

Forming Compatible Teams in Signed Networks

Ioannis Kouvatis¹, Konstantinos Semertzidis²
Maria Zerva¹, Evaggelia Pitoura¹, Tsaparas Panayiotis¹

¹ Department of Computer Science and Engineering, University of Ioannina, Greece
{ikouvatis,mzerva,pitoura,tsap}@cse.uoi.gr

² IBM Research, Dublin, Ireland
konstantinos.semertzidis1@ibm.com

ABSTRACT

The problem of team formation in a social network asks for a set of individuals who not only have the required skills to perform a task but who can also communicate effectively with each other. Existing work assumes that all links in a social network are positive, that is, they indicate friendship or collaboration between individuals. However, it is often the case that the network is *signed*, that is, it contains both positive and negative links, corresponding to friend and foe relationships. Building on the concept of structural balance, we provide definitions of compatibility between pairs of users in a signed network, and algorithms for computing it. We then define the team formation problem in signed networks, where we ask for a *compatible* team of individuals that can perform a task with small communication cost. We show that the problem is NP-hard even when there are no communication cost constraints, and we provide heuristic algorithms for solving it. We present experimental results with real data to investigate the properties of the different compatibility definitions, and the effectiveness of our algorithms.

1 INTRODUCTION

Given a task that requires a set of skills, a pool of workers who possess some of the skills and are organized in a social network, team formation refers to finding a subset of the workers that collectively cover the skills and can communicate effectively with each other [9]. The communication cost of the team is measured using the distances between the team members in the network. The idea is that socially well connected users will be more effective in working together.

Since the pioneering work in [9], there has been considerable research activity on the problem [1, 8, 12]. All existing work assumes that the social network contains only positive ties between individuals. That is, the edges denote friendship or successful collaboration between two users. However, very often, we have *signed* networks with both positive and negative ties. A negative edge indicates a contentious relationship and inability of two users to collaborate and thus in this case, we do not want such users to be in the same team.

In this paper, we study the problem of team formation in signed networks. In addition to the known requirements of the team formation problem, we ask that the team contains users that are all *compatible* with each other. Defining compatibility in a signed network is an interesting problem in itself. Clearly, users connected with a positive edge are compatible, while users connected with a negative edge are incompatible. We infer the compatibility of non-connected pairs of users by using the structure of the graph, and the principle of *structural balance*. Structural balance [4] is based on the premise that “the friend of my friend is my friend”, “the enemy of my enemy is my friend”, and “the enemy of my friend is my enemy”. Using this premise, we determine the compatibility of two users by looking at the paths that connect

them. For example, a path of two positive or two negative edges indicates compatibility, while a path of one positive and one negative edge indicates incompatibility. We formalize this idea, and we provide definitions of compatibility of varying strictness. We perform experiments with four real datasets, where we evaluate the different compatibility definitions, and the performance of the algorithms for the team formation problem.

2 PROBLEM DEFINITION

We are given as input a pool of n individuals organized in an *undirected signed* graph $G = (V, E)$. Each node in V corresponds to an individual, and $E = \{(u, v, \ell) : u, v \in V, \ell \in \{+1, -1\}\}$ is a set of edges *labeled* as either positive or negative to indicate that u and v are friends or enemies respectively. We assume that G is connected. We will use a function $sign : E \rightarrow \{+1, -1\}$ that returns the label of each edge in E .

We are also given as input a universe S of skills. Each individual u in V possesses a set of skills, $skill(u) \subseteq S$. We define a task as the subset of skills $T \subseteq S$ required for its completion. Given a task, the team formation problem asks for a team X of individuals, $X \subseteq V$, that collectively covers the required skills and whose members can work together *effectively*. The effectiveness of a team is typically quantified by the communication cost, $Cost(X)$, of the team defined as some function of the distances of its members in the graph.

However, when the graph contains both positive and negative edges, we need to take into account that some individuals, although close in the graph, may not be *compatible* with each other. To capture whether two users are compatible, we introduce a relation $Comp \subseteq V \times V$ such that $(u, v) \in Comp$, if and only if, u and v can work together. Two natural requirements for $Comp$ are (1) reflexivity: $(u, u) \in Comp$, and (2) symmetry: if $(u, v) \in Comp$, then $(v, u) \in Comp$. Furthermore, we require that the $Comp$ relation satisfies the following two intuitive properties:

- (1) *Positive Edge Compatibility*: For all $(u, v) \in E$, such that $sign(u, v) = +1$, $(u, v) \in Comp$.
- (2) *Negative Edge Incompatibility*: For all $(u, v) \in E$, such that $sign(u, v) = -1$, $(u, v) \notin Comp$.

