Multi-team Formation using Community Based Approach in Real-World Networks

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Abstract

In an organization, tasks called projects that require several skills, are generally assigned to teams rather than individuals. The problem of choosing a right team for a given task with minimal communication cost is known as team formation problem and many algorithms have been proposed in the literature. We propose an algorithm that exploits the community structure of the social network and forms a team by choosing a leader along with its neighbours from within a community. This algorithm is different from the skill-centric algorithms in the literature which start by searching for each skill, the suitable experts and do not explicitly consider the structure of the underlying social network. The strategy of community-based team formation called TFC leads to a scalable approach that obtains teams within reasonable time over very large networks. Further, for one task our algorithms TFC-R and TFC-N generate multiple teams from the communities which is showcased as a case-study in the paper.

The experimentation is carried out on the well-known DBLP data set where the task is considered as writing a research paper and the words of the title are considered as skills. Team formation problem is translated to finding possible authors for the given paper, who have the required skills and having least communication cost. In the process, we build a much larger bench-mark data set from DBLP for team formation for experimentation. We do not retrieve communities using community discovery algorithms, but consider the subsets of DBLP based on research areas like DB and VLDB as communities. Clearly there is a trade-off between the time taken and communication cost. Even though the benchmark algorithm Rarestfirst takes least time, our algorithms TFC-N and TFC-R give much better communication cost. They also outperform the standard algorithms like MinLD and MinSD with respect to the time taken in finding a team. Further, the teams found by TFC-N show similar or lesser communication cost in comparison. The time taken by our algorithms on communities are several orders faster than the time taken on the larger network without compromising too much on the communication cost.

keywords : social networks, team formation, degree centrality, power law, DBLP network, communities

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1 Introduction

Many real-world challenges like hackathons, community-based software development or the software challenges thrown open by major conferences are examples of tasks requiring multiple skills that can only be tackled as a team. Teams in the conventional sense are co-located and consist of individuals working in physical proximity. On the other hand, in the context of software industry or even technical hackathons, typically the teams are built across geographical boundaries. Hence it is important to find algorithms that can constitute teams having the skills required as well as keep the cost of the project within the budget. Conventionally, members have been largely selected based on their functional skills. There may or may not be collaboration among team members. On the other hand, many studies like Gulla [2020], Marr [2016] show that insufficient communication and ineffective management are some of the reasons for project failure. As per Tavrizyan [2019] only 2.5% of the companies complete their projects 100% successfully. Josh Steimle Josh [2019], claim that most of the technology implementation projects fail because of people, and not due to technology. Lappas et al. [2009] were the first to incorporate this aspect into the mathematical model of the team formation problem by embedding the members on a social network and including communication cost as one of the main costs of the project.

In the era of information and communication technology, there is an explosion of social networking sites that have emerged in the last decade providing a platform to share common interests. The volume of interactions has increased tremendously leading to very large and modular networks. Hence there is a need for algorithms that are scalable for social networks.

In this paper we propose an algorithm that takes advantage of the power law and the community structure that is intrinsic to a social network. Our algorithm adopts a kind of divide and conquer strategy. First a community of members having majority of the skills required for the task is retrieved from the social network. Then a leader is picked from the heavy tail of the community who in turn chooses team members having expertise from within his/her neighbourhood. This certainly ensures good communication among the team members. Since this algorithm works at community-level rather than the whole network, it runs very fast, much faster than many of the well-established algorithms in the literature.

The organization of the paper is as follows. The problem statement and the notation required is set in Section 2 and the related literature is given in Section 3. The algorithms of TFC-R and TFC-N are proposed in Section 5. The construction of the dataset is described in Section 6. In Section 7, the insights gained from network analysis of the DBLP data set with respect to the skill coverage vs expert degree distribution are explained. Finally in Sections 8 and 9, the comparative results obtained for the algorithms in terms of execution time and the various communication cost measures and the community-wise performance of the algorithm are given. The paper ends by discussing the results of the algorithm in terms of the multiple teams obtained for each task on the case-study of Wang et al. [2015] in Section 10 followed by conclusions.
2 Background

A social network is modeled as a graph $G = (V, E)$ in which experts are considered as nodes and their mutual interactions are depicted as edges with weights given by a distance measure based on the strength/weakness of the interaction.

2.1 Notation

The notation required for the team formation problem formulation is given in Table 1.

| Symbol | Description |
|--------|-------------|
| $G$    | Graph representation of network |
| $V$    | Set of experts as nodes for $G$ |
| $E$    | Set of weighted edges for $G$ |
| $S$    | Universal set of skills of $V$ |
| $T$    | Set of skills required for a task $T$ |
| $s(v)$ | Set of skills possessed by an expert $v \in V$ |
| $HD$   | Set of high degree nodes having at least one skill in $T$ |

Table 1: Notation used for the Team formation problem

2.2 Problem statement

Given a set of experts $V$ in $G$ and a set of skills $S$, an expert $v \in V$ is associated with skill set represented as $s(v)$ and given a task $T = \{s_1, s_2, ..., s_k\}$ contained in $S$, team formation problem is to find a team $X \subseteq V$ such that $\bigcup_{v \in X} s(v) \supseteq T$, such that the communication cost of the team $X$ is minimized.

2.3 Communication cost

A few of the popular communication cost functions that measure the quality of a team formation algorithm (TF) as given in a survey of Wang et al. [2015] are described below.

Let $sp(u, v)$ denote the weight of the shortest path found between nodes $u$ and $v$ in the graph $G$.

