Better Edges not Bigger Graphs: An Interaction-Driven Friending Algorithm for the Next-Generation Social Networks

Aadil Alshammari and Abdelmounaam Rezgui

March 29, 2020

Better Edges not Bigger Graphs: An Interaction-Driven Friending Algorithm for the Next-Generation Social Networks

Aadil Alshammari
Dept. of Computer Science and Engineering
New Mexico Institute of Mining and Technology
Socorro, NM 87801
Email: adelregh@gmail.com

Abdelmounaam Rezgui
School of Information Technology
Illinois State University
Normal, IL 61761
Email: arezgui@ilstu.edu

***Abstract*—Online social networks, such as Facebook, have been massively growing over the past decade. Recommender algorithms are a key factor that contributes to the success of social networks. These algorithms, such as friendship recommendation algorithms, are used to suggest connections within social networks. Current friending algorithms are built to generate new friendship recommendations that are most likely to be accepted. Yet, most of them are *weak* connections as they do not lead to any interactions. Facebook is well known for its Friends-of-Friends approach which recommends familiar people. This approach has a higher acceptance rate but the strength of the connections, measured by interactions, is reportedly low. The accuracy of friending recommendations is, most of the time, measured by the *acceptance rate*. This metric, however, does not necessarily correlate with the *level of interaction*, i.e., how much friends do actually interact with each other. As a consequence, new metrics and friending algorithms are needed to grow the next generation of social networks in a meaningful way, i.e., in a way that actually leads to a higher levels of social interactions instead of merely growing the number of edges in the graph of the given social network. This paper is a step towards this vision. We first introduce a new metric to measure the accuracy of friending recommendations by the probability that they lead to interactions. We then briefly investigate existing recommender systems and their limitations. We also highlight the side effects of generating easily accepted, but *weak* connections between people. To overcome the limitations of current friending algorithms, we present and evaluate a novel approach that generates friendship recommendations that have a higher probability of leading to interactions between users than existing friending algorithms.**

***Keywords*— Recommender Algorithms, Social Networks, Friending, Friendship Recommendation**

1. Introduction and Motivation

The massive amount of data available online has created a challenge for users to easily find the most relevant information or services [1] [2]. As a result, recommender systems were introduced [3] [4]. A recommender system is a filtering system that is used to provide personalized content to users, based on a variety of different factors. These factors depend on the purpose behind such a system. For instance, a friendship recommender system would focus on the users' interests, likes and dislikes or even geo-locations to match users based on their similarities.

Several friendship recommender algorithms have been used. Facebook, as an example, is well known for its recommender system, that suggests friendship connections among its enormous community [5] [6]. Facebook uses a Friends-of-Friends *(FoF)* algorithm that finds and connects already-known people. The algorithm connects hundreds of millions of people from all over the world, reaching more than 2 billion monthly active users in December 2017 [6] [7]. One of the main reasons users look for friends in social networks is to communicate and interact with them [8].

TABLE 1: Interaction Rate

Users interacting with friends using comments	2.45%
Users interacting with friends using likes	13.23%

However, even though Facebook's algorithm has a high acceptance rate, which is useful for increasing the size of the users' friends' lists, the interactions with declared friends are very low (Table 1) in relation to the total number of declared friends. The results in Table 1 are based on our fetched dataset explained in section 3. In other words, current friending approaches are focused on recommending friendships that are very likely to be accepted but that will not translate into significant interactions amongst friends.

1.1. Business Impact of Online Interactions

Interactions and participation among friends within an asynchronous social network such as Facebook are crucial factors for maintaining and growing the business. Clemons [9] emphasized that the *4 Ps* including *Participatory* are essential to "ensure traffic". The author argues that active participation and interactions are one of the keys for the success of a social network business.In addition to this, interactions and participation within a social network do not only improve the profit of the social network itself but also help other companies that take advantage of successful social networks to interact with their customers. In [10], Bolotaeva et al. emphasized brand awareness and how companies should encourage their employees to connect and interact with the community through social networks.

1.2. Social Impact of Online Interactions

A study conducted by the UK Ministry of Housing, Community and Local Government stated that interactions with a diverse network of people are proven to be very beneficial to people's mental, as well as their physical health [11]. Facebook is the largest social network and it has become one of the main means of socializing for a very large number of people. Building a friending algorithm that suggests relationships with higher probability of leading to more interactive social life can positively impact and improve the quality of people's lives. In addition, unlike recommending *weak* relationships that lead to little to no interactions, this can help in minimizing loneliness and social isolation.

