Finding teams that balance expert load and task coverage

Sofia Maria Nikolakaki    Mingxiang Cai    Evimaria Terzi

Abstract

The rise of online labor markets (e.g., Freelancer, Guru and Upwork) has ignited a lot of research on team formation, where experts acquiring different skills form teams to complete tasks. The core idea in this line of work has been the strict requirement that the team of experts assigned to complete a given task should contain a superset of the skills required by the task. However, in many applications the required skills are often a wishlist of the entity that posts the task and not all of the skills are absolutely necessary. Thus, in our setting we relax the complete coverage requirement and we allow for tasks to be partially covered by the formed teams, assuming that the quality of task completion is proportional to the fraction of covered skills per task. At the same time, we assume that when multiple tasks need to be performed, the less the load of an expert the better the performance. We combine these two high-level objectives into one and define the \textsc{BalancedTA} problem. We also consider a generalization of this problem where each task consists of required and optional skills. In this setting, our objective is the same under the constraint that all required skills should be covered. From the technical point of view, we show that the \textsc{BalancedTA} problem (and its variant) is NP-hard and design efficient heuristics for solving it in practice. Using real datasets from three online market places, Freelancer, Guru and Upwork we demonstrate the efficiency of our methods and the practical utility of our framework.

1 Introduction

Creating effective teams by combining experts with diverse skills allows organizations to successfully complete tasks from different domains, while also helping individual experts position themselves in highly competitive job markets. The rise of online labor markets, like Freelancer, Guru and Upwork has motivated a significant amount of research on the problem of team formation [2, 4, 8, 9, 11, 16, 18]. Although many variants of this problem have been considered, they all rely on the same model of coverage of tasks by experts. According to this model, both tasks and experts are characterized by a set of skills. Each task consists of a set of skills required for the task completion and each expert acquires a set of skills. A team consisting of one or more experts completes a task if the union of the skills of the team’s experts covers all the required skills of the task. In all existing work complete coverage of tasks is required by the formed teams.

However, there are cases where tasks are described generically and require teams to have strong background in many areas, whereas clearly not all these areas can (or need to) be simultaneously covered. Oftentimes, the list of required skills is more like the wishful thinking of the entity that posts the task and not all of the skills need to be covered for its completion. For example, think of a post that describes potential cluster hires for an academic institution. Moreover, when looking at job posts in online labor markets, oftentimes the skills required by the posted tasks are repetitive. An example of a job post in \texttt{guru.com} is: basic, oracle, html, java, javascript, mysql, css, sql, http, ajax, mvc, architecture, jquery, software, software development, web development, developer, web developer. Another example from \texttt{freelancer.com} is: Advertising, Facebook Marketing, Internet Marketing, Marketing, Social Networking. In these examples the task descriptions could be repetitive; someone who is good at Marketing

*Department of Computer Science, Boston University. \{smnikol,marcocai,evimaria\}@bu.edu
is also good at Facebook and/or Internet marketing. Therefore, in such cases not all skills of a task need to be covered.

Motivated by these settings, we relax the requirement of completely covering a task and we allow for partial task coverage by the formed teams. However, we assume that the quality of task completion is proportional to the fraction of covered skills.

Another important factor for the quality of task completion is the load of the experts. For example, an expert assigned to several tasks may be too busy to devote a lot of effort in each one of them and consequently underperform [1]. Thus, our second objective is to avoid loading the experts with many tasks.

We combine these two objectives as follows: given a set of tasks, form one team per task such that the tasks are partially covered, while at the same time, the maximum number of teams an expert participates in is kept as small as possible. Thus, our goal is to both fulfill the tasks as much as possible and not overload the experts involved with the formed teams.

Formally, our goal is the following: given a set of \( k \) tasks \( J \) and a set of experts \( P \) form \( k \) teams \( Q = \{Q_1, \ldots, Q_k\} \), one for each task such that \( \lambda L(Q) + C(Q,J) \) is minimized. In this equation, \( L(Q) \) denotes the maximum number of teams an expert participates in and \( C(Q,J) \) denotes the sum of the fraction of uncovered skills per task. Both these components are quantities that we aim to minimize, while \( \lambda \) is a trade-off parameter that controls the importance of each objective.