- **Diameter**: Diameter of a team $X$ is defined as the weight of the longest among the shortest paths between all pairs of nodes of the team $X$.

- **Sum Distance**: A measure that computes the sum of distances between each pair of skills (i.e. experts chosen by the algorithm for the skill) of task $T$.

$$\sum_{i=1}^{[T]} \sum_{j=i+1}^{[T]} sp(v_i, v_j)$$ (1)

where $v_i, v_j$ are experts responsible for skills $i, j$ in $T$ and $v_i, v_j \in X$. Since one expert may be responsible for more than one skill, the cost is calculated with respect skills rather than experts.
• **Leader Distance**: Sum of distances from leader $v_L$ in the team to other members of the team.

$$\sum_{v_i \in X, v_i \neq v_L} sp(v_i, v_L)$$ (2)

where $v_L$ is leader and $v_i, v_L \in X$.

### 3 Related literature

In the field of combinatorial optimization one of the classical problems is assignment problem also referred to as task assignment problem (TAP). In TAP, given $m$ agents with certain skills and $n$ tasks, the problem is to find an assignment that matches the tasks with the agents having the required skills. Since each agent incurs a cost, the problem is that of finding an assignment of minimum cost. With a constraint that at most one agent can be assigned to each task and at most one task to each agent, TAP is to find an allocation that maximizes task allocation with minimum cost. Lappas et al. [2009] were the first to introduce social network into the assignment problem. They name the agents as ‘experts’ and that the experts are interacting on a social network. They propose the problem of Team formation (TFP) as one in which given a task requiring a set of skills, the problem is to find a team of experts who can perform the task incurring minimum communication cost. As explained in 2.3, there are many communication costs that have been proposed in the literature. Lappas et al. [2009] propose two communication cost measures for evaluating the collaboration among the team members, namely diameter and Steiner tree communication costs. Gaston and desJardins [2003] note that teams from scale-free networks perform well.

McDonald [2003] observe that workplace collaborations are strongly influenced by social relationships. In the same year Wi et al. [2009] proposed an algorithm based on finding a team leader who then identifies the team members. They used a multi-objective fuzzy model giving importance to both interpersonal (collaboration) and technical skills (knowledge) for team formation.

Several variations of TFP have been proposed in the literature. Li and Shan [2010], Gajewar and Sarma [2012] consider redundant number of experts demanded for each skill. Anagnostopoulos et al. [2012], constrain the problem by allowing each agent to participate in more than one project with an upper bound called as workload of the agent. The authors propose two greedy heuristics in this work. An online team formation problem is proposed by Anagnostopoulos et al. [2010, 2012], in which formation of multiple teams is considered where the tasks keep coming online. The experts that have been assigned for a team may not be available for the next task and hence the algorithm needs to keep track of the workload of the agents. This problem is termed as Balanced social task assignment problem (BSTAP).

Limiting maximum skills contributed by an expert to a project is called the \textit{capacitated team formation problem} Majumder et al. [2012]. Problem defined by Lappas et al. [2009] is further extended by Kargar et al. [2012] by adding financial cost of agents to the team cost. They proposed heuristics for this bi-objective TFP that optimizes both financial cost and communication cost. TFP has been further expanded by Kargar and An [2011] who propose two new...
communication cost measures to evaluate the team, namely, leader distance and 
sum distance that have been defined in Section 2.3.

We find that in the literature, TFP has not been limited to skill coverage
and collaboration. Li et al. [2018] consider a minimum set of people influencing
maximum number of people; Demirović et al. [2018] study a team that can with-
stand damage caused by a member leaving the team; team member replacement
problem is studied by Li et al. [2015]. Majority of the papers on TFP in the
literature consider finding one team for a given task Lappas et al. [2009], Wi
et al. [2009], Kargar and An [2011], Kargar et al. [2012], Majumder et al. [2012],
Kargar et al. [2013], Demirović et al. [2018] . Another branch of TFP deals
with building teams for multiple tasks called Multiple team formation problem
Gutiérrez et al. [2016], Baghel and Bhavani [2018]. In this work, we aim to find
many teams for the same task which has not been done in the literature.

Here we give a comparison of time complexities incurred by a few of the
popular algorithms, namely Rarestfirst of Lappas et al. [2009], Best leader dis-
tance(BLD) and Best sum distance (BSD) of Kargar and An [2011]. BLD and
BSD algorithms are renamed as MinLD and MinSD by Wang et al. [2015] which
we follow in this paper. The algorithm of Kargar and An [2011] MinLD takes
longer than the other algorithms since in many cases since it is constrained to
consider all the nodes of the network. The algorithm MinSD of Kargar and
An [2011] considers large number of experts for each skill and that too not the
rarest skill which results in decrease of its performance.

The time complexities of the different algorithms that we use for comparison
in this paper are tabulated in Table 2.

| Algorithm                      | Worst case Time Complexity |
|--------------------------------|----------------------------|
| Rarestfirst Lappas et al. [2009]| $O(|V|^2)$                 |
| CoverSteiner Lappas et al. [2009]| $O(|V|^3)$                 |
| EnhancedSteiner Lappas et al. [2009]| $O(|T||V|^2)$             |
| MinSD Kargar and An [2011]    | $O(|T|^2|V|^2)$            |
| MinLD Kargar and An [2011]    | $O(|T| \times |C_{max}| \times |V|)$ |

Table 2: Time complexity of different TF algorithms

4 Motivation

Social networks are increasing in size and hence the team formation algorithms
that process the networks have to be scalable. In the case of DBLP which is
a repository of publications, even if we consider only the conferences, it can be
seen that the number of conferences increased from thousands to nearly two
lakhs in the last two and half decades\(^1\). Thus an approach that adopts a kind
of divide and conquer strategy may be more profitable.