The key motivation behind our research is to develop a novel friending recommender algorithm that can be used to generate a new type of social networks where users interact at a substantially higher rate than in current social networks. One practical benefit of our research is that it would contribute significantly in reducing the phenomenon of *social isolation* that has become increasingly challenging, in particular among certain segments of the population, e.g., the elderly, people with certain psychological disorders, etc.

In this paper, we study the social behavior between users in social networks and identify the common characteristics of interactive relationships. Based on these characteristics, we propose an algorithm that generates recommendations for connections that have a higher probability of leading to interactions between users than currently available friending algorithms.

1.3. Terminology

The following terminology will be used in this paper:

- a ***friending*** algorithm is a friendship recommendation algorithm.
- a ***weak*** relationship is a friendship connection that led to little to no interactions.
- an ***interactive*** relationship is a friendship connection that led to interactions.
- a ***target*** is a user for which a friending algorithm recommends friendship connections.

1.4. Paper Organization

This paper is organized as follows. In the next section, we overview some related work with more focus on friending algorithms. We also highlight the interaction problem that exists in current friending algorithms. In Section 3, we explain our data collection process. In particular, we describe the real social networks data that we fetched to test our proposed friending approach. We also present a brief analysis of our dataset. In Section 4, we present our approach and demonstrate how it generates better friendship recommendations than current friending algorithms. Then, in Section 5, we present the results of our experiments on a real dataset that illustrate how our algorithm compares to previous ones.

2. Related Work

2.1. Friending Algorithms

Most recommender systems fall under a few different types of recommenders: collaborative filtering, content-based recommender algorithms and hybrid recommender algorithms. Collaborative filtering is one of the most successfully used algorithms in recommending items [3] [12]. Content-based recommender algorithms are also a well-known class of recommender systems that take users' content, such as their profile, preferences, interests and likes/dislikes, as the main input to filter and suggest recommendations [13]

Despite the success of collaborative filtering and content-based algorithms in suggesting items, they still lack effectiveness in friending recommender systems. A thorough study [13] was conducted to evaluate the effectiveness of friendship recommender systems. The study compared different recommendation algorithms by conducting an experiment on 3000 users to test four different recommendation algorithms. This study dissects friending algorithms and identifies the essential characteristics of successful friending approaches.

The experiment in [13] concluded that, when it comes to friendship recommendations, the main problem with techniques other than FoF is that, even though they can use more dimensions to capture more relevant factors to match potential friends, they still result in a lower acceptance rate in comparison with an FoF technique.

A collaborative-filtering framework was proposed in [14] to recommend friendship connections between users based on their similarities and their interaction intensity. Users' interactions intensity were used as a similarity measure between users in terms of interactivity within social networks. The proposed framework was tested using a synthetic dataset.

2.2. Interaction Problem in Existing Friending Algorithms

The study in [13] showed that the more we recommend already-known people, the more these recommendations are considered as good and they end up being accepted. This is why the Facebook approach (i.e., FoF) has a high acceptance rate. However, it has been reported that most of Facebook friending recommendations lead to no interactions. This was confirmed through a study [15] that was conducted on a Facebook users dataset that contained 4.2 million users with 378 million friendship connections. Over a period of two years, although around 90% of messages and pokes were exchanged between friends, only 15.1% of the total number of connections were involved in those interactions. This means that, on average, users interact with about 15% of their declared friends (some of whom may have been found by the users themselves and not recommended), which, in turn, means that most of the accepted connections were *weak*.

Another study [5] also stated that, even though Facebook users have a large number of declared friends, they only interact with a small number of those friends. In addition, another study [16] concurred with the studies mentioned above that the number of interactions between a user and his/her declared friends does not correlate with the size of the user's friends list.

Wilson et al. conducted a thorough study on users' interactions in Facebook [17]. The authors derived an *interaction graph* from a Facebook's social graph dataset by eliminating non-interactive social links. The study concluded the following:

- The interaction graph only shows a significantly smaller version of the social graph which means low interaction rate.
- Social links do not always translate into meaningful relationships that involve interactions.
- Meaningful interactive friendships are keys for a trustworthy and reliable social network.

To overcome the issue of lack of interactions and encourage meaningful relationships, the authors suggest building social networks with interactions graphs in mind.