We call the above problem the BalancedTA problem. Note that the problem definition is such that combines the two, seemingly unrelated objectives, into a single objective, and asks from the algorithm to find the right balance between the two, according to the trade-off parameter \( \lambda \), and without placing a hard constraint on one of the objectives.

For the BalancedTA problem we show that there are values of \( \lambda \) such that the BalancedTA problem is NP-hard and we design algorithms for solving it efficiently in practice. The effectiveness and the efficiency of our algorithms is shown in our experimental evaluation with datasets from three major online labor markets.

We also note that in many applications, there may be tasks that have both absolutely required and optional skills. For instance, a task might require workers with expertise in Facebook Marketing and Advertising and optionally broader knowledge in the areas of Internet Marketing, Marketing and Social Networking. Thus, we also consider a generalization of the BalancedTA, where there is a hard constraint on the coverage of the required skills for every task. Not only do we show that this variant of the problem is also NP-hard, but also that the same algorithms we designed for BalancedTA can be applied to this version of the problem as well, with minimal changes.

Our contributions are summarized as follows:

- We define the BalancedTA problem, which tries to find teams for a set of tasks such that both the coverage of task requirements (in terms of skills) is maximized and the load of every individual worker (in terms of the number of teams she participates in) is minimized. We combine these two requirements in a single objective and use a trade-off parameter \( \lambda \) to control the importance of each.
- We study the computational complexity of the BalancedTA problem and show that while there are cases for which it is trivial, there are also cases for which it is NP-hard.
- We design a set of heuristics for solving BalancedTA in practice.
- We study a variant of the BalancedTA problem where the set of skills required for each task is split into required and optional. We show that this version is NP-hard and also demonstrate that our algorithms for BalancedTA can be applied to it with few modifications.
- Finally, using three datasets from real online labor markets, we test the practical utility and the efficiency of our methods.

**Roadmap:** Section 2 reviews the related work. We present our problem in Section 3 and our algorithms in Section 4. In Section 5 we evaluate the performance of our methodology using real datasets. We
conclude the paper in Section 6.

2 Related Work

Recent studies raise the importance of team formation in different settings [13, 21]. To the best of our knowledge, we are the first to introduce the BALANCEDTA problem, where we simultaneously optimize for the coverage of the task requirements and the load of the experts. However, our work is related to existing work on team formation as described below.

Team formation in network of experts: Lappas et al. [11] were the first to introduce the notion of team formation in the setting of a social network. Given a network of experts with skills, their goal is to find a team that collectively covers all the requirements of a single task, while establishing small communication cost (in terms of the network) between the team members. A series of subsequent works extended this work towards different directions [2, 4, 10, 8, 9, 16, 12, 15, 14, 18, 22] All the aforementioned works share two common assumptions: (i) the experts are organized in a network that quantifies how well they can work together and (ii) all the required skills of the tasks need to be covered by the formed teams. Our model does not assume the existence of a network among the experts and the tasks need not be fully covered. Therefore, the computational problem that we are solving is different from the ones above.

Team formation with load balancing: Anagnostopoulos et al. [1], were the first to consider minimizing the load of experts in the online setting where a stream of tasks arrives and experts form teams in order to cover all the required skills for each task. The offline version of this problem resembles the load-balancing requirement of our problem. However, our work allows partial task coverage, while Anagnostopoulos et al. [1] form teams that entirely cover the requirements of a task. Moreover, our framework also provides the flexibility of defining a desirable trade-off between the two costs and creates effective teams based on the importance of each.

Multiple tasks coverage: A key characteristic of our work is that we consider the offline setting where there are multiple tasks, known a-priori, and there is a team formed for each one of them. The offline versions of Anagnostopoulos et al. [1, 2], the work of Golshan et al. [6], as well as the recent work of Barnabó et al. [3] consider multiple tasks and multiple teams. However, contrary to our setting, all the above works require that all skills required by the sequence of tasks are completely covered.