\(^1\)https://dblp.uni-trier.de/statistics/recordsindblp
A social network exhibits modular property Newman [2006] and the ensuing clusters of nodes are called communities. A typical social network with recursive community structure is pictorially depicted in Figure 1. As can be seen in the picture, these communities may be overlapping, disjoint or nested communities. If teams can be extracted from each of the communities, then we get multiple teams for a task.

![Figure 1: Modular property: Social network and its communities.](image)

4.1 Idea of the algorithm

In general, while a team is being formed for, say, a hackathon, in the real world challenges, a team leader is identified at the initial step and the team leader sets about choosing the team members who possess the necessary skills required for the task $T$ from within ‘her community’, that is, with whom she has good communication. Hence as a first step in forming a team, the team leader searches in her neighborhood. If the task is not still covered, then she looks beyond her neighbourhood to add members for the remaining skills.

A natural choice for a team leader is one possessing at least a few of the required skills and having many friends. The degree distribution of the network exhibits a typical heavy tail since the real world social networks satisfy power law. We propose that the team leader be selected from the high degree nodes in the heavy tail in order to choose highly connected person, thus reducing the expensive computations.

5 Proposed algorithm

It is well known that the social networks exhibit modular property i.e. social network comprises of communities. Taking benefit of this structure, we first identify communities, called desirable communities, containing members possessing skills relevant to the task $T$. All skills are treated as equally important. The algorithm is given in Algorithm 2 which takes as input the desirable communities computed using Algorithm 1. If the threshold is set as 0.9, then a desirable community must possess at least ninety percent of skills of $T$. 

6
Algorithm 1: Algorithms DC to find desired communities

1: for $C \in \text{communities}$ do
2:   $cs \leftarrow \{s(v) \forall v \in C\}$
3:   if $|cs \cap T| \geq \text{threshold}$ then
4:     $X \leftarrow \text{TFC-R}(G(C), T)$
5:   end if
6: end for

We propose novel algorithms, namely, TFC-R and TFC-N, based on team leader selection who then builds the team ensuring skill coverage as well as compatibility among the team members. TFC Algorithm 2 first locates a leader within a desirable community. A leader is defined as an expert whose degree is greater than twice the average degree of the network. Then the other team members are searched within two hop-neighbourhood of the leader in the network so that experts covering majority of the skills of $T$ may be added. In fact, this idea is reinforced by Majumder et al. [2012] who empirically establish that searching within two hops of a leader achieves skill coverage to a great extent and with low communication cost. By this step, if skills of $T$ are not yet covered fully, then we add the experts in two ways.

5.1 TFC-R and TFC-N algorithms

In TFC-R, random experts possessing the remaining skills are added to the team. In TFC-N, nearest expert to the leader from $k$-hop neighborhood, $k > 2$ is chosen. Since the two algorithms are different only in this step, we present only the TFC-R algorithm here.

Since social networks are very large in size, this kind of approach provides a scalable alternative to the existing algorithms which may be forced to search through the entire network.
Algorithm 2 Algorithm TFC-R

1: \( \text{team} \leftarrow \emptyset \)
2: \( \text{best\_team} \leftarrow \emptyset \)
3: \( \text{ldbt} \leftarrow \infty \)
4: \( \text{HD} \leftarrow \{ i | i \in G, d(i) > 2 \times d_{\text{avg}}, |s(i) \cap T| > 0 \} \)
5: \( \text{while } |\text{HD}| > 0 \text{ do} \)
6: \( v \leftarrow \text{dequeue HD} \)
7: \( T_{NYC} \leftarrow T \)
8: \( \text{hop} \leftarrow 1 \)
9: \( \text{while } \text{hop} \leq 2 \text{ and } |T_{NYC}| > 0 \text{ do} \)
10: \( T_{NYC} \leftarrow T \)
11: \( \text{team} \leftarrow \emptyset \)
12: \( \text{team} \leftarrow \text{team} \cup \{ v \} \)
13: \( T_{C} \leftarrow s(N_{hop}(v)) \cap T \)
14: \( \text{Nbd} \leftarrow N_{hop}(v) \)
15: \( \text{while } |T_{C}| > 0 \text{ do} \)
16: \( e \leftarrow \text{argmax}_{i \in \text{Nbd}}(T_{C} \cap s(i)) \)
17: \( \text{team} \leftarrow \text{team} \cup \{ e \} \)
18: \( T_{C} \leftarrow T_{C} \setminus \{ s(e) \} \)
19: \( T_{NYC} \leftarrow T_{NYC} \setminus \{ s(e) \} \)
20: \( \text{Nbd} \leftarrow \text{Nbd} \setminus \{ e \} \)
21: \( \text{end while} \)
22: \( \text{hop} + + \)
23: \( \text{end while} \)
24: \( \text{for skill} \in T_{NYC} \text{ do} \)
25: \( \text{re} \leftarrow \text{rand}(v(\text{skill})) \)
26: \( \text{team} \leftarrow \text{team} \cup \{ \text{re} \} \)
27: \( \text{end for} \)
28: \( \text{if } LD(\text{team}) < \text{ldbt} \text{ then} \)
29: \( \text{ldbt} \leftarrow LD(\text{team}) \)
30: \( \text{best\_team} \leftarrow \text{team} \)
31: \( \text{end if} \)
32: \( \text{end while} \)
33: \( \text{return } \text{best\_team} \)

5.2 Tracing on a toy example

In order to compare and contrast the proposed algorithm with some of the popular ones in the literature, we design a toy example as shown in Figure 2. Skill-centric algorithms like RarestfirstLappas et al. [2009] and MinLD, MinSD of Kargar and An [2011], design heuristics that start with a skill and find expert who has the least communication distance to the team built so far. We can appreciate the difference in the approaches of the different algorithms by looking at the Toy example2.