We will provide various definitions of compatibility in Section 3. We now define formally our problem.

Definition 2.1. (TEAM FORMATION IN SIGNED NETWORKS (TFSN)) Given a signed graph $G = (V, E)$, a compatibility relation $Comp$, and a task T , find $X \subseteq V$ such that (1) $\bigcup_{u \in X} skill(u) \supseteq T$, (2) for each $u, v \in X$, $(u, v) \in Comp$, and (3) $Cost(X)$ is minimized.

The TFSN problem contains as a special case the original team formation problem which is NP-hard [9], thus TFSN is also NP-hard. Moreover, we have shown that just finding a set of compatible users is NP-hard. Let TFSNC denote the simplified

version of the TFSN problem, where we drop the third requirement of minimizing the cost. In particular, we have proven the following theorem.

THEOREM 2.2. *The decision version of TFSNC is NP-hard for any compatibility relation that satisfies positive edge compatibility and negative edge incompatibility.*

3 USER COMPATIBILITY

We start with two basic definitions of compatibility.

Definition 3.1. Direct Positive Edge (DPE) compatibility: $Comp_{DPE} = \{(u, v) \subseteq V \times V : (u, v, +1) \in E\}$.

Definition 3.2. No Negative Edge (NNE) compatibility: $Comp_{NNE} = \{(u, v) \subseteq V \times V : (u, v, -1) \notin E\}$.

DPE is the strictest form of compatibility, while NNE is the most relaxed one. Specifically, $Comp_{DPE}$ is the minimal subset of pairs of nodes that satisfies the positive edge compatibility property, while $Comp_{NNE}$ is the maximal subset of pairs of nodes that satisfies the negative edge incompatibility property.

We will now use the theory of *structural balance* [2, 4, 7] to provide more refined definitions of compatibility. The theory is based on the following socially and psychologically founded premises: (1) the friend of my friend is my friend, (2) the friend of my enemy is my enemy, and (3) the enemy of my enemy is my friend.

Let $P = (v_0, \dots, v_{k+1})$, $(v_i, v_{i+1}) \in E$ denote a path between nodes v_0 and v_{k+1} in a signed graph G . We define the sign of the path as $sign(P) = \prod_{i=0}^k sign(v_i, v_{i+1})$. We say that path P is positive if $sign(P) = +1$ and negative if $sign(P) = -1$.

CLAIM 1. *A positive path P_{uv} between two nodes u and v indicates compatibility, while a negative one indicates incompatibility.*

The claim follows from the basic principle of structural balance. To see this, let $P_{uv} = (x_0, x_1, \dots, x_k, x_{k+1})$, $x_0 = u$, $x_{k+1} = v$ be a path that connects u and v . Let F_u be the set of friends of u and E_u be the set of enemies of u . We start by placing node u in F_u and traverse the path as follows. When we traverse edge (x_i, x_{i+1}) , if the edge is positive we place x_{i+1} in the same set as x_i . That is, the friends of my friends are also my friends, and the friends of my enemies are my enemies. If the edge (x_i, x_{i+1}) is negative then we place x_{i+1} in the opposite set of x_i . That is, the enemies of my enemies are my friends, and the enemies of my friends are my enemies. If the path P_{uv} is positive then v will be placed in F_u , while if the path is negative it will be placed in E_u .

We first look at shortest paths. A *shortest path* between two nodes u and v is a path from u to v such that no other such path has a smaller length. We use SP_{uv} to denote the set of shortest paths between nodes u, v , SP_{uv}^+ to denote the positive, and SP_{uv}^- the negative ones.

Definition 3.3. Shortest Path (SP) compatibility relations: – All Shortest Path (SPA) compatibility: $Comp_{SPA} = \{(u, v) \subseteq V \times V : \forall P_{uv} \in SP_{uv}, sign(P_{uv}) = +1\}$.

– Majority Shortest Path (SPM) compatibility: $Comp_{SPM} = \{(u, v) \subseteq V \times V : |SP_{uv}^+| \geq |SP_{uv}^-|\}$.

– One Shortest Path (SPO) compatibility: $Comp_{SPO} = \{(u, v) \subseteq V \times V : \exists P_{uv} \in SP_{uv}, sign(P_{uv}) = +1\}$.