To conclude, even though more advanced filtering algorithms could connect people who have similarities in common, they still cannot outperform a simple FoF algorithm. Simply put, when it comes to friending, there is one crucial factor that is the most important which is the fact that people do not want to be connected online with strangers, regardless of their similarities. Therefore, Facebook's approach can be useful to identify connections that are easily accepted but further filtering is needed to identify connections with a higher probability to foster interactions.

3. Dataset

In order to test our approach and validate the accuracy of its results, we require a real dataset from an asynchronous social network. Facebook is the largest social network that offers two-way (undirected) friendship connections which is the core of our research. Therefore, Facebook will be the case study of our research.

We have designed and implemented a web crawler to fetch publicly available profiles from Facebook.com. The web crawler is designed to take a user ID (seed) as an argument and then it fetches the user's and the user's friends' data. Only public data can be fetched. If any part of a user's data is not publicly available, it will be presented as an empty list. For example, if a user sets his/her list of friends as private, then in our dataset his/her friends list will be presented as an empty list. The users' IDs are replaced with randomly generated numbers for anonymity.

In our dataset, every user profile we have fetched contains the following types of data:

- Randomly generated user ID.
- Gender.
- Current city and hometown.
- Self-reported interests such as movies, music, etc.
- Friends list.
- Interactions.

The interactions data contains the latest posts fetched from the most recent 4-6 time-line pages. The number of posts we have fetched for each user depends on how many there were in each time-line page. It ranges from 25 to 50 posts, and mostly around 30 posts per user/profile.

For each post fetched, we collect the following:

- Post title.
- Post ID.
- IDs of users who commented on the post.
- IDs of users who liked the post.

Sometimes users comment on their own posts which can be counted as interaction to the post. Therefore, we remove the ID of the post's author from the list of users who commented on a given post.

To collect an effective dataset, we ran our web crawler on different user IDs (seeds) from different parts of the US and the UK. After a period of 1 month, we stopped our crawler and ran a simple code on the collected data to find and return all user IDs whose declared friends' profiles exist in our collected dataset. This resulted in 25 subgraphs. Each subgraph contains the respective user and his/her friends. As a result, we have accumulated 16624 user profiles in total.

3.1. Accuracy Metric & Interactions

A high acceptance rate of recommended relationships does not mean that such suggested connections would end up being interactive. Therefore, this way of measuring the accuracy of friending recommendations is irrelevant to the main purpose of connecting people. Instead, in this research, a recommendation is accurate only if it leads to interactions.

In our accuracy metric, an algorithm's accuracy of recommending interactive friendships (noted θ) can be defined as follows:

$$\theta(Alg) = \frac{R_i}{R_{all}}$$

Where:

- R_i is the total number of *interactive* friendships recommended by Alg.
- R_{all} is the total number of all friendships recommended by Alg.

We consider as an *interaction* within the social network (i.e., Facebook) any of the two following events:

1) commenting on a friend's post or
2) liking a friend's post.

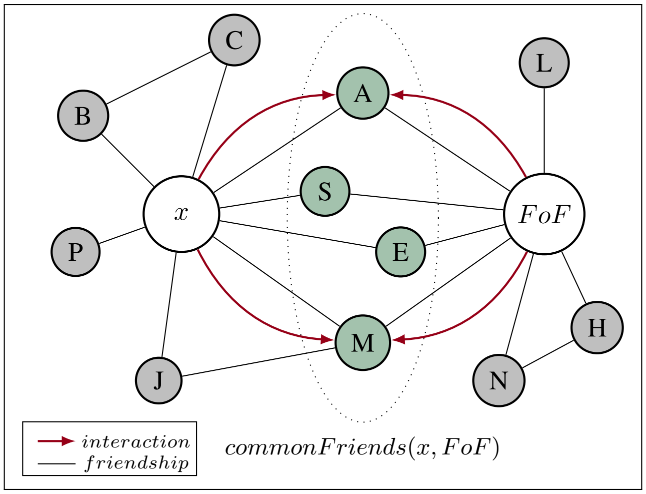

Figure 1: Sub-graph example

A user is *interactive* with his/her friend if he/she commented on at least one of that friend's posts. A comment, intuitively, is a stronger type of interaction than a like. Therefore, when there is no comment in a given relationship, at least two "likes" must be made for that relationship to be considered interactive relationship. For example, as shown in Figure 1, user x is interactive with user A because one of the following conditions was met:

1) User x commented on at least ONE of user A's posts.
2) User x liked at least TWO of user A's posts.