We trace the algorithm on the toy example in Figure 2 and the comparative results are given in Table 3. For a task requiring skills \( \{ a, b, c, d, e \} \), the teams \( ABCQ \) and \( DEFJ \) tie in terms of cardinality. Consider node \( C \), whose closest experts with skill \( d \) are \( S \) and \( T \). Since \( T \) is at least distance from \( C \), the algorithms Rarestfirst, MinSD and MinLD choose \( T \). But this choice increases
cardinality. TFC-R chooses $S$ instead of $T$, thus obtaining the team \{A, C, S\}. Hence the expert-centric algorithms result in smaller teams.

| Algorithm | Team (Leader) | distance metrics | Diameter | SD | LD |
|-----------|---------------|------------------|----------|----|----|
| TFC-R     | ACS (C)       |                  | 2        | 26 | 5  |
| Rarestfirst | JFGI (J)     |                  | 2        | 30 | 10 |
| MinSD     | ACS (S)       |                  | 2        | 26 | 8  |
| MinLD     | AQCB (A)      |                  | 3        | 28 | 7  |

Table 3: Cost of teams obtained by Rarestfirst, MinSD, MinLD and TFC-R algorithms on the toy example

6 Benchmark dataset

We curated a large collaboration network from DBLP database\(^2\). DBLP data is modeled as a social network with experts as nodes and distance based on mutual collaboration denoting the edge weight giving rise to an undirected and weighted network. We have followed the modeling method exactly as suggested originally by Lappas et al. Lappas et al. [2009] and followed by Anagnostopoulos et al. [2010], Kargar and An [2011], Majumder et al. [2012], Kargar et al. [2012], Anagnostopoulos et al. [2012]. The snapshot of DBLP data set considered has been restricted to conferences pertaining to four major research areas of computer science: Database(DB), Data Mining(DM), Artificial Intelligence(AI)

\(^2\)https://dblp.uni-trier.de/xml/
Table 4: Research areas are taken as big communities and constituting conferences as small communities

| Research area | Conferences |
|---------------|-------------|
| DB | VLDB, SIGMOD, ICDT, ICDE and PODS |
| DM | WWW, SDM, KDD, ICDM, PKDD and WSDM |
| AI | NIPS, IJCAI, ICML, UAI, COLT and CVPR |
| TH | FOCS, SODA, STOC, ICALP, STACS and ESA |

Table 4: Research areas are taken as big communities and constituting conferences as small communities

and Theory(TH). Data comprises of publications in the conferences specified in Table 4. We treat the data of each research area as a bigger community and the publications in each conference as smaller community. Details of the total benchmark data set is given in Table 1 of Appendix.

Individuals who have published papers in the conferences are considered as authors. Authors having at least three publications are considered as experts. Now to associate skills to each expert, the words in the titles of the publications are utilized. Each title is segmented into constituent words then from these words, non-trivial words are extracted by removing stop words. Roots of the words are retained using the stemming procedure available in Natural Language Tool Kit (NLTK)\(^3\). The words that appear at least twice in the publication titles of an expert are considered as skills possessed by the expert. Two experts \(v_i\) and \(v_j\) are treated as collaborating nodes if only if they have minimum three joint publications indexed in DBLP. The amount of collaboration between \(v_i\) and \(v_j\) is calculated by using Jaccard distance measure which is taken as edge weight \(e_{ij}\), given by
\[
1 - \frac{|P_{v_i} \cap P_{v_j}|}{|P_{v_i} \cup P_{v_j}|}
\]
where \(P_{v_i}\) represents the number of papers published by \(v_i\). Hence in the network lesser the Jaccard distance is, more their collaboration and vice-versa.

The data sets considered by the authors so far in the literature are small in size. Number of nodes in these networks is less than ten thousand. In this work we build a network containing more than 30,000 authors and nearly 98,000 edges. The details of the data sets that have been considered by the other papers as well as ours are given in Table 5.

6.1 Problem setting

The problem is to find a team of authors who are capable of performing the task of writing a given research paper. The non-trivial words from the title of the paper are considered as skills required and the problem is to find experts from the DBLP data set having the required skills and incurring minimum communication cost.

\(^3\)https://www.nltk.org
Table 5: DBLP data set taken by TFC-R is much larger than those considered by the other algorithms in the literature. TF survey∗ is not an algorithm

7 Network analysis of DBLP network

A preliminary network analysis of the DBLP network is conducted on (i) connected components, (ii) degree distribution and (iii) the neighbourhoods of high degree nodes from the perspective of choosing experts with the required skills for team formation. The insights gained from this analysis that helped us design TFC-R are explained in this section.

7.1 Connected components in DBLP

It is interesting to note that the connected components of the DBLP network satisfy power law as seen in the Figure 3. That is, there exist large number of connected components having less number of nodes and smaller number of components having a large number of nodes, Greatest Connected Component (GCC) being one of them. In this context, let us analyze the existing algorithms in the literature, most of whose initial step is to choose an expert with rarest skill. By empirical analysis we see that if the initial expert falls within one of the smaller components, the search for other experts takes longer time as well as the cost incurred may be higher as the other experts lie at longer distances from the initial expert. Hence it is useful to start the search in GCC of the network which the TFC-R, TFC-N algorithms carry out.

