Authority-based Team Discovery in Social Networks

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ABSTRACT

Given a network of experts, we tackle the problem of finding a team of experts that covers a set of required skills in order to complete a project. Previous work ranks different teams based on the communication cost among the team members. However, it does not consider the effect of the authority of the experts. The authority of an expert is application dependent and might be related to the expertise of the team members. In addition to the authority of the skill holders, in a big social network, the authorities of the experts connecting the skill holders are also important. In this work, we introduce and analyze the effect of the authority of both skill holders and middle experts on the quality of a team of experts for performing a project. Since the proposed problems are NP-hard, we propose greedy algorithms to solve them. We verify effectiveness of our approach on a real dataset.

1. INTRODUCTION

An expert network contains a group of professionals who can provide specialized skills and services. With the widespread use of the web services, online expert networks have become popular and more businesses seek to find experts to complete a task or project. There are many expert network providers, such as business and employment oriented social service LinkedIn, repository hosting service GitHub and bibliography based websites such as DBLP and Google Scholar. In such networks, an expert is described by his areas of expertise, education background and location, etc. In addition, previous collaborations among experts are provided. A previous collaboration could be working on the same project in the same company, co-authoring the article or even co-supervising the student [2][4].

We consider the problem of finding a team of experts from such a network to complete a project. A project is composed of a set of skills and each skill needs to be covered by at least one expert that posses that skill. The success of a project heavily depends on how well the experts of the team collaborate and communicate with each other. If some team members have collaborated in the past, they are more likely to finish a project faster than a group of people that have never worked together before. Depending on the level of the work conducted in collaboration in the past (e.g., number of articles published together), each expert may have a different level of communication with other experts. Thus, minimizing the communication cost among the experts is of paramount importance to improve the efficiency of the team. This problem was studied thoroughly in the past [3][5].

However, while the previous approaches certainly have merit, a technical challenge is to find a team of experts that can perform the required tasks in a timely manner. In addition of optimizing the communication cost among team members, we are also interested to optimize the overall authority of the team. Each expert in an expertise-based social network is associated with a value that represents his authority in the network. The authority of an expert is application-specific; such as the social credibility of the expert, expertise in the field, author-level metrics such as h-index and/or the number of publications. The authority of the skill holders have a direct effect on the quality of the team. Furthermore, in a big social network, there are many cases in which the team members have not had direct collaboration experience in the past. Hence, they only know each other through other experts in the network. In this work, we call such experts middle experts or connectors. Middle experts do not directly participate in a team but they help skill holders to get to know each other and they may advice them for performing the project. In this scenario, the authority of the middle experts also affects the quality of the team.

To motivate our approach and illustrate the shortcomings of existing techniques, consider two different teams of experts as shown in Figure[1]. Assume that we need to perform a research project that needs expertise in the area of social network (SN) and text mining (TM). Assume that for performing the SN research, we have two graduate students: Jialu Liu (h-index: 9) and Behzad Golshan (h-index: 5). Also, for performing the TM research, we have two other
graduate students: Xiang Ren (h-index: 11) and Dimitrios Kotzias (h-index: 3). Graduate students with higher h-index have more expertise and authority than the one with smaller h-index. Now consider teams (a) and (b) in Figure 2. Each of the skill holders are connected together via one expert in the network. Assuming the communication cost of teams (a) and (b) are the same, we recommend team (a) since the skill holders have higher h-index and their authority is higher than the skill holders of team (b).

Now, let’s consider another scenario. Assume that the authority of all of the skill holders (i.e., Jialu, Behzad, Xiang and Dimitrios) are the same since all of them are graduate students. Members of team (a), composing of Jialu and Xiang, are connected and introduced to each other via Jiawei Han whose h-index is 139. On the other hand, Behzad and Dimitrios (team (b)), are introduced to each other by Theodoros Lappas whose h-index is 12. We argue that team (a) could be more successful in satisfying the project’s requirements since the team members can rely on someone with more expertise in conducting research projects. On the other hand, team (b) does not have such an advantage. We say that team (a) outperforms team (b) since the middle expert (connector) of team (a) has higher authority than the one from team (b).

Our contributions are as follows.

1. We formally define the problem of authority-based team formation in social networks. We formulate three objective functions for ranking the teams which optimize: communication cost, experts’ authority, and middle experts’ authority.