3.2. Dataset Statistics

Our analysis of the collected dataset confirmed the findings of the papers mentioned above about the low interactions amongst Facebook's users. To calculate the average percentage of users who interacted with their friends, a key element was the friends size of each profile. Out of the 16624 profiles, 6551 users have their friends list private. Therefore, the dataset statistics presented in Figure 2 is based on the calculation over 10073 users.

As shown in Figure 2, the average percentage of users interacting with their friends is very low. Only an average of 2.45% of users commented on their friends' posts. Interacting with friends' posts using likes accounts for an average of 13.23%. Overall, the average percentage of interaction using likes or comments within our collected dataset is 13.93%. This means that about 86% of the declared friendship relationships are *weak*. This is the best case scenario of Facebook's (FoF) approach assuming that all of the interactive relationships were actually recommended by the algorithm and were not discovered by the users themselves. In addition, the overall percentage of interactive edges is only 14.91%.

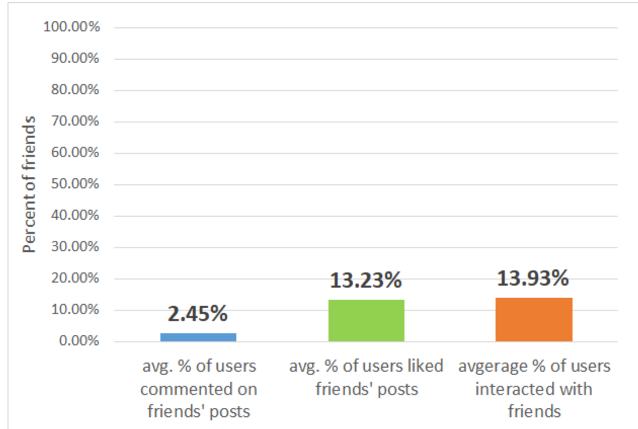

Figure 2: Dataset statistics

4. Our Approach

In this section, we first explain the logic behind our approach. Then, we present our friending algorithm that is designed not only to generate easily accepted friendship recommendations, but more importantly recommendations that likely lead to interactions.

We have seen that the intention behind the FoF algorithm is to find already known people within a social graph. We have also seen that such intention is key to incentivize users to accept and, eventually, try a recommendation suggested by the recommender system. Therefore, when recommending friendships, FoF is an essential approach because it is built to find already known people and it avoids any user who might be considered as a stranger. A simple and intuitive way is to further filter all FoFs by matching their content with the *target* content. However, users' content are usually self-reported content (like interests) which are not necessarily accurate and do not reflect the actual interests of users. In [18], the authors showed how friending algorithms based on self-reported interests failed to recommend interactive connections. Therefore, in our algorithm, we only consider real-life interactions between users to identify possible interactive relationships.

Facebook's approach and our approach have one common characteristic which is exploiting the advantage of $commonFriends$. In reality, the persons best qualified to suggest a friendship between two people are the ones who best know those two people. Hence, the most useful source of information to connect a pair of candidate friends is possessed by the set of their $commonFriends$. Facebook uses $commonFriends$ to identify already known people whereas, in our approach, we use $commonFriends$ to identify interactive relationships between already known people.

For example, as shown in Figure 1, user x and his/her friend-of-friend (user FoF) have 4 $commonFriends$ A, S, E and M. Our algorithm would recommend FoF as a possible interactive friend because user x and FoF both interacted by commenting and/or liking the same content of the same $commonFriends$.

Simply put, the intuition behind Facebook's FoF approach is "if many of my friends know FoF, then I probably know FoF". Our approach's intuition is "if a user FoF has *interacted* with many of my *interactive* friends, then I too will probably interact with FoF".

4.1. *Interaction-Driven* Friending Algorithm

In this section, we present our interaction-driven friending (IDF) algorithm (Algorithm 1). Our fetched dataset contains, beside interaction data, users' genders, places and self-reported interests. Currently, our approach is only taking advantage of users' interactions.