7.2 Degree distribution

DBLP network is a typical social network whose degree distribution follows power law as can be seen in Figure 4. Once again for the same reason, if the rarest expert is one of the low degree nodes, the search for the team becomes longer and hence it will be useful to start with a higher degree node. It is found that the ratio of high collaborating (having degree higher than twice the average degree of the community) nodes to low collaborating nodes in DBLP network is 1:9(3293:29184). Hence choosing a high collaborating node as a leader is a good starting point for the Team formation algorithm.
Figure 3: **Power law**: Connected components satisfying power law for DBLP network

Figure 4: **Power law**: Degree distribution satisfying power law for DBLP network

### 7.3 Neighbourhoods of high degree nodes

Let skill coverage of an expert node be the skills possessed by the expert. The plot given in Figure 5 shows an interesting structure of the social network from the point of view of skill coverage. For each node of degree $k$, though its skill coverage may be low, by including its 1-hop and 2-hop neighbours improves the skill coverage between 90 to 100%.

The proposed Team Formation Algorithm TFC-R starts by choosing an expert from high collaborating nodes, one who possesses at least one skill required for the task, as team leader, then adds the other team members from unit hop neighbourhood and by successively increasing the hop length up to 2 or 3 steps. It is evident from Figure 5, that the two hop neighborhood of high degree nodes having degree greater than average degree covers above 90% of community skills. Skill coverage by 3-hop neighborhood alone does not add too much. Therefore,
we can limit the neighbourhood up to 2-hops i.e. (immediate friend network and friend’s friend network) for team formation.

![Image](image_url)

Figure 5: Percentage of skills covered cumulatively by the node alone and by adding 1-hop, 2-hop and 3-hop neighbourhoods.

The results obtained by the proposed algorithms are discussed in detail in the next section.

8 Implementation and results

The algorithms have been implemented in Python on Intel(R) Core(TM) i5-4300M CPU @ 2.60GHz. In this paper, it is important to note that, we do not retrieve communities using community discovery algorithms, but consider the subsets of DBLP based on research areas like DB, DM, VLDB etc as communities. The largest connected components (LCC) of DBLP, DB and VLDB networks have been considered for experimentation.

We carry out 100 experiments for each $k$ by randomly choosing subsets of size $k$ as tasks $T$, for $k = 4, 5, \ldots, 20$ and the algorithms are implemented on these data sets to find teams for $T$. The average cost/cardinality of the teams obtained for the 100 tasks is tabulated for each $k$. We compare TFC-R and TFC-N algorithms with respect to the communication cost measures of diameter, sum distance and leader distance against MinSD, MinLD* and RF* algorithms. The asterisk indicates modified faster implementations. Since MinLD considers every node as a leader and hence takes too long a time, it has been modified to consider only those nodes having degree greater than twice the average degree as leaders. The modified implementation by Wang et al. [2015] is taken for Rarestfirst algorithm.

Further, in order to keep the comparison fair, all the algorithms have been implemented on VLDB network. We also compare the performance of TFC-R algorithm on the entire DBLP network in relation to that of its performance on the communities of DBLP network (DB and VLDB). The datasets and code are available in public domain.

https://github.com/abrameshba/teamformation
The results are organized as follows:

(A) Execution time of the algorithms

(B) Comparison of Team size obtained by the algorithms

(C) Comparison of the algorithms with respect to the communication costs
   I diameter distance
   II leader distance
   III sum distance

(D) Scaling of the results as the experiments are carried over each of the sets DBLP, DB and VLDB. Note that VLDB is a subset of DB which is a part of the whole network DBLP.

8.1 Execution time

![Figure 6: Comparison of average processing time taken by TFC-R, TFC-N, Rarestfirst(RF), MinLD and MinSD algorithms for VLDB network. *Note that RF* and MinLD* are modified and faster implementations.]

The faster version of Rarestfirst RF* gives the fastest results, followed closely by TFC-R and TFC-N. Clearly both the proposed algorithms are several order faster than both MinSD and MinLD* as seen in Figure 6.

8.2 Team size

As seen in Table 6, the average sizes obtained by TFC-N are better for tasks of size greater than 12 and MinLD for smaller tasks. Both TFC-R and TFC-N give far better team sizes when compared to RF* as well as MinSD.
Table 6: Average cardinality of teams given by TFC-R, TFC-N, RF*, MinSD and MinLD* algorithms on VLDB network

| $|T|$ | RF*  | MinLD* | MinSD  | TFC-R | TFC-N |
|-----|------|--------|--------|-------|-------|
| 4   | 3.87 | 3.27   | 3.87   | 3.82  | 3.81  |
| 5   | 4.84 | 4.19   | 4.77   | 4.76  | 4.75  |
| 6   | 5.82 | 5.19   | 5.74   | 5.67  | 5.65  |
| 7   | 6.73 | 6.08   | 6.62   | 6.57  | 6.56  |
| 8   | 7.73 | 6.92   | 7.5    | 7.34  | 7.3   |
| 9   | 8.69 | 8.01   | 8.52   | 8.3   | 8.28  |
| 10  | 9.55 | 8.8    | 9.27   | 8.99  | 9.02  |
| 11  | 10.4 | 9.68   | 10.24  | 9.69  | 9.69  |
| 12  | 11.37| 10.44  | 11.09  | 10.47 | 10.47 |
| 13  | 12.29| 11.39  | 11.98  | 11.4  | 11.33 |
| 14  | 13.12| 12.38  | 12.9   | 12.28 | 12.18 |
| 15  | 14.07| 13.11  | 13.65  | 13.07 | 12.97 |
| 16  | 14.85| 13.89  | 14.45  | 13.77 | 13.75 |
| 17  | 15.66| 14.75  | 15.36  | 14.64 | 14.49 |
| 18  | 16.47| 15.51  | 16.08  | 15.11 | 15.05 |
| 19  | 17.59| 16.43  | 17.16  | 16.1  | 15.99 |
| 20  | 18.53| 17.38  | 18.01  | 16.76 | 16.73 |