Team formation with partial coverage: Probably, the closest to our work is the work by Dorn and Dustdar [5], which introduces a multi-objective team composition problem with two objectives: skill coverage and communication cost. Their goal is to identify the best balance between the two costs. For this purpose, they use a set of heuristics that self-adjust a trade-off parameter to decide team configurations. In our setting, we do not consider the communication cost, but the workload of the experts. Moreover, our algorithms focus on allocating experts to teams, based on a user-defined trade-off between load and coverage. Dorn and Dustar focus on finding a “best” trade-off between connectivity and coverage, where the notion of “best” is defined in a rather adhoc manner. Finally, although they touch upon the issue of partial coverage, they focus on data extraction rather than algorithm design.

3 Preliminaries

This section provides the notation used throughout the paper and presents the formal definition and the complexity analysis of the problem that we study.

Throughout the discussion, we consider a set of $m$ skills $S$, a set of $n$ experts $P = \{P_i; i = 1, \ldots, n\}$ and a set of $k$ tasks $J = \{J_j; j = 1, \ldots, k\}$. In this setting, every expert and every task is a subset of the skills, i.e., $P_i \subseteq S$ and $J_j \subseteq S$, respectively. To complete a task we need to assign a team of experts to it. We let $Q_j \subseteq P$ denote the team assigned to the $j$th task. For $k$ tasks, we form $k$ teams.
$\mathcal{Q} = \{Q_1, \ldots, Q_k\}$. We call $\mathcal{Q}$ the team assignment for tasks $\mathcal{J}$. For each team $Q_j$ we compute its skill profile $\text{Cov}(Q_j)$ representing the union of the skills of its members. That is, $\text{Cov}(Q_j) = \cup_{i \in Q_j} P_i$.

**Load cost** ($L$): An important quantity is the load of a person, which is the number of tasks a person is assigned to. That is, for person $P$ we have that the load of $P$ is $L(P, \mathcal{Q}) = |\{j : P \in Q_j\}|$. We are interested in the maximum load among all experts, i.e.,

$$L(\mathcal{Q}) = \max_{P \in \mathcal{P}} L(P, \mathcal{Q})$$

**Incompleteness cost** ($C$): Given a task $J$ and a team $Q \subseteq \mathcal{P}$ assigned to it we define the incompleteness cost of $Q$ with respect to $J$ to be the fraction of the required skills, which are not covered by the team’s skill profile. That is,

$$F(Q, J) = \frac{|J \setminus \text{Cov}(Q)|}{|J|}$$

Intuitively, our goal is to minimize the incompleteness cost since we want the assigned team to cover as many of the skills required by the corresponding task as possible. Thus, we define the total incompleteness cost of a team assignment $\mathcal{Q}$ to be:

$$C(\mathcal{Q}, \mathcal{J}) = \sum_{j \in \mathcal{J}} F(Q_j, J_j)$$

**Team-assignment cost** ($B$): Given a trade-off parameter $\lambda$, the cost of a team assignment $\mathcal{Q}$ for a set of tasks $\mathcal{J}$ is denoted by $B(\mathcal{Q}, \mathcal{J}, \lambda)$ and it is a linear combination of the maximum workload and the incompleteness cost as defined above. That is,

$$B(\mathcal{Q}, \mathcal{J}, \lambda) = \lambda L(\mathcal{Q}) + C(\mathcal{Q}, \mathcal{J})$$

The trade-off parameter $\lambda$ provides an easy way to control the relative importance of each objective, where $\lambda = 0$ ignores the workload, and conversely $\lambda > k$, where $k$ is the number of tasks, ignores the incompleteness cost. In our experiments, we considered different values of $\lambda \in \mathbb{R}^+$ and we discuss our findings.

### 3.1 The BalancedTA problem

We can now define the main problem addressed in this paper:

**Problem 1 (BalancedTA).** Given a set of $k$ tasks $\mathcal{J} = \{J_1, \ldots, J_k\}$, a set of $n$ experts $\mathcal{P} = \{P_1, \ldots, P_n\}$ and a real non-negative value $\lambda \in \mathbb{R}^+$, find a team assignment $\mathcal{Q} = \{Q_1, \ldots, Q_k\}$ consisting of $k$ teams, such that team $Q_i$ is associated with task $J_i$ and $B(\mathcal{Q}, \mathcal{J}, \lambda)$ is minimized.