Algorithm 1

```
1:  procedure IDF(x,G)
2:      for each vertex f ∈ friends(x) do
3:          for each vertex ff ∈ friends(f) do
4:              if ff ∉ friends(x) then
5:                  append(FoFs, ff)
6:      for each vertex FoF ∈ FoFs do
7:          commonFriends = friends(x) ∩ friends(FoF)
8:          interactiveCounter = 0
9:          for each vertex c ∈ commonFriends do
10:             if (x and FoF) interacted with c then
11:                 interactiveCounter += 1
12:         if counter < T then
13:             remove(FoFs, FoF)
        return FoFs
```

Our IDF algorithm shown in (Algorithm 1) takes user x and the social graph as arguments. It starts by generating the set of x's friends-of-friends ($FoFs$). Lines 3 and 4, are to make sure that the generated $FoFs$ list contains user x's friends-of-friends who are NOT already friends of x. Then, it considers every FoF in the $FoFs$ set to determine whether the FoF would have an interactive relationship with user x or not. This is done by the following four steps:

1) Generate the $commonFriends$ of x *and* FoF by calculating the intersection of their friends.
2) Iterate on every user c in the $commonFriends$ set. If both x *and* FoF interacted with c, $interactiveCounter$ is increased by 1. This keeps track of the number of $commonFriends$ whom x *and* FoF interacted with.
3) If both x *and* FoF interacted with a least a T number of $commonFriends$, then FoF remains in the $FoFs$ set. Otherwise, FoF would not be considered as a possible interactive friend of x and, consequently, will be removed from the $FoFs$ set.
4) After iterating on the last FoF, the algorithm will return the modified $FoFs$ set which only contains possible interactive friends-of-friends.

The parameter "T" used in the algorithm (in line 12) is the algorithm's threshold which controls the intensity of the filtering process. This parameter is the least number of interactive $commonFriends$ to qualify a friendship connection between x and FoF. In our experiments, we set T to 4 in which the algorithm recommends a high percentage of interactive connections while still generating a high number of recommendations. When this number is increased, the accuracy of the algorithm ($\theta(Alg)$) increases but the number of recommendations decreases. For example, lowering the parameter to 3 results in a higher number of recommendations with a lower $\theta(Alg)$ while increasing the parameter to 5 results in a lower number of recommendations with a higher $\theta(Alg)$. Figure 3 , shows a graphical representation of the algorithm's results of recommending interactive and weak connections using different values of the threshold T.

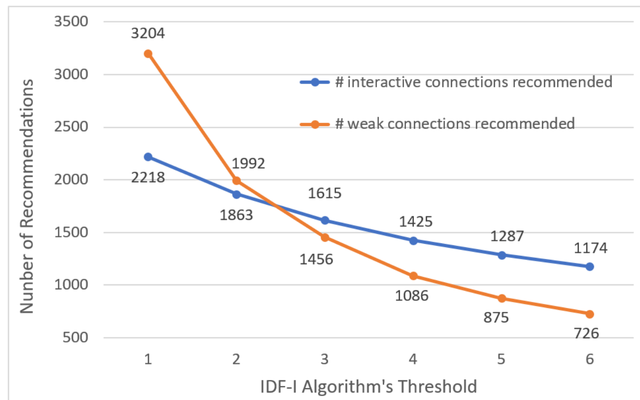

Figure 3: IDF algorithm threshold impacts

5. Experiments

The fetched dataset contains 25 subgraphs with 10500 publicly available users' profiles. Each subgraph has a *target* user whose friends' profiles all exist in our dataset. The algorithm takes the social graph (dataset) and the 25 *target* users as input. After scanning and analyzing 10500 profiles, the algorithm recommended 2,511 friendship connections. Both IDF and Facebook algorithms were tested on the same set of users.

5.1. Validation Methodology

To accurately validate our algorithm, we will not use a list of FoFs of a given *target* user. This is because, in our algorithm, the FoFs do not have relationships with that user and, as a result, have no prior history of interactivity with that user. Instead, we use another approach to accurately validate the proposed algorithm. In this approach, we run the algorithm on each of the 25 *target* users to recommend friendship connections from their already declared friends list who are also FoFs. For example, in Figure 1, user M is a friend of user x and also a FoF of user x because both x and M are friends of user J.