2. We prove that optimizing the objectives is NP-hard.

3. We perform a comprehensive evaluation using the DBLP dataset to confirm the effectiveness of our approach.

2. PRELIMINARIES

Let \( C = \{c_1, c_2, \ldots, c_m\} \) denote a set of \( m \) experts, and \( S = \{s_1, s_2, \ldots, s_r\} \) denote a set of \( r \) skills. Each expert \( c_i \) has a set of skills, denoted as \( S(c_i) \), and \( S(c_i) \subseteq S \). If \( s_j \in S(c_i) \), expert \( c_i \) has skill \( s_j \). Furthermore, a subset of experts \( C' \subseteq C \) have skill \( s_j \) if at least one of them has \( s_j \). For each skill \( s_j \), the set of all experts having skill \( s_j \) is denoted as \( C(s_j) = \{c_i | s_j \in S(c_i)\} \). A project \( P \subseteq S \) is defined as a set of required skills required to complete the project. A subset of experts \( C' \subseteq C \) is said to cover a project \( P \) if \( \forall s_j \in P \exists c_i \in C', s_j \in S(c_i) \).

The experts are connected together via a social network which is modeled as an undirected graph \( G \). Each node in \( G \) is an expert in \( C \). In this work, terms an expert and a node might be used interchangeably. Each node in the graph is associated with an authority value. The authority values are application dependent. The authority of an expert \( c_i \) is denoted as \( a(c_i) \). Let \( a'(c_i) = \frac{1}{a(c_i)} \). We use the inverse of authority to convert later maximization problem into a minimization problem. Two experts may be connected by an edge in the graph. The weight on an edge represents the communication cost between the two experts. The lower the weight, the more easily the two experts can collaborate or communicate, and thus the lower the communication cost between them. The communication cost between two experts can be defined based on the application needs. The communication cost can be defined by the familiarity or collaboration ability between the two experts. In this case, two nodes are connected by an edge if the experts have collab-

![Figure 2: The Proposed Approach](image-url)
**Problem 2.** Given a graph $G$ and a set of required skills, find a team of experts $T$ in $G$ that covers the required skills and minimizes the referral authority $RA(T)$.

**Theorem 1.** Problem 2 is NP-hard.

**Proof.** We prove that the decision version of the problem is NP-hard. Thus, as a direct result, minimizing referral authority objective is NP-hard too. The decision problem is specified as follows. Given a graph $G$ and a set of required skills, determine whether there exists a team of experts with referral authority value of $const_{ra}$, for some constant $const_{ra}$.

The problem is obviously in NP. We prove the theorem by a reduction from group Steiner tree problem. First, consider a graph in which all edges have the same weight of 1.0 and all nodes have the same authority of 1.0. A feasible solution to the above problem with the referral authority at most $const_{ra}$ is a solution for the group Steiner tree problem with the weight at most $(const_{ra} - 1)$. This is the case since for any tree, the number of edges is equal to the number of nodes minus one. Thus, if there exists a tree with the referral authority at most $const_{ra}$, then there exists a tree with the sum of the edge weights at most $(const_{ra} - 1)$. On the other hand, a tree with edge weights at most $(const_{ra} - 1)$ determines a feasible tree with the referral authority at most $const_{ra}$. Therefore, the proof is complete.

Furthermore, we are interested in the bi-criteria optimization problem of minimizing the communication cost and the referral authority. A common way to solve a bi-criteria optimization problem is to convert it into a single objective problem by combining the two objective functions into one. Therefore, we define a single objective that combines these two objectives with a tradeoff parameter $\gamma$ as follows ($\gamma$ varies from 0 to 1).

**Definition 4. RA-CC (RC) Objective:** Given a team of experts $T$ from graph $G$ for a given set of skills and a tradeoff parameter $\gamma$, where $0 \leq \gamma \leq 1$, the RA-CC objective of $T$ is defined as $RCO(T) = \gamma \cdot RA(T) + (1 - \gamma) \cdot CC(T)$.

**Problem 3.** Given a graph $G$, a set of required skills and a tradeoff parameter $\gamma$, find a team of experts $T$ in $G$ that covers the required skills and minimizes the RC objective (i.e., $RCO(T)$).

**Theorem 2.** Problem 3 is NP-hard.

**Proof.** We showed that finding a team of experts covering the input skills with minimized communication cost (CC($T$)) or minimized referral authority (RA($T$)) is NP-hard. Since both CC($T$) and RA($T$) are linearly related to $RCO(T)$ (the objective of Problem 3), then minimizing $RCO(T)$ is also an NP-hard problem.

We believe that the authority of skill holders should be treated differently than the authority of the middle experts (connectors). In real scenarios, we might prefer to give a higher weight to the authority of skills holders and a lower weight to the authority of the middle experts that do not necessarily hold an expertise and do not necessarily participate in performing project’s tasks. Therefore, we define the expert authority as follows.

**Definition 5. Expert Authority:** Suppose that the skill holder experts of a team $T$ are denoted as $\{c_1, c_2, \ldots, c_n\}$. The expert authority of $T$ is defined as $EA(T) = \sum_{i=1}^{n} a(c_i)$.

**Problem 4.** Given a graph $G$ and a set of required skills, find a team of experts $T$ in $G$ that covers the required skills and minimizes the expert authority $EA(T)$.

