between them [18]. That kind of social network is built by a process of analyzing communication of employees through different corporation communication channels. Also, it is interesting to build a social network where tie strength describes similarity of consumer interests (similar interest in music, movies, theater, art, etc.) or level of trust between users [6][13]. All of those are different, but correlated relations.

In the context of educational data mining, building and analyzing of social networks is important for understanding and analyzing connection between students or course participants [19]. Interaction of participants in collaborative tasks can be analyzed and, as a result of this analysis social network can be constructed. Instructor can subsequently use this social network to find which participants are most important for the propagation of information, i.e. who is central node in social network [20]. If those participants acquire certain course knowledge, it is also likely that this knowledge will be more easily transferred and acquired by other participants.

III. METHODOLOGY

A. Model for calculating friendship strength on an online social network

Model introduced in [1] is used to calculate tie strength, i.e. strength of friendship. Friendship is calculated based on the analysis of interaction between users and includes, with certain (differing) level of significance, all communication parameters (such as "like"s, private messages, mutual photos, etc.).

Friendship is shown as a one-way connection from *user A* to *user B*, where *user A* is the *ego-user*, and *user B* is his network friend. Friendship weight between *user A* and *user B* is not necessarily equal in both ways.

Friendship weight is calculated as sum of multiplication of communication parameters, with the corresponding weight of communication parameters:

$$\begin{aligned} & friendship\_weight = w(likes) \times number\_of\_likes \\ & + w(comments) \times number\_of\_comments \\ & + w(messages) \times number\_of\_messages \\ & + w(tags) \times number\_of\_tags + ... \end{aligned} \tag{1}$$

The weight of communication parameter p for the *ego-user A* – $w(p,A)$ depends on two factors:

- The general significance of each communication parameter $w_g(p)$
- The specific significance of each communication parameter for each user $w_s(p,A)$,

and is calculated with formula (2).

$$w(p, A) = w_g(p) \cdot w_s(p, A) \tag{2}$$

The general significance of each communication parameter is equal for each user and is being defined experimentally as it is described in [1].

The specific significance of each communication parameter is different for each user, because each user uses different communication parameters in a different ratio. For example, some users communicate mostly via private messages, while others prefer *liking* everything that appears on their *News Feed.*

The specific significance of each communication parameter p for *ego-user A* – $w_s(p,A)$ is inversely proportioned to this parameter's usage frequency (if the user is a frequent *liker*, each *like* is individually worth less), is calculated by formula (3), in which $n_p(A)$ defines the quantity of the communication parameter p between *ego-user* and all of his friends. The overall communication of *ego-user A* - $n(A)$ is the sum of all communication parameters of *ego-user A* (the total number of messages, likes etc.)

$$w_s(p,A) = (1 - \frac{n_p(A)}{n(A)}) \quad (3)$$

The specific significance of communication parameter shows how much the specific communication parameter is important in user's communication and how large is its part in overall user's communication (etc. is the user a "*liker*" or a "message sender").

The final formula of friendship strength form *user A* to *user B* is:

$$friendship\_weight_{(A \to B)} = \sum_p w(p,A) \cdot n_p(A \to B) \quad (4)$$

in which $n_p(A \to B)$ defines the amount of communication parameters, in other words, how many communication parameter units were exchanged between *user A* and *user B*. (e.g. number of messages between *user A* and *user B*).

B. Division of friends into subgroups

To test research hypothesis we divided ego-user's Facebook friends into 9 subgroups (**Figure 1**). Division is based on calculation of model described in previous subsection. First step is to make an ordered (by tie strength) list of ego-user's friends. The 1st subgroup consists of friends with the highest strength of friendship and the 9th subgroup holds friends with lowest strength of friendship. First subgroup is filled with 1% the best friends of ego-user, second group is filled with following 1%, third with following 1%, fourth with following 2%, fifth with following 5%, sixth with following 10%, seventh with following 20%, eighth with following 30% and ninth with following 30%. It is mandatory to have each subgroup filled with at least one friend and each friend cannot be assigned to two different subgroups. Thus, total ordered list of friends is divided into 9 disjunctive subgroups with ordered the same as in the initial list. Subgroups are different-sized because of the assumption that strength of friendship is mostly distinguish between ego-user and his close friends. With lower friendship strengths, relations are mutually more similar, i.e. ego-user in survey is not able to decide which of his acquaintances is closer to him.