The algorithm has access to the relationship between user x and J and the relationship between M and J. The algorithm has no access to the relationship between x and M. Simply put, to the algorithm, user M is only an FoF

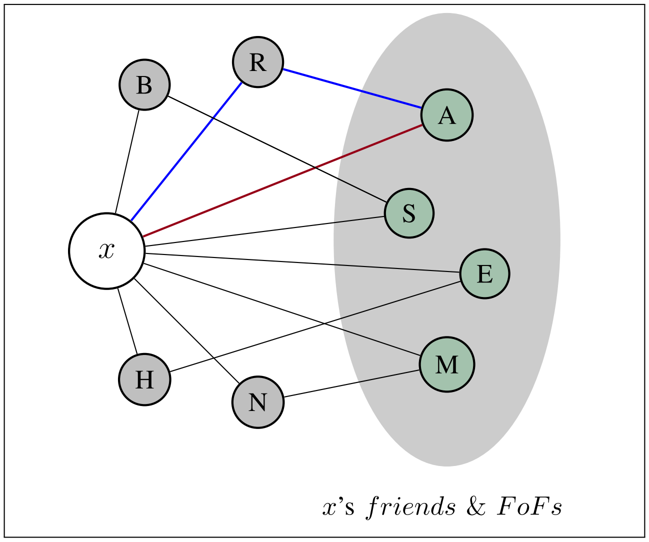

Figure 4: Validation methodology example

of user x and we are using the actual friendship between x and M only to validate and measure the accuracy of our IDF algorithm.

5.2. Experimental Results

In this section, we present the experimental results of our IDF algorithm using our collected Facebook dataset. We tested the accuracy of IDF in generating interactive relationships and compared the results with Facebook's FOF accuracy. The fetched dataset contains 25 subgraphs with 10,500 publicly available users' profiles. Each subgraph has a target user whose friends' profiles all exist in our dataset. The algorithm takes the social graph (dataset) and the 25 target users as input. After scanning and analyzing 10,500 profiles, the algorithm recommended 2,451 friendship connections. Both IDF and Facebook approaches were tested on the same set of users.

Since Facebook's approach recommends every valid fof, it recommends all of the interactive connections. However, it also ends up recommending all of the *weak* connections which account for 73.54% of the total recommendations. The large number of dead connections Facebook's FoF recommends can result in a significantly higher number of posts from *weak* connections that make *interactive* posts harder to be noticed. This explains, in part, the reason behind the effect of too many *weak* friendships in producing a low interaction rate in today's online social networks.

Overall, as shown in Figure 5, our IDF algorithm recommends 1425 interactive connections out of a total of 2511 recommendations.

The accuracy of Facebook's FoF algorithm to recommend interactive connections is:

$$\theta(FoF) = \frac{2791}{10549} = 0.26$$

The accuracy of our IDF algorithm to recommend interactive connections is:

$$\theta(IDF) = \frac{1425}{2511} = 0.57$$

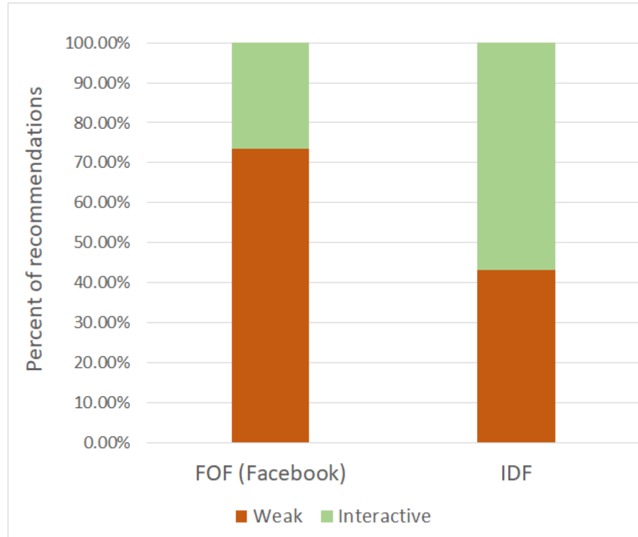

Figure 5: FoF vs IDF Experimental Results

Figure 6 shows that our IDF algorithm only recommended 14% of the *weak* relationships by identifying and ignoring 6672 *weak* relationships that were still recommended by Facebook's FoF algorithm. In addition, out of 2791 interactive relationships, the algorithm detected and recommended 1425 interactive relationships. This is a 51.06% of the total interactive connections. This percentage could have been even higher if a sufficient number of $commonFriends$ were publicly available. This is because some of the interactive friends have few to no $commonFriends$ whose data are publicly available. In fact, our IDF algorithm was able to detect 74% of the interactive friends who have at least 30 publicly available $commonFriends$ with the *target* user. This percentage increases as accessible $commonFriends$ increase.