The solution of the case where $\lambda = 0$ is trivial: when $\lambda = 0$ then the optimal solution assigns all workers to all tasks, leaving this way the minimum number of non-covered skills.

On the other hand, when $\lambda > k$, where $k$ is the number of tasks, we prove that only the workload matters and thus the trivial solution of not assigning experts to tasks is the best strategy. This is summarized in the following lemma.

**Lemma 3.1.** For a set of $k$ tasks and $\lambda > k$, the optimal solution of the BalancedTA problem is the one that leaves all tasks completely uncovered; i.e., $\mathcal{Q} = \emptyset$.

**Proof.** Assume for the sake of contradiction an optimal solution $\mathcal{Q}^* \neq \emptyset$ with corresponding workload $L(\mathcal{Q}^*) \geq 1$. By the definition of incompleteness we know that $0 \leq C(\mathcal{Q}^*) \leq k$ and therefore $B(\mathcal{Q}^*, \mathcal{J}, \lambda) > k$, for $\lambda > k$. However, we see that there exists a solution $\mathcal{Q}'$ with corresponding workload $L(\mathcal{Q}') = 0$ whose team-assignment cost is exactly equal to $k$, i.e., $B(\mathcal{Q}', \mathcal{J}, \lambda) = k$. By the definition of load this solution can only be $\mathcal{Q}' = \emptyset$ which contradicts the initial assumption. $\square$
Therefore, we consider problem instances where $\lambda$ takes values in the range $(0, k]$, where $k$ is the number of tasks. For a subset of these values of $\lambda$ we can prove that the BalancedTA problem is NP-hard. More specifically, we have the following complexity result.

**Theorem 3.2.** For a set of $k$ tasks the BalancedTA problem is NP-hard for $0 < \lambda < \frac{1}{kN}$, with $N$ being the cardinality of the largest task.

**Proof.** For the rest of the proof, we will refer to the BalancedTA problem for the case $0 < \lambda < \frac{1}{kN}$. We reduce an instance of the NP-hard BALANCED TASK COVERING problem [1] to the BalancedTA problem. A reduction from BALANCED TASK COVERING to BalancedTA exists, if and only if a solution instance of BalancedTA for $0 < \lambda < \frac{1}{kN}$ is also a solution to BALANCED TASK COVERING.

An instance of BALANCED TASK COVERING consists of a pool of experts and tasks $\mathcal{P}, \mathcal{J}$, respectively, and asks for a set of teams $\mathcal{Z}$, one team for each task such that the maximum workload of a worker is minimized and all tasks in $\mathcal{J}$ are completely covered. We transform an instance of BALANCED TASK COVERING to an instance of BalancedTA, by setting $\mathcal{P}$ and $\mathcal{J}$ to be the experts and the tasks, respectively, of the BalancedTA problem. We now claim that for $0 < \lambda < \frac{1}{kN}$, $\mathcal{Q}$ is a solution to the BalancedTA problem if and only if it is also a solution to the BALANCED TASK COVERING problem.

To see this consider the following: If $\mathcal{Q}$ is the solution to the BALANCED TASK COVERING problem with load $L(\mathcal{Q})$, then $\mathcal{Q}$ is also a solution for BalancedTA with load $L(\mathcal{Q})$ and incompleteness $C(\mathcal{Q}) = 0$; this is because $\mathcal{Q}$ covers all skill requirements in the BALANCED TASK COVERING problem.