We further relax compatibility by asking for positive paths that are not necessarily the shortest ones. Based on structural balance, certain triangles are more stable. A general signed graph is structurally balanced, if it does not contain any cycle with an odd number of negative edges [7].

Algorithm 1 The SP-compatibility algorithm.

Input: Signed graph G , query node q .

Output: The number of positive and negative shortest paths from q to all other nodes in the graph.

```

1: Initialize  $N^+(q) = 1$ ,  $N^-(q) = 0$ ,  $N^+(x) = N^-(x) = 0$ ,  $L(q) = 0$ ,
    $L(x) = \infty$ , empty queue  $Q$ .
2:  $Q.enqueue(q)$ 
3: while  $Q \neq \emptyset$  do
4:    $u = Q.dequeue()$ 
5:   for  $x$  adjacent to  $u$  do
6:     if  $L(u) + 1 \leq L(x)$  then
7:       if  $x \notin Q$  then
8:          $Q.enqueue(x)$ 
9:          $L(x) = L(u) + 1$ 
10:        if  $sign(u, x) = +1$  then
11:           $N^+(x) += N^+(u)$ ;  $N^-(x) += N^-(u)$ 
12:        else if  $sign(u, x) = -1$  then
13:           $N^-(x) += N^+(u)$ ;  $N^+(x) += N^-(u)$ 
14: return  $(N^+, N^-, L)$ 

```

Given a path P , let $G_P = (P, E[P])$ be the graph induced by the nodes of P . We say that path P is structurally balanced if the subgraph G_P is structurally balanced. Let BP_{uv} denote the set of all structurally balanced paths between u and v .

Definition 3.4. Structurally Balanced Path (SBP) compatibility: $Comp_{SBP} = \{(u, v) \subseteq V \times V : \exists P_{uv} \in BP_{uv}, sign(P_{uv}) = +1\}$.

The motivation for SBP compatibility is that, in addition to P_{uv} being positive, asking for G_P to be structurally balanced means that the sign of any edge connecting u and v must be positive, otherwise a cycle with an odd number of negative edges will be created. Note that SBP-compatibility does not imply SP-compatibility. Consider the example in Figure 1(a). The (only) shortest path between u and v is (u, x_1, v) which is negative, and thus u, v are not SP-compatible. However, u and v are SBP-compatible, since the path (u, x_2, x_3, x_4, v) is positive and structurally balanced. Note that there is a shorter path (u, x_2, x_1, v) between u and v that is positive, but not structurally balanced, since the shortcut edge (u, x_1) creates the unbalanced triangle (u, x_1, x_2) .

It is easy to see that the following holds:

PROPOSITION 3.5. $Comp_{DPE} \subseteq Comp_{SPA} \subseteq Comp_{SPM} \subseteq Comp_{SPO} \subseteq Comp_{SBP} \subseteq Comp_{NNE}$.

Algorithms. We now present algorithms for SP and SBP compatibility. Algorithm 1 shows the modified BFS algorithm for counting positive and negative shortest paths. Given the query node q , for each node $x \in V$ in the graph, the algorithm maintains the numbers $N^+(x)$ and $N^-(x)$ of positive and negative shortest paths respectively and the length of the shortest path $L(x)$ from q to x . When reaching node x from node u through a shortest path (line 6), if the edge (u, x) is positive, we increment the number of positive and negative paths of x by $N^+(u)$ and $N^-(u)$ respectively, since all paths retain their sign. If the edge (u, x) is negative, we increment $N^-(x)$ by $N^+(u)$, and $N^+(x)$ by $N^-(u)$, since the sign of the paths change. Each edge is examined only once.

The efficient enumeration of shortest paths is possible due to the prefix property that a shortest path between q and x that goes through node u must use a shortest path from q to u . However, this is not the case for shortest structurally balanced paths. Consider the example in Figure 1(b). The shortest structurally balanced path from u to x_4 is (u, x_3, x_4) . However, the shortest structurally balanced path $(u, x_1, x_2, x_4, x_5, v)$ from u to v goes through node

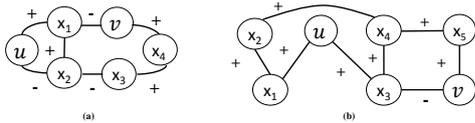


Figure 1: (a) u and v are SBP but not SP compatible. (b) It does not suffice to keep a single path from u to x_4 .