Table 7: Average diameter distance of teams generated by TFC-R, TFC-N, RF*, MinSD and MinLD* algorithms on VLDB network

| $|T|$ | RF*  | MinLD* | MinSD  | TFC-R | TFC-N |
|-----|------|--------|--------|-------|-------|
| 4   | 5.99 | 5.25   | 5.75   | 6.2   | 5.63  |
| 5   | 6.9  | 6.1    | 6.82   | 7.3   | 6.58  |
| 6   | 7.71 | 6.78   | 7.43   | 8.05  | 7.18  |
| 7   | 8.08 | 7.12   | 7.83   | 8.49  | 7.43  |
| 8   | 7.96 | 7.11   | 7.83   | 8.58  | 7.39  |
| 9   | 8.95 | 7.91   | 8.58   | 9.22  | 8.2   |
| 10  | 8.57 | 7.7    | 8.15   | 8.82  | 7.77  |
| 11  | 8.86 | 7.8    | 8.35   | 9.08  | 7.95  |
| 12  | 9.37 | 8.13   | 8.63   | 9.37  | 8.29  |
| 13  | 9.77 | 8.66   | 9.01   | 9.97  | 8.76  |
| 14  | 9.57 | 8.6    | 8.97   | 10.09 | 8.81  |
| 15  | 9.71 | 8.78   | 9.31   | 10    | 8.8   |
| 16  | 9.97 | 9.17   | 9.48   | 10.5  | 9.31  |
| 17  | 9.84 | 8.96   | 9.22   | 10.36 | 9.03  |
| 18  | 10.19| 8.99   | 9.22   | 10.45 | 9.07  |
| 19  | 10.14| 9.07   | 9.25   | 10.59 | 9.06  |
| 20  | 10.26| 9.41   | 9.86   | 10.98 | 9.59  |
8.3 Communication cost: diameter

Table 7 shows that the best performance is obtained by MinLD\(^*\) closely followed by TFC-N. Our proposed algorithm TFC-N gives teams with better average diameter when compared to all the other algorithms of RF\(^*\), MinSD as well as TFC-R. The diameter of the teams obtained by TFC-R algorithm seem slightly inferior in comparison as TFC-R may be adding a distant random expert.

8.4 Communication cost: leader distance

![Figure 7: Comparison of average leader distance of teams obtained by TFC-R, TFC-N, Rarestfirst\(^*\), MinSD, MinLD\(^*\) algorithms on VLDB network](image)

The results in Figure 7 show that MinLD, TFC-R and TFC-N are performing well with respect to leader distance measure. Rarestfirst and MinSD algorithms are not based on choosing a leader hence do not perform well and Rarestfirst algorithm does not seem to scale well as the size of the task increases.

8.5 Communication cost: sum distance

The plot in Figure 8 indicates that all the algorithms have similar performance with respect to the sum distance measure.

9 Performance of TFC-R on communities

In this section, the algorithms TFC-N and TFC-R are studied closely for their scalability and correctness with respect to the search being restricted to a community. The results are presented for TFC-R and these are the most attractive experiments that show-case the importance of the algorithm with respect to its scalability for large networks.

All the tasks are selected from VLDB community. For each task skills are randomly selected. Note that the VLDB network is contained in DB and DB in DBLP. Each experiment is repeated 100 times for all the tasks of sizes varying between 4 to 20 and the average results are tabulated. The experiments for tasks
of size greater than 16 have not been conducted on DBLP since 100 experiments have to conducted where each experiment takes more than 30 minutes for each task.

9.1 Processing time

Clearly this is the most important experiment as it shows that the algorithm is much faster when run on smaller communities by orders of magnitude in comparison to the larger network. The plot in Figure 9 shows that the algorithm runs between 50 to 100 times faster on average on VLDB when compared to DB and DB is clearly 10 times faster than when run on the whole network.

Figure 8: The performance of TFC-R, TFC-N, Rarestfirst*, MinSD, MinLD* algorithms w.r.t. average sum distance in VLDB network

Figure 9: Average processing time taken by TFC-R for DBLP, DB and VLDB networks
9.2 Cardinality

In this experiment, we would like to test the size of the team obtained by the TFC algorithm when tested on different communities: VLDB which is smaller than DB and on the whole network DBLP. The team found if the search is restricted to the smaller VLDB network naturally may be of larger size, in comparison to when the search is expanded to DB and then DBLP. As seen in Figure 10, the cardinality of teams found in smaller communities are slightly bigger than those found in the whole of DBLP, but the difference is negligible. Hence this algorithm would be very useful in the case of large networks since it can find teams from within communities of the network.