Conversely, let $\mathcal{Q}$ be a solution of BalancedTA for $0 < \lambda < \frac{1}{kN}$. We will show that $\mathcal{Q}$ is also a solution for the BALANCED TASK COVERING problem by claiming that for any $0 < \lambda < \frac{1}{kN}$ the solution of BalancedTA always yields $C(\mathcal{Q}) = 0$. In order to ensure that $C(\mathcal{Q}) = 0$ (all task skills are covered), any possible team assignment $\mathcal{Q}'$ should lead to $AL(\mathcal{Q}') < C(\mathcal{Q}')$. Intuitively, this means that adding more workload to the experts is always preferred, than leaving any of the task requirement skills unsatisfied. This is always true if the cost of the largest possible workload, which is assigning one or more experts to all tasks ($L_{max} = k$), multiplied by our trade-off parameter $\lambda$, is less than the smallest possible incompleteness cost, which is leaving one skill of the task with the largest cardinality uncovered. This is true for $\lambda < \frac{1}{kN}$.

\[ \square \]

### 3.2 Variant of the BalancedTA problem

A natural variant of BalancedTA is one where some skills of a task are required while others are not. In this variant, each task $J_i$ has a set of required skills $J_i^r$ and a set of optional skills $J_i^o$, such that $J_i = J_i^r \cup J_i^o$ and $J_i^r \cap J_i^o = \emptyset$. The required skills have to be covered while the optional skills behave as before. This problem variant is formally defined as follows:

**Problem 2** (R-BalancedTA). Given a set of $k$ tasks $\mathcal{J} = \{J_1, \ldots, J_k\}$, with $\mathcal{J}^r = \{J_1^r, \ldots, J_k^r\}$ and $\mathcal{J}^o = \{J_1^o, \ldots, J_k^o\}$, a set of $n$ experts $\mathcal{P} = \{P_1, \ldots, P_n\}$ and a real non-negative value $\lambda \in \mathbb{R}^+$, find $k$ teams $\mathcal{Q} = \{Q_1, \ldots, Q_k\}$, such that $B(\mathcal{Q}, \mathcal{J}^o, \lambda)$ is minimized and $C(\mathcal{Q}, \mathcal{J}^r) = 0$.

From the complexity viewpoint we have the following result.

**Theorem 3.3.** The R-BalancedTA problem is NP-hard.

This is because this problem is NP-hard even for the case where all skills of all tasks are required by a reduction from the BALANCED TASK COVERING problem [1].

### 4 Algorithms

In this section, we describe the algorithms we designed for solving the BalancedTA problem.
The ExpertGreedy algorithm: ExpertGreedy finds $\ell$ solutions (team assignments), each of which with a different maximum workload $\ell = 1, \ldots, k = |\mathcal{J}|$ and at the end reports the solution with the best score. In order to do so, for each $\ell$ it finds for each expert $P_i$ the $\ell$ tasks with the least uncovered skills when assigning $P_i$ to these tasks, and it assigns $P_i$ to teams that correspond to those tasks. The algorithm reports the solution of the $\ell$ value that resulted in the smallest $B(Q, J, \lambda)$ team-assignment cost.

The pseudocode of ExpertGreedy is shown in Algorithm 1. We draw attention to line 5 of this pseudocode. Routine TopTasks retrieves the indexes of the $\ell$ tasks with the smallest fraction of uncovered skills when expert $P_i$ is assigned to them. To find these tasks we use a binary min-heap to preserve the incompleteness cost of all tasks in sorted order. Furthermore, lines 6 and 7 perform update operations. In particular, routine UpdateTeams (line 6) assigns expert $P_i$ to the selected $\ell$ tasks, while routine UpdateTasks (line 7) removes skills from the selected tasks that are covered by expert $P_i$ chosen at any given round $i$.

A natural property of ExpertGreedy is that it essentially assigns the same amount of workload to every expert. Note, that when deciding which teams to select for an expert, for a specific $\ell$, the algorithm does not take into account the first part of the objective function, i.e. $\lambda L(Q)$, since it is equal to $\lambda \ell$ for all experts.

The runtime complexity of ExpertGreedy is $O(k^2 n \log k + k^2 nm)$. For each maximum load and for each expert, the algorithm sorts the tasks in ascending order based on the number of skills not covered.