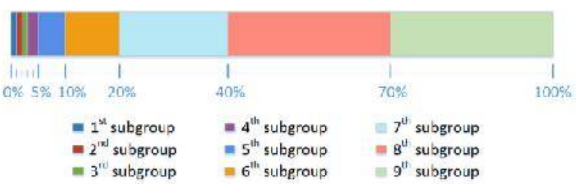

Figure 1. Subgroups of friends

C. Description of the survey

Survey is held through a web application. Application, on one side, fetches data about interaction between ego-user (examinee in survey) and his friends and, on the other side, through survey records ego-user's (subjective) opinion about strength of friendship between him and his Facebook friends (ground truth). Survey is divided into 2 sections of questions. In first section ego-user should compare his two friends (**Figure 2**) and select better in pair. In total he should make 24 comparisons. Each friend is randomly chosen from one of 9 subgroups. Although ego-user compares friends, they are actually representatives of their subgroups. **Table 1** shows which subgroups are compared.

Figure 2. Comparing friends – application screenshot

1. – 9.	1. – 3.	2. – 5.	5. – 7.
2. – 8.	1. – 4.	3. – 5.	5. – 8.
3. – 7.	2. – 3.	4. – 5.	5. – 9.
4. – 6. (twice)	2. – 4.	7. – 9.	4. – 7.
5. – 6. (twice)	3. – 4.	8. – 9.	
1. – 2.	1. – 5.	7. – 8.	

Table 1. Compared subgroups of friends

In second section ego-users are asked to classify their friends into 3 groups: *the best friends*, *friends* and *acquaintances* (**Figure 3**). In total they should classify 34 friends – it is chosen randomly 4 friends from first 7 subgroups and 3 from 8th and 3 from 9th subgroup. As in first section, in this section offered friends are representatives of their subgroups.

Tie strength between ego-user and his friends is being calculated by using model introduced in subsection III-A and based on data about interaction between users fetched by application. All examinees approved fetching data about them and their interaction with their friends.

Figure 3. Classifying friends into groups – application screenshot

Answers of ego-users in survey are considered as ground truth and it is analyzed if ego-users answers are matched with results of model. In first section it is considered that by model better friend is that one in pair who has higher tie strength (by calculation of model) to ego-user. In second section it is expected that friends with higher tie strength to ego-users will be classified in higher subgroup, i.e. *the best friends* will be from 1st, 2nd and 3rd subgroup, but friends from 8th and 9th subgroup will be *acquaintances*.

IV. RESULTS

A. Demographic structure

In survey were included more than 3 300 examinees. 2 626 examinees have successfully finished survey. We fetched data about their interaction with more than unique 650 000 of their Facebook friends and analyzed 1 400 000 friendships. Examinees are divided into groups by age, i.e. occupation (**Figure 5**): elementary school (43 participants), secondary school (593 participants), faculties (1 466 participants), employed (444 participants) and unemployed (80) participants. Since we plan to use these results in the future for improvement of educational system, most of examinees were faculty students. Individually most examinees were from electrotechnical faculties in Zagreb (Croatia), Osijek (Croatia) and Belgrade (Serbia). In survey 57.7% of examinees were men and 42.3% women. Questions were written in Croatian language so survey involved only people that understand that language – mostly citizens of the former Yugoslav republics.

B. Comparing friends

In this subsection user's answers in first section of survey are presented where examinees were asked to choose the better friend from two friends in pair. Each friend was representative for one subgroup so comparison of friends can be interpreted as a comparison of subgroups. **Figure 4** and **Table 2** show results, i.e. the percent in which user chose first or second friend in pair as better.