Algorithm 2 Team formation algorithm.

Input: Signed graph G , task T , compatibility relation $Comp$.

Output: Team X .

- 1: Initialize $S \leftarrow \emptyset$. // S : skills covered so far
- 2: Initialize $\mathcal{L} \leftarrow \emptyset$. // \mathcal{L} : set of candidate teams
- 3: Select skill s from T // skill selection
- 4: **for** each u with skill s **do**
- 5: $X \leftarrow \{u\}$ // X : candidate team
- 6: $S \leftarrow S \cup (T \cap skills(u))$
- 7: **while** $S \neq T$ **do**
- 8: Select skill s from $T - S$ // skill selection
- 9: Select user v with skill s // user selection
- 10: s.t. $(v, x) \in Comp$ for all x in X
- 11: $X \leftarrow X \cup \{v\}$
- 12: $S \leftarrow S \cup (T \cap skills(v))$
- 13: $\mathcal{L} \leftarrow \mathcal{L} \cup X$
- 14: **return** $argmin_{X \in \mathcal{L}} (Cost(X))$

x_4 but not through the shortest structurally balanced path from u to x_4 , since the path (u, x_3, x_4, x_5, v) is not structurally balanced.

Since the exact algorithm is prohibitively expensive for large graphs, due to the exponential number of paths, we also consider a heuristic alternative for SBP-compatibility that counts only paths having the prefix property. We will use SBP to denote the compatibility relation computed by the exact exhaustive algorithm, and SBP_H the output of the heuristic algorithm.

4 TEAM FORMATION

We now present algorithms for the TFSN problem. Recall that our goal is to find a team of compatible users, that covers all skills, and minimizes the communication cost. The communication cost is defined as the largest distance between any two pairs of users in the team. We define the distance between two users looking at the positive paths connecting them. Specifically, for DPE and SP compatibility, distance is the length of the shortest path, while for SBP the length of the shortest structurally balanced positive path. For NNE compatibility, since there be no positive paths, we define distance as the length of the shortest path ignoring its sign.

Algorithm 2 is a generic algorithm that incrementally builds a solution, each time considering an uncovered skill and adding a compatible user having this skill, until all skills are covered. There are two placeholders in this algorithm. The first is the policy for selecting a skill (lines 3 and 8), and the second the policy for selecting a candidate user (line 9).

We consider two policies for selecting skills: select the rarest skill first (as in [9]), and select the least compatible skill first. We define the compatibility degree $cd(s)$ of skill s based on the compatibility between the users with skill s and the users with all other skills: $cd(s) = \sum_{s_j \in S, s_i \neq s} cd(s, s_j)$, where $cd(s, s_j) = |\{(u_i, u_j) : (u_i, u_j) \in Comp, s \in skills(u_i) \text{ and } s_j \in skills(u_j)\}|$.

We also consider two policies for selecting users: select the user that has the minimum distance, and select the user that is most compatible among the remaining users. The first selection aims at minimizing the cost, while the second at maximizing the

Table 1: Dataset Statistics

	<i>Slashdot</i>	<i>Epinions</i>	<i>Wikipedia</i>
#users	214	28,854	7,066
#edges	304	208,778	100,790
#neg edges	89 (29.2%)	34,941 (16.7%)	21,765 (21.5%)
diameter	9	11	7
#skills	1,024	523	500

Table 2: Comparison of compatibility relations

	SPA	SPM	SPO	SBP _H	SBP	NNE
<i>Slashdot</i>						
comp. users	44.72	55.72	72.45	97.85	99.38	99.64
comp. skills	80.57	86.19	92.63	99.11	99.47	99.50
avg distance	4.13	4.37	4.57	4.95	4.97	4.53
<i>Epinions</i>						
comp. users	29.61	62.98	86.46	99.82	–	99.99
comp. skills	97.25	98.90	99.66	99.99	–	99.99
avg distance	3.48	3.82	3.87	3.97	–	3.83
<i>Wikipedia</i>						
comp. users	21.98	59.33	87.51	99.56	–	99.91
comp. skills	66.17	87.31	97.32	99.87	–	99.96
avg distance	2.85	3.23	3.30	3.38	–	3.25

Table 3: Comparison with unsigned team formation

	SPA	SPM	SPO	SBP	NNE
Ignore sign	0%	2%	2%	26%	30%
Delete negative	0%	2%	18%	66%	76%

chances of finding a group of compatible users. We experimentally evaluate different combinations of these policies in Section 5.