IDF results in more than double the accuracy of Facebook's FoF approach. The average percentage of *weak* connections recommended by our algorithm is reduced from 0.74, found in DS1, to 0.43 which can be reduced even more considering the limited access to users' data. Full details and results breakdown of our experiment can be found in Table 2.

Each target is an independent special case study. The individual experimental results on the 25 targets are higher than 20% except for one single case, i.e., user 25 in Table 2. The algorithm only recommended 1 *interactive* connection out of 7 recommendations. This is due to the fact that user 25 has only 5% of interactive connections. This is also the case for user 18 who has only 5 *interactive* friends which are 4.46% of his/her friends. In addition, the limited number of $commonFriends$ may have affected the accuracy of our experiments since $commonFriends$ are fundamentally essential to compute interactive connections in our approach. As we mentioned earlier, IDF is able to find more interac-

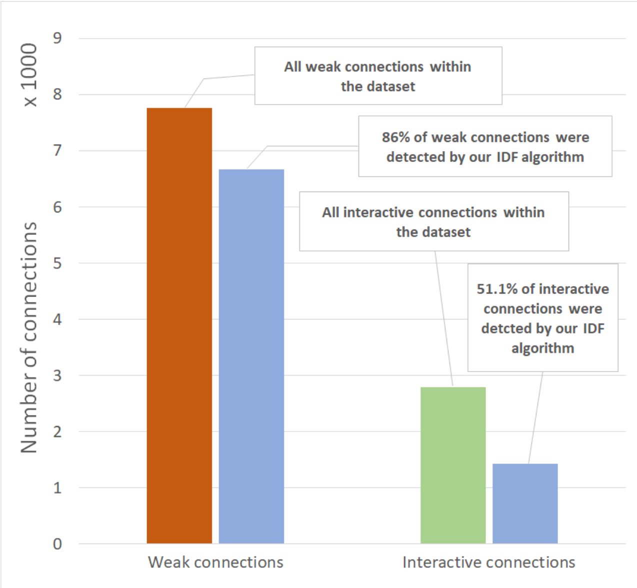

Figure 6: IDF algorithm Effectiveness

tive friendships when more $commonFriends$ have publicly accessible profiles.

Except for the case of user 25, in each case our IDF algorithm recommended a higher percentage of interactive friends than Facebook's FoF algorithm. There is one case where our algorithm does not recommend any friendship which is case number 10. As we can see in Table 2, user 10 has a small number of friends with a few *interactive* connections which is 20.

6. Conclusion

In this paper, we identified and proposed a solution to the problem of lack of interactivity amongst connected users in online social networks. We also showed that the problem is caused by the fact that existing friending algorithms focus solely on generating easily accepted friendship connections. We developed an algorithm that generates easily accepted connections, but with a higher probability of leading to interactions. Our IDF algorithm was able to recommend about two times more interactive friendships than those generated by Facebook's FoF algorithm. 84.22% of the *weak* connections recommended by Facebook's FoF algorithm were also detected by our approach. By lowering the number of *weak* connections and increasing the overall percentage of interactive connections, more interactive posts can be noticed. This leads to more interactions in online social networks.
lives. Consequently, given the large number of active users and the lack of interactions in today's online social net-

Our proposed algorithm is built with the intention to offer meaningful relationships to users. These are relationships with a higher probability of exchanging communications and interactions which, in essence, is the ultimate purpose of a meaningful friendship. As stated by the UK study mentioned above, social interactions improve the quality of people's works, our research can result in a big positive impact of online social networking on people's life in general.

References

[1] J. K. Kim, H. K. Kim, and Y. H. Cho, "A user-oriented contents recommendation system in peer-to-peer architecture," *Expert Systems with Applications*, vol. 34, no. 1, pp. 300–312, 2008.

[2] Z. Zaier, R. Godin, and L. Faucher, "Recommendation quality evolution based on neighborhood size," in *Automated Production of Cross Media Content for Multi-Channel Distribution, 2007. AXMEDIS '07. Third International Conference on*, Nov 2007, pp. 33–36.

[3] R. Burke, "Hybrid recommender systems: Survey and experiments," *User modeling and user-adapted interaction*, vol. 12, no. 4, pp. 331–370, 2002.

[4] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE transactions on knowledge and data engineering*, vol. 17, no. 6, pp. 734–749, 2005.