Problem 2 can be solved in polynomial time. Since we do not consider the structure of the underlying graph in the objective, for each skill, we choose the expert which has the highest authority value. However, the experts may not be able to communicate effectively and team members might be far away from each other in the social network. Furthermore, the middle experts may not have high authority. Therefore, we define a combined objective that considers the three main objectives of this paper as follows.

**Definition 6. EA-RC (ERC) Objective:** Given a team of experts $T$ from graph $G$ for a given set of skills and a tradeoff parameter $\lambda$, where $0 \leq \lambda \leq 1$, the EA-RC objective of $T$ is defined as $ERCO(T) = \lambda \cdot EA(T) + (1 - \lambda) \cdot RCO(T)$.

**Problem 5.** Given a graph $G$, a set of required skills and two tradeoff parameters $\gamma$ and $\lambda$, find a team of experts $T$ in $G$ that covers the required skills and minimizes the ERC objective (i.e., $ERCO(T)$).

**Theorem 3.** Problem 5 is NP-hard.

**Proof.** We showed that finding a team of experts covering the input skills with minimized RC objective ($RCO(T)$) is NP-hard. Since $RCO(T)$ is linearly related to $ERCO(T)$ (the objective of Problem 5), then minimizing $ERCO(T)$ is also an NP-hard problem.

Since trade-off parameters $\gamma$ and $\lambda$ are application-dependent, we leverage user and domain expert feedback to set and update them over time. Incorporating user feedback is a vital component towards achieving high precision.

### 3.2 Search Algorithms

Since solving Problems 2, 3, and 5 is NP-hard, we propose a series of efficient and effective greedy algorithms to solve them in polynomial time.

**Opt. CC:** Given a graph $G$ that only its edges are weighted, Algorithm 1 finds the best team by minimizing the edge weights. For finding the best team minimizing the communication cost (i.e., edge weights), it finds a sub-tree of the graph that covers the input skills. We assume that each expert $c_i$ in the graph could be a potential root for the tree $c_i$ might or might not contain a required
To build a tree around \( c_r \), for each given skill \( s_i \), we assign the closest expert \( c_{k_i} \) in the graph \( G \) that contains skill \( s_i \) to the tree rooted at \( c_r \). The tree with the lowest sum of the edge weights is the best team. Since we run this polynomial operation on every node (i.e., potential root) of the graph once, the total run time of the algorithm is also polynomial.

To improve the efficiency of above algorithm, the shortest distance between each pair of experts \( c_{k_p} \) and \( c_{k_q} \) in \( G \), denoted as \( d_{\min}^i(c_{k_p}, c_{k_q}) \), has been computed and a hash table is used to store the shortest distances of all pairs for quick retrieval by the algorithm. For minimizing the communication cost, we first calculate the shortest path hash using the edge weights (i.e., communication cost between any pair of experts with prior collaboration) in \( G \). Then, we use Algorithm 2 to find the best team.

The above operations can be computed in polynomial time. Moreover, we use distance labeling or 2-hop cover \( i \) to find the shortest path between each pair of experts. Therefore, the path communication costs only on the edges. The new graph \( G \) is converted into a new graph \( G' \) with both authority and communication costs only on the edges. The new graph \( G' \) has the same set of experts as the original graph \( G \), but the authority of nodes in \( G \) is moved onto the edges in \( G' \). Assume that the edge weight between nodes \( c_i \) and \( c_j \) in \( G \) is denoted by \( w(c_i, c_j) \). In \( G' \), the edge weight between nodes \( c_i \) and \( c_j \) is defined as \( w'(c_i, c_j) = \gamma_i(d_i'(c_i) + d_j'(c_j)) + (1 - \gamma_i)w(c_i, c_j) \). Then, we find the shortest path between any pair of experts in \( G' \) (i.e., \( d_{\min}^i(c_{k_p}, c_{k_q}) \)). Using new edge weights and the new shortest path hash, Algorithm 2 is called to solve Problem 2. It should be noted that if \( \gamma \) is set to 1.0, this algorithm only minimizes the referral authority (i.e., Problem 3).

**Opt. RCO:** For optimizing Problem 3 the input graph \( G \) is converted into a new graph \( G' \) with both authority and communication costs only on the edges. The new graph \( G' \) has the same set of experts as the original graph \( G \), but the authority of nodes in \( G \) is moved onto the edges in \( G' \). Assume that the edge weight between nodes \( c_i \) and \( c_j \) in \( G \) is denoted by \( w(c_i, c_j) \). In \( G' \), the edge weight between nodes \( c_i \) and \( c_j \) is defined as \( w'(c_i, c_j) = \gamma_i(d_i'(c_i) + d_j'(c_j)) + (1 - \gamma_i)w(c_i, c_j) \). Then, we find the shortest path between any pair of experts in \( G' \) (i.e., \( d_{\min}^i(c_{k_p}, c_{k_q}) \)). Using new edge weights and the new shortest path hash, Algorithm 2 is called to solve Problem 2. It should be noted that if \( \gamma \) is set to 1.0, this algorithm only minimizes the referral authority (i.e., Problem 3).