5 EXPERIMENTAL EVALUATION

In this section, we compare the different compatibility relations on real datasets and evaluate the team formation algorithm.

Datasets. Table 1 details our real-world datasets. *Slashdot* contains information about users and their posts on Slashdot. We obtained a network of Slashdot users [11], where users have tagged their relationships as friend or foe. Then we used the categories of users’ posts as skills. *Epinions* contains information about users and their reviews about products. The dataset is created by combining a signed network of Epinions users [11] with the RED¹ dataset which contains information about the products and product categories the users have reviewed. We used the unique user ids to match users in the two datasets, and we assigned as skills to users the categories of the products they have reviewed. *Wikipedia* [11] is a signed network of editors. The edge sign corresponds to a positive or negative vote in admin elections. Since there was no skill information, we assigned synthetically generated skills to its users. We generated 500 distinct skills with frequencies following a Zipf distribution as in real data. Each skill is assigned to users in the network uniformly at random.

Compatibility Relations. In Table 2, we report the percentage of compatible pairs of users and skills. We exclude the DPE compatibility from our analysis, since this corresponds to finding cliques and team formation is too restrictive. Two skills s_1 and s_2 are compatible if they have compatibility degree $cd(s_1, s_2) > 0$, i.e., there is at least one compatible pair of users (u, v) such that u has s_1 and v has s_2 (including self-compatibility, if the same user has both skills).

As expected, the number of compatible user and skill pairs increases as we relax the notion of compatibility. For SPA, less than half of the pairs of nodes are compatible, and as low as 21.98% for the case of *Wikipedia*. Also, in most cases, for a sizeable fraction of pairs of skills there are no compatible users, indicating that for many skill combinations there can be no compatible team.

¹<https://projet.liris.cnrs.fr/red/>

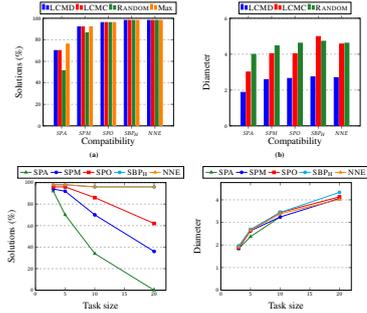


Figure 2: Team formation: comparison of algorithms ((a) and (b)), varying task size (c) and (d).

Another interesting observation is that the fraction of compatible pairs for SBP is comparable with that for NNE. This means that, for all pairs that are not directly connected with a negative edge, there exists at least one positive structurally balanced path that connects them.

Distance. In Table 2, we also report the average distance between compatible users. The distance steadily increases as we relax the compatibility definition. The exception is NNE in which we allow negative paths, and thus we are able to discover shorter ones.

Comparison of SBP and SBP_H. We also compare the exact (SBP) and heuristic (SBP_H) structurally balanced compatibility for the *Slashdot* dataset, for which we can compute the exact relation. Table 2 shows the difference between SBP and SBP_H which is only $\sim 2.5\%$

Team Formation. Due to space limitation, in this set of experiments, we only report results using *Epinions*. Results are similar for the other networks. We generate tasks of different sizes. For a given task of size k , we generated 50 tasks by randomly selecting k skills. First, we compare the four different team formation algorithms obtained by combining the two different skill and user selection policies. We report results for the two algorithms that performed the best which are the algorithms that select the least compatible skill. The first one, termed LCMD, selects the user with the minimum distance, while the second one, termed LCMC, the user who is the most compatible with the existing team. We also experiment with a baseline RANDOM that selects a compatible user at random.

In Figure 2(a), we report the percentage of times that each algorithm was able to find a compatible team for $k = 5$. The last bar (MAX) shows the percentage of tasks that contain compatible skills. This is a rough upper bound on the number of compatible teams, since it is based on compatible skills and not the compatibility of users. The two algorithms perform equally well indicating that optimizing for compatibility makes very little difference. Figure 2(b) shows the average cost of the teams produced. LCMD produces the teams with the smallest cost which makes LCMD the best choice.

In Figures 2(c) and (d), we report results for teams of varying task sizes using LCMD. As expected, more skills means that more people need to co-operate to complete the task, making it harder to form a compatible team, and more likely to include a distant node. The number of solutions drops steeply for more strict compatibility relations, while it remains more or less constant for NNE and SBP_H.