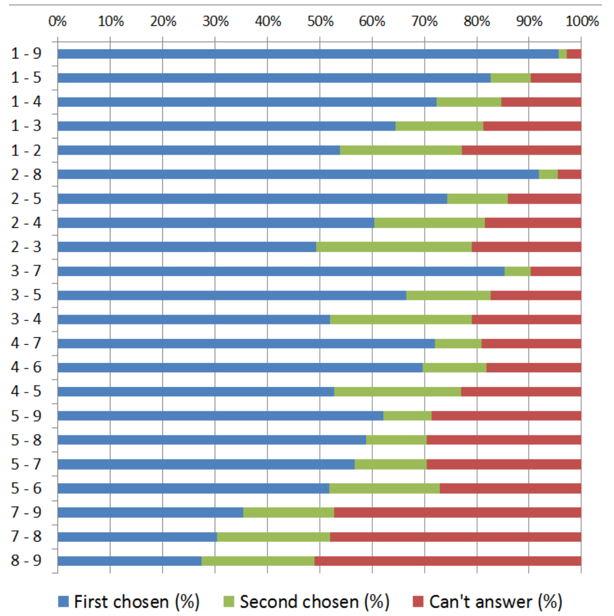

Figure 4. Comparison of pairs of subgroups

Pairs of subgroups	First chosen (%)	Second chosen (%)	Can't answer (%)	Total pairs
1 – 9	95.65%	1.53%	2.82%	2 622
1 – 5	82.64%	7.69%	9.67%	2 615
1 – 4	72.28%	12.41%	15.31%	2 619
1 – 3	64.47%	16.73%	18.80%	2 612
1 – 2	53.88%	23.27%	22.85%	2 617
2 – 8	91.91%	3.51%	4.58%	2 620
2 – 5	74.32%	11.67%	14.01%	2 605
2 – 4	60.50%	21.07%	18.43%	2 610
2 – 3	49.41%	29.72%	20.87%	2 611
3 – 7	85.33%	5.04%	9.63%	2 618
3 – 5	66.55%	16.09%	17.36%	2 604
3 – 4	52.04%	26.96%	21.00%	2 600
4 – 7	71.97%	8.97%	19.06%	2 608
4 – 6	69.64%	12.19%	18.17%	5 234
4 – 5	52.79%	24.18%	23.03%	2 601
5 – 9	62.14%	9.25%	28.60%	2 594
5 – 8	58.81%	11.66%	29.52%	2 598
5 – 7	56.76%	13.72%	29.52%	2 595
5 – 6	51.87%	21.06%	27.06%	5 203
7 – 9	35.47%	17.39%	47.14%	2 588
7 – 8	30.38%	21.63%	48.00%	2 594
8 – 9	27.52%	21.50%	50.98%	2 591

Table 2. Comparison of pairs of subgroups

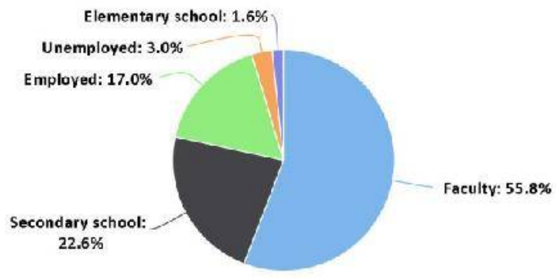

Figure 5. The distribution of participants by occupation

C. Classifying friends into groups

In this subsection ego-user's classifications of their friends into 3 groups are presented: *the best friends*, *friends* and *acquaintances*. Each friend was a representative for one subgroup so classifying of friends can be interpreted as classification of subgroups. **Figure 6** and **Table 3** show results per subgroups.

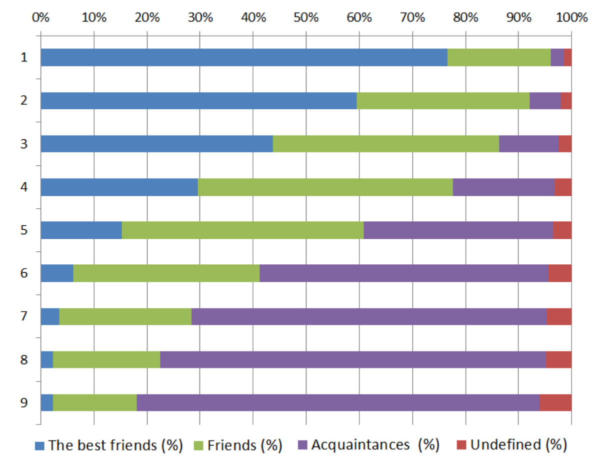

Figure 6. Classifying friends into groups

Subgroup	The best friends (%)	Friends (%)	Acquaintances (%)	Undefined (%)	Total classified
1	76.58%	19.47%	2.53%	1.42%	8 664
2	59.52%	32.56%	5.87%	2.05%	7 989
3	43.77%	42.64%	11.08%	2.51%	7 953
4	29.54%	48.02%	19.29%	3.14%	10 016
5	15.34%	45.46%	35.66%	3.53%	11 376
6	6.13%	35.04%	54.47%	4.35%	11 885
7	3.40%	24.95%	67.03%	4.63%	12 062
8	2.30%	20.14%	72.77%	4.79%	9 532
9	2.28%	15.77%	75.91%	6.04%	9 399