**Opt. ERCO:** Assume the shortest path between any pair of experts \( c_{a_r} \) and \( c_{v_r} \) in \( G' \) is denoted as \( d'(c_{a_r}, c_{v_r}) \). In order to remove the authority of the end nodes (skill holders) from \( d' \), we define an updated \( d'' \) as follows: \( d''_{\text{new}}(c_{a_r}, c_{v_r}) = d'_{\text{new}}(c_{a_r}, c_{v_r}) - \gamma_i(d_i'(c_{a_r}) + d_j'(c_{v_r})) \). Then, we define a new edge weighting function \( d'' \) as \( d''(c_{a_r}, c_{v_r}) = \lambda_i(a'(c_{a_r}) + a'(c_{v_r})) + (1 - \lambda_i)d_{\text{new}}(c_{a_r}, c_{v_r}) \). If we run the Algorithm 2 using \( d'' \), we find the best team of experts optimizing Problem 3.

### 4. EXPERIMENTAL RESULTS

In this section, the proposed algorithms are evaluated. All the algorithms are implemented in Java. The experiments are conducted on an Intel(R) Core(TM) i7 2.80 GHz computer with 4 GB of RAM. The DBLP XML data\(^1\) is used in the experiments. DBLP graph is produced using DBLP XML data similar to [3]. The set of top-tier conferences are also similar to the one in [3]. In this graph, experts are the authors that have at least three papers in DBLP. The weight of the edge between two experts \( n_i \) and \( n_j \) is equal to \( 1 - \frac{p_{n_i} \cap P_{n_j}}{p_{n_i} \cup P_{n_j}} \) where \( p_{n_i} \) is the set of papers of author \( n_i \). We define authority of an expert as the number of publications of the author. This is based on the assumption that the more publications an author has, the more authority he has in the network. The final graph has 9,237 nodes (experts) and 14,656 edges. The number of skills in a project is set to 4, 6, 8 or 10. For each number of skills, we generate 50 sets of skills randomly, corresponding to 50 random projects. The results are presented as the average result over the 50 projects for each number of skills.

In this experiment, we evaluate the performance of following methods: 1) CC finds the best team by minimizing the communication cost, 2) RCO finds the best team by minimizing the RC objective, 3) ERCO finds the best team by minimizing the ERC objective, 4) Random selects the team with the lowest ERC cost among 10,000 random teams, and 5) Exact uses exhaustive search to find the best exact team, w.r.t the ERC objective, among all possible teams. In practice it is too expensive to use it as users expect to receive answers in real time.

Figure 3 shows the average combined cost values of teams for different methods in DBLP dataset. Since the Exact algorithm does not finish in reasonable time for eight and ten skills, its results are only provided for four and six skills. Figure 3 suggests that ERCO produces teams whose quality is close to that of the exact algorithm. In addition, the results of RCO for solving Problem 3 is slightly closer to the exact results than CC which solves Problem 3. We also note that all of our methods are scalable and have similar runtime since they use the same indexing method.

The top team returned by CC and ERCO methods for required skills [ranking, visual, communities, constraints] is shown in Figure 4. Figure 4 suggests that the team returned by ERCO is...
more efficient since the authors chosen by ERCO published more papers in average. This means the total authority of the team is significantly better than that of CC. Moreover, Figure 5 shows the skill holders of the team returned by ERCO are connected through authors with more publications, thus higher referral authority. We argue that the team returned by ERCO is more efficient than the one returned by CC since it reveals a deeper connection between the experts that may not have been discovered by existing team formation methods.

We also design and conduct a user study to evaluate the top-k precision of the methods. We give the top-5 teams along with the average number of publications of each expert (both skill holders and middle experts) to five students in computer science. The required skills are randomly selected. We asked 6 Computer Science graduate students to judge the quality of the top-5 teams using a score between zero and one. Figure 5 shows the top-5 precision of each method on a given set of skills. In this experiment we set both \( \lambda \) and \( \gamma \) to 0.5. Both of our methods, RCO and ERCO, obtain better precision than communication cost for all projects.

5. CONCLUSIONS

We studied the problem of finding an authority-based team from a network of experts that minimizes different objectives. We proved and showed that the problems we tackle are NP-hard and proposed a series of efficient algorithms to solve them. We evaluated the proposed algorithms on the DBLP dataset and showed that our proposed algorithms are effective and efficient.

6. REFERENCES

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