Finally, we compare our approach with previous work on team formation. Since there is no previous work on team formation on signed network, we create two unsigned *Epinions* networks by (1) ignoring the sign of the edges and (2) deleting the negative edges. We run a team formation algorithm [9] on each of these two

networks using the same tasks with $k = 5$ skills as in the previous experiments. In Table 3, we report the percentage of the returned teams that satisfy compatibility for the different compatibility relations. As shown, most of the teams returned are incompatible.

6 RELATED WORK

To the best of our knowledge, our work is the first to address team formation in signed networks.

Team Formation. Lappas et al. [9] were the first to formally define the problem of finding a team of experts using the network structure to quantify the quality of the team as a whole. There is considerable amount of work extending their model, (e.g., [1, 8, 12]), but none of these works addresses team formation in a signed network.

Signed Networks. There is a fair amount of work on signed networks [13]. A problem somehow related to our work is that of link and sign prediction [3, 11]. However, our work is different, since we are not interested in predicting future links, but rather in evaluating the compatibility between any two individuals in the network. There is also work on detecting communities in signed networks (e.g., see [14]). The notion of the team is somehow related to that of the community, but the objective of team formation is different.

Structural Balance. There is a rich literature in psychology on positive and negative relations among groups of people using structural balance theory, e.g., [2, 4]. Structural balance has been used e.g., for identifying clusters [5] and polarization in networks [10], finding communities [6].

7 CONCLUSIONS

In this paper, we introduced the novel problem of team formation in a signed network. The problem poses the challenge of defining node compatibility in a signed network. To this end, we provided a principled framework by utilizing the theory of structural balance. In the future, we plan to investigate different ways to combine compatibility and communication cost and to exploit compatibility for other tasks, such as link prediction or clustering.

REFERENCES

- [1] Aris Anagnostopoulos, Luca Becchetti, Carlos Castillo, Aristides Gionis, and Stefano Leonardi. 2012. Online Team Formation in Social Networks. In *WWW*.
- [2] Dorwin Cartwright and Frank Harary. 1956. Structural balance: a generalization of Heider's theory. *Psychological review* 63, 5 (1956).
- [3] K. Chiang, N. Natarajan, A. Tewari, and Inderjit S. D. 2011. Exploiting Longer Cycles for Link Prediction in Signed Networks. In *CIKM*.
- [4] James A Davis. 1963. Structural balance, mechanical solidarity, and interpersonal relations. *Amer. J. Sociology* 68, 4 (1963).
- [5] Lúcia Maria de A. Drummond, Rosa M. V. Figueiredo, Yuri Frota, and Mário Levorato. 2013. Efficient Solution of the Correlation Clustering Problem: An Application to Structural Balance. In *OTM*.
- [6] Hongzhong Deng, Peter Abell, Ofer Engel, Jun Wu, and Yuejin Tan. 2016. The influence of structural balance and homophily/heterophobia on the adjustment of random complete signed networks. *Social Networks* 44 (2016).
- [7] David Easley and Jon Kleinberg. 2010. *Networks, Crowds, and Markets: Reasoning About a Highly Connected World*. Cambridge University Press. <http://books.google.co.uk/books?id=atfCl2agd8C>
- [8] Mehdi Kargar and Aijun An. 2011. Discovering top-k teams of experts with/without a leader in social networks. In *CIKM*.
- [9] Theodoros Lappas, Kun Liu, and Evimaria Terzi. 2009. Finding a team of experts in social networks. In *KDD*.
- [10] Duan-Shin Lee, Cheng-Shang Chang, and Ying Liu. 2016. Consensus and Polarization of Binary Opinions in Structurally Balanced Networks. *IEEE Trans. Comput. Social Systems* 3, 4 (2016).
- [11] Jure Leskovec, Daniel P. Huttenlocher, and Jon M. Kleinberg. 2010. Signed networks in social media. In *CHI*.
- [12] C. T. Li and M. K. Shan. 2010. Team Formation for Generalized Tasks in Expertise Social Networks. In *SocialCom/PASSAT*.
- [13] Jiliang Tang, Yi Chang, Charu Aggarwal, and Huan Liu. 2016. A Survey of Signed Network Mining in Social Media. *ACM Comput. Surv.* 49, 3 (2016).
- [14] Bo Yang, William Cheung, and Jiming Liu. 2007. Community Mining from Signed Social Networks. *IEEE Trans. on Knowl. and Data Eng.* 19, 10 (2007).