![Figure 10: Cardinality comparison of TFC-R on DBLP, DB, VLDB](image)

9.3 Random experts

![Figure 11: The (%) of teams in which random experts are required to be added for TFC on DBLP, DB and VLDB](image)
TFC-R is almost like the reverse of Rarestfirst algorithm. In Rarestfirst algorithm expert possessing rarest skill is first added to the team whereas TFC adds rarest skilled person last. A random expert possessing rarest skill is added if he/she explicitly is required to be added to the team. Figure 11 indicates that the number of teams having a random expert is high for the small network of VLDB. On the other hand, only 60-70% of the teams on average require random expert to be added for the larger networks of DB and DBLP.

9.4 Communication cost

The performance of the TFC algorithm is assessed by searching for teams within different communities: small one like VLDB, a bigger one like DB and the whole network of DBLP. The performance is evaluated by computing the communication costs of diameter, leader distance and sum distance. As can be seen in Figures 12, 13 and 14, the costs are slightly higher for teams retrieved from the small community of VLDB in comparison to those from the bigger communities of DB and the whole network DBLP. On the other hand, the teams found in DB have almost the same cost as those of the whole network.

![Figure 12: Comparison of TFC-R on DBLP, DB and VLDB with respect to diameter distance measure](image)

10 Case study

In this section, we show-case the ability of TFC-R (and TFC-N) algorithm for finding multiple teams for a task with less communication cost. We considered three papers that have achieved best paper awards in VLDB given in Huang [2020] that is chosen as part of the case-study by Wang et al. [2015]. These translate to three tasks $T_1$, $T_2$ and $T_3$ with 5, 8 and 10 skills respectively. The actual authors of these papers are listed in Table 8.

Table 9 shows the teams identified community-wise by TFC-R algorithm. The communities given here are nested, overlapping or disjoint as shown in Figure 1. The research paper belongs to a particular conference contained in a community, it will be interesting to find teams when the search is carried out...
in the other desirable communities as well as the entire social network. Clearly the experts who have high collaborations within the communities like Samuel Madden have been identified by TFC-R for task 2 in all the three networks of VLDB, DB and DBLP. Madden also happens to be one of the authors of the paper given for task 2. The communities which do not have the necessary skill coverage are kept blank. It can be seen that experts with high collaboration and having research in multiple domains have been identified for tasks 1 and 3. Experts marked with * are authors who are added in the random step who may not have come up in the 2-hop neighbourhoods in the first instance.

This case-study shows that for some tasks the high degree nodes make the teams into singleton sets (single-author papers). Since all the tasks are from database research area, we find that interesting teams can be found in non-database communities like AI, Theory(TH), STOC etc. In fact, it may be more interesting, if we exclude the high degree author, in order to obtain teams with
diversity.

| Task | Paper title                                                                 | Skills                                                                 | Authors                           |
|------|------------------------------------------------------------------------------|-----------------------------------------------------------------------|-----------------------------------|
| T1   | A Unified Approach to Ranking in Probabilistic Databases                     | approach, databases, probabilistic, ranking, unified                   | Jian Li, Barna Saha, Amol Deshpande|
| T2   | Semantic Web Data Management Using Vertical Partitioning                     | data, management, partitioning, scalable, semantic, using, vertical, web| Kate Hollenbach, Samuel R. Madden, Adam Marcus, Daniel J. Abadi |
| T3   | Dense Subgraph Maintenance under Streaming Edge Weight Updates for Real-time Story Identification | dense, edge, identification, maintenance, real, streaming, subgraph, time, updates, weight | Albert Angel, Nick Koudas, Nikos Sarkas, Divesh Srivastava |

Table 8: Case study: Three tasks T1, T2 and T3 are best papers in VLDB (2009, 2007 and 2012 respectively) in the order of increasing skills.

11 Conclusions and future work

Generally for all the algorithms of team formation in the literature, the starting point is skill rather than an expert. The skills are ordered according to a greedy heuristic and the expert of the skill is chosen based on his/her distance to the team already formed. In fact, in the case of Rarestfirst algorithm, the pre-processing step requires the distances between all the pairs of experts to be computed apriori. On large networks this step takes a few days even on systems with reasonable configuration, hence the implementation has been modified by Wang et al. [2015]. The core principle of our algorithm is to ensure that traversal of the entire network does not happen even in the worst case scenario. Our heuristic for choice of a leader uses nodes from the heavy tail ensured by the important property of power law underlying the degree distribution of a social network. Further we show that searching within a community is enough. We simply take members from 2 or 3 hops from the leader and the rest of the skill gap is filled by choosing a nearest neighbour or randomly. We tabulate in Figure 11 to show the number of times this random step was needed. It shows that even for tasks of size 14, 70% of the teams have not needed a random expert to be added in the case of DB and DBLP. TFC-N shows very good performance by managing the trade-off between time and cost efficiently.

We computed numerically the different ratios of the running time taken of our algorithms with respect to the others given in Figure 6. Our algorithms are 22.3 and 7.3 times faster when compared to MinSD and MinLD respectively on average in finding a team for a given task. In fact, TFC-R shows 95% and 86% improvement on average time taken when compared to MinSD and MinLD respectively.