[5] C. Battistella and F. Nonino, "Open innovation web-based platforms: The impact of different forms of motivation on collaboration," *Innovation*, vol. 14, no. 4, pp. 557–575, 2012.

[6] Facebook, "Company info," https://newsroom.fb.com/company-info/, 2018, accessed: February 9, 2018.

[7] Statista, "Number of facebook users worldwide 2008-2017 — statistic," 2018.

[8] C. M. Cheung, P.-Y. Chiu, and M. K. Lee, "Online social networks: Why do students use facebook?" *Computers in Human Behavior*, vol. 27, no. 4, pp. 1337–1343, 2011.

[9] E. K. Clemons, "The complex problem of monetizing virtual electronic social networks," *Decision Support Systems*, vol. 48, no. 1, pp. 46–56, 2009.

[10] V. Bolotaeva and T. Cata, "Marketing opportunities with social networks," *Journal of Internet Social Networking and Virtual Communities*, vol. 2010, pp. 1–8, 2010.

[11] UK. Department for Communities and Local Government, "The benefits of meaningful interaction: Rapid evidence assessment of existing literature," 2011.

[12] A. Thomas and A. Sujatha, "Comparative study of recommender systems," in *Circuit, Power and Computing Technologies (ICCPCT), 2016 International Conference on*. IEEE, 2016, pp. 1–6.

[13] J. Chen, W. Geyer, C. Dugan, M. Muller, and I. Guy, "Make new friends, but keep the old: recommending people on social networking sites," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2009, pp. 201–210.

[14] V. Agarwal and K. Bharadwaj, "A collaborative filtering framework for friends recommendation in social networks based on interaction intensity and adaptive user similarity," *Social Network Analysis and Mining*, vol. 3, no. 3, pp. 359–379, 2013.

[15] S. A. Golder, D. M. Wilkinson, and B. A. Huberman, "Rhythms of social interaction: Messaging within a massive online network," in *Communities and technologies 2007*. Springer, 2007, pp. 41–66.

[16] A. Iamnitchi, J. Blackburn, and N. Kourtellis, "The social hourglass: An infrastructure for socially aware applications and services," *IEEE Internet Computing*, vol. 16, no. 3, pp. 13–23, 2012.

[17] C. Wilson, B. Boe, A. Sala, K. P. Puttaswamy, and B. Y. Zhao, "User interactions in social networks and their implications," in *Proceedings of the 4th ACM European conference on Computer systems*. Acm, 2009, pp. 205–218.

[18] A. Alshammari and A. Rezgui, "Cidf: A clustering-based interaction-driven friending algorithm for the next-generation social networks," *IEEE Access*, vol. 7, pp. 153 555–153 565, 2019.

TABLE 2: Experimental Results Breakdown

Subgraph	***target* ID**	**Available Friends**	**Total Recomm.**	**Interactive Recommended**	**%**	**Weak Eliminated**	**%**
1	1037	575	379	233	61.48%	151	50.84%
2	16663	257	43	31	72.09%	161	93.06%
3	22758	273	75	33	44.0%	163	79.51%
4	16665	624	19	11	57.89%	553	98.57%
5	30170	645	253	127	50.2%	315	71.43%
6	16664	436	70	39	55.71%	299	90.61%
7	4103	855	635	415	65.35%	159	41.95%
8	30970	192	8	7	87.5%	128	99.22%
9	13343	737	291	158	54.3%	361	73.08%
10	239642	117	0	0	-	97	100.0%
11	24221	543	205	67	32.68%	308	69.06%
12	43070	296	27	14	51.85%	238	94.82%
13	16718	256	8	5	62.5%	216	98.63%
14	2	274	9	7	77.78%	222	99.11%
15	34151	544	127	75	59.06%	263	83.49%
16	51620	410	4	3	75.0%	359	99.72%
17	16662	109	26	20	76.92%	54	90.0%
18	318828	112	2	1	50.0%	99	99.0%
19	3267	206	16	8	50.0%	161	95.27%
20	47786	111	19	16	84.21%	53	94.64%
21	186804	387	3	2	66.67%	328	99.7%
22	16688	519	20	18	90.0%	448	99.56%
23	6727	517	76	47	61.84%	354	92.43%
24	26595	1027	189	87	46.03%	759	88.15%
25	777	453	7	1	14.29%	423	98.6%
Total		**10475**	**2511**	**1425**	**56.75%**	**6672**	**86.00%**