Table 3. Classifying friends into groups

V. Discussion

A. Comparing friends

Results of first section of questions in survey, where examinees were asked to select better friend in pair, are shown in **Figure 4** and **Table 2**. The fact that the higher percent is tied with a chosen friend from higher subgroup suggests that model work properly and confirms the hypothesis that in most cases model is able to detect which friend in pair is better to the ego-user. Furthermore, big differences in percentage are visible between subgroups whenever the subgroups are relatively far apart. It confirms the hypothesis that online social network contains both strong and weak friendships. By comparing subgroups 1 and 9, a friend who represents the 1st subgroup is in 95.65% cases chosen as better, but if we compare subgroups 1 and 2, 1st subgroup is chosen in only 53.88% of cases – though still more than double in comparison with cases where friend from 2nd group is selected as better than friend from 1st subgroup. It shows that the first subgroup truly contains the closest friends, but also that the bigger the real-life difference in tie strength is, the larger is the probability that the model will give correct output. Friends from 1st subgroup are chosen as better in 70% of cases (exclude pairs 1-3 and 1-2). That shows the ability of the model to distinguish strong from weak friendships, but indicates possible problems in the correct ordering of close friends. It is most evident in comparing 2nd and 3rd subgroups where 2nd subgroup is chosen in only 49.41% cases and 3rd in 29.72% cases.

The biggest percentage of answers *can't answer* is for subgroup pairs 7-9, 7-8 and 8-9, which is around 50%. This is understandable since these subgroups contain ego-user's friends with whom he communicates relatively rarely so ego-user is in a difficult position to state which of these Facebook friends is his better friend in real life – both are seen as merely acquaintances. Also, examinees were in 22.85% of the cases unable distinguish between subgroups 1 and 2 which indicates that it is also hard to decide which friend is better if both are ego-user's close friends.

Taking all this into account, it can be stated that these results confirm subhypothesis (1) and (2).

B. Classifying friends into groups

In the second section of questions in survey examinees were asked to classify friends into 3 groups: *the best friends*, *friends* and *acquaintances*. An assumption is that it is possible classify ego-user's friends into groups based on strength of friendship. As friends in main friends list are ordered by strength of friendship, the question is where the border between groups is.

Results are shown in **Figure 6** and **Table 3** and they are in accordance with hypothesis that with rising number of the subgroup, percentage of *the best friends* is decreasing, but percentage of *acquaintances* is increasing. 76.58% friends from 1st subgroup are classified as *the best friends* and only 19.47% as *friends*. It suggests that it is really possible to find ego-user's best friends by using described model. 59.52% friends from 2nd subgroup are classified as *the best friends* and 32.56% as *friends*. It shows that first two subgroups are mostly filled with ego-user's closest friends. In 3rd subgroup is 43.77% of *the best friends* and 42.64% of *friends*. As it is a very small difference we can conclude that 3rd subgroup is the bordering subgroup between groups of *the best friends* and *friends*. Subgroups 3, 4 and 5 are mostly filled with *friends*. Subgroup 6 is first subgroup where *acquaintances* are majority so we can conclude that border between *friends* and *acquaintances* is between 5th and 6th subgroup. It means that about 90% of ego-users Facebook friends are in fact his *acquaintances*.

These results confirm subhypothesis (3).

VI. Conclusion and Future Work

This paper describes research aimed to examine, as a proof of concept, the possibility of using a model for calculating tie strength between ego-user and his Facebook friends, based on analyzing their interaction on Facebook, to compare pairs of friends and to classify friends into predefined groups: *best friends*, *friends* and *acquaintances*. Results show that in most cases this is possible – although perfect detection and classification cannot realistically be expected.

For research purposes a survey was held which included a total of 2 626 examinees. This survey allowed collection of a large amount of data about Facebook users. This dataset is planned also to be used as a referent data set in future for similar types of researches. By using a data set described in this paper as a referent data set we plan to explore new approaches for calculating tie strength based on algorithms for supervised learning. The ultimate goal is to build an enriched social graph which will contain information about different relations between people (friendship, influence, sharing interests, etc.) and information about intensity of each relation. We will explore the possibility of applying enriched social graph in education with special emphasize on using its results in e-learning solutions.

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