Further, in community-wise performance analysis seen in Section 9, it is interesting to see how fast the algorithms run on the smallest community of VLDB. The communication costs on VLDB are only slightly higher even though it is almost 1/23rd of the whole network. Further the communication costs
| Network | T1 | T2 | T3 |
|---------|----|----|----|
| DBLP    | Haixun Wang | Samuel Madden | Nick Koudas, David Eppstein, Dimitrios Gunopulos |
| DB      | Raymond T. Ng, Jiawei Han | Samuel Madden | Divesh Srivastava, Abraham Silberschatz, Dimitrios Gunopulos, Yehoshua Sagiv, Lise Getoor |
| DM      | Yi Chang, Jiawei Han | Hui Xiong, Qiang Yang 0001 | Jiawei Han, Qiaozhu Mei, C. Lee Giles, George Karypis, Wei Ding 0003 |
| AI      | Thomas S. Huang, Shuicheng Yan, Marc Pollefeys, Xindong Wu | Gang Zeng, Xian-Sheng Hua, | Michael I. Jordan, Fei Sha, Alan S. Willsky, Vittorio Murino, Larry S. Davis* |
| TH      | Rajeev Motwani, Joseph Naor, Frank Mesherry, Madhu Sudan | Amos Fiat, Haim Kaplan, | S. Muthukrishnan, David Eppstein, Roberto Grossi, Andris Ambainis |
| VLDB    | Surajit Chaudhuri, Raymond T. Ng | | |
| SIGMOD  | Ruoming Jin, Jiawei Han | Jeffrey F. Naughton, S. Sudarshan 0001, Shalom Tsur | |
| ICDE    | Xuemin Lin, Zhifeng Bao | Philip S. Yu, Sanghyun Park | Beng Chin Ooi, Kian-Lee Tan, Yueguo Chen, Elke A. Rundensteiner, Wynne Hsu, Yinghui Wu, Stanley B. Zdonik* |
| WWW     | C. Lee Giles, Hang Li, Pavel Serdyukov | Xin Li, Wei-Ying Ma, Weiguo Fan, Xin Qi*, Dongmei Wang*, Alan Mislove* | |
| KDD     | Jiawei Han, Anthony K. H. Tung, Michael R. Lyu | Jian Pei, Haixun Wang, Jiawei Han, Ke Wang, Bin Gao | |
| ICDM    | Zheng Chen, Philip S. Yu, Jun Yan | | Philip S. Yu, Suh-Yin Lee, Jeffrey Xu Yu, Bing Liu 0001, Bin Wu, Wei Ding 0003, Qiaozhu Mei, |
| CVPR    | Thomas S. Huang, Jianchao Yang | Changshui Zhang, Shipeng Li, Nils Krahnstoever, Marc Pollefeys | |
| STOC    | Mihalis Yannakakis, Michael Sipser, Jeffrey D. Ullman, Baruch Schieber | | Venkatesan Guruswami, Sudipto Guha, Oded Regev, Yury Makarychev, Brent Waters, Baruch Awerbuch, Moses Charikar, | |

Table 9: Results of TFC-R algorithm for tasks T1, T2 and T3
obtained by the algorithms on DB community which is almost 1/5th of the size of DBLP network are as good as the results obtained on the whole network validating the scalability of our proposed approach. Of course it is still an question to be explored on how to choose an ‘apt’ community, so to say, for the team formation.

The case-study discussed in the paper shows the versatality of the proposed algorithms. They can produce multiple optimal teams for a task and it is part of our future work to evaluate their ability to produce teams with diversity. It will be interesting to repeat the experimentation to datasets other than DBLP like Bibsonomy, IMDB, Stackoverflow, github etc. which is part of future work. Also the many variations of team formation problem like capacitated TF, TF with personnel cost, TF with budget constraints etc can be addressed with our community-based approach to team formation.

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| Network | | | | | |
|---|---|---|---|---|---|
| DBLP | 32477 | 98676 | 13232 | 6.08 | 17.24 |
| DB | 6053 | 19607 | 4310 | 6.48 | 14.58 |
| DM | 8323 | 23667 | 4912 | 5.69 | 13.93 |
| AI | 14197 | 36514 | 7605 | 5.14 | 15.62 |
| TH | 5401 | 16399 | 5626 | 6.07 | 19.94 |
| VLDB | 1391 | 3605 | 1609 | 5.18 | 11.30 |
| SIGMOD | 2020 | 5865 | 1948 | 5.81 | 11.29 |
| ICDT | 190 | 402 | 461 | 4.23 | 11.80 |
| ICDE | 2977 | 8392 | 2406 | 5.64 | 11.48 |
| PODS | 549 | 1203 | 1029 | 4.38 | 12.03 |
| WWW | 1904 | 4827 | 1788 | 5.07 | 10.40 |
| SDM | 642 | 1605 | 898 | 5.00 | 11.37 |
| KDD | 2111 | 5906 | 2036 | 5.60 | 11.54 |
| ICDM | 1945 | 4894 | 1897 | 5.03 | 12.04 |
| PKDD | 220 | 414 | 499 | 3.76 | 10.66 |
| WSDM | 378 | 944 | 540 | 4.99 | 9.89 |
| NIPS | 3887 | 8647 | 3465 | 4.45 | 13.26 |
| IJCAI | 2448 | 4878 | 2814 | 3.99 | 11.28 |
| ICML | 2083 | 4229 | 2039 | 4.06 | 11.69 |
| UAI | 794 | 1459 | 1408 | 3.68 | 12.80 |
| COLT | 446 | 903 | 1015 | 4.05 | 14.00 |
| CVPR | 5291 | 14351 | 3534 | 5.42 | 15.38 |
| FOCS | 1425 | 3444 | 2297 | 4.83 | 15.20 |
| SODA | 1883 | 4665 | 2418 | 4.95 | 13.56 |
| STOC | 1349 | 3328 | 2267 | 4.93 | 16.26 |
| ICALP | 1418 | 2751 | 2109 | 3.88 | 11.34 |
| STACS | 435 | 781 | 946 | 3.59 | 10.81 |
| ESA | 865 | 1885 | 1240 | 4.36 | 10.35 |

Table 1: Network statistics

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## A Networks