The TaskGreedy algorithm: This algorithm also finds $\ell$ solutions (team assignments), each with a different maximum workload $\ell = 1, \ldots, k = |\mathcal{J}|$ and then selects the solution with the smallest cost. However, it differs from the previous algorithm: while ExpertGreedy greedily assigns tasks to experts, TaskGreedy finds a set of "good" candidate experts for a specific task. In particular, for each $\ell$, the algorithm computes for each task $J_j$ the cost of the objective value when expert $P_i$ is assigned to team $Q_j$, for all $i = 1, \ldots, n$. The algorithm keeps these costs in a binary min-heap data structure, for running time efficiency. After computing the costs of all experts, it removes the root of the heap and assigns the corresponding expert to team $Q_j$, only if her skillset overlaps with the uncovered skills of task $J_j$. If the expert is assigned to the team, then all covered skills of $J_j$ are removed. This process continues until, either all skills of $J_j$ are covered, or the remaining skills do not overlap with any of the unassigned experts.

After creating $Q_j$, the algorithm checks if there are any experts whose loads are equal to $\ell$, and removes those experts from the pool. At the end of each loop of $\ell$, there is a team associated with every task, and
the cost $B(Q, J, \lambda)$ is computed. The algorithm reports the solution with the lowest team-assignment cost.

The pseudocode of TaskGreedy is presented in Algorithm 2. Routine TopExperts (line 5) computes and returns the indexes of those experts whose skillsets cover the requirements of the given task and that have the smallest objective value. Routines UpdateTeams (line 6) and UpdateExperts (line 7) perform update operations, i.e., assign the selected experts to the team of the current task, and remove from the pool of experts those with load cost equal to $\ell$, respectively.

In contrast to ExpertGreedy, TaskGreedy does not assign the same amount of workload to every expert. In fact, some experts might not be assigned to any team at all; this is the case when there are other experts whose skillsets overlap more with the tasks.

Another difference between ExpertGreedy and TaskGreedy is their running time. In particular, the running time of TaskGreedy is $O(k^3 n^2 + k^3 nm + k^2 n \log n + k^2 m^2)$. For each $\ell$ value and for each task, the algorithm sorts the experts in ascending order, based on the cost obtained after considering each of them separately, and then traverses them in the same order to allocate a team, based on the experts’ overlap with the task. We improve the running time, by observing that the objective value computation when considering an expert for a specific task, does not require finding the total incompleteness cost of all tasks, but only how much the specific task is covered by the expert since the incompleteness cost in the other tasks remains constant for all experts that are being evaluated for that task. Then, the runtime complexity becomes $O(k^3 n^2 + k^2 nm + k^2 n \log n + k^2 m^2)$. Finally, keeping a variable that stores the overall maximum load during an $\ell$ loop decreases the runtime complexity to $O(k^2 nm + k^2 n \log n + k^2 m^2)$.

The BestLoad algorithm: The BestLoad algorithm is a natural extension of the Load algorithm proposed by Anagnostopoulos et al. [1] for the offline setting of the BALANCED TASK COVERING problem. Recall that in that problem the goal is given a set of tasks, find an assignment of teams to tasks so as to minimize the maximum load of the workers subject to the constraint that all skills of all tasks are covered.

The Load algorithm has two steps. The first step solves optimally the linear programming relaxation of the ILP formulation of the above problem (see Theorem 2 [1]). This creates a fractional solution $\hat{X}$. The second step of Load performs $R$ rounds, with $R = (\ln \frac{2T}{\delta})$, where $T = \max\{mk, n\}$, where $m$ is the number of skills, $k$ is the number of tasks and $n$ is the number of experts. The algorithm assigns an expert $P_{j_i}$ to the task $J_{j_i}$ with probability $\hat{X}_{j_i}$, independently of other rounds and of other assignments within the same round. If expert $P_{j_i}$ was assigned to task $J_{j_i}$ in at least one round, the algorithm adds the
expert to the team $Q_i$. The authors show that $R$ rounds are required to achieve complete coverage of the skills acquired by the tasks.

The BestLoad algorithm we propose has the same first step as Load. To take into account the weighing trade-off parameter $\lambda$ our BestLoad modifies the second step. In particular, notice that as the number of rounds increases, more experts are assigned to tasks, i.e., the load increases and the coverage decreases. Therefore, for larger values of $\lambda$ (load becomes more important than coverage) running fewer rounds leads to a better solution. Conversely, for smaller values of $\lambda$ (coverage becomes more important than load) the algorithm needs to run a number of rounds closer to $R$. Based on this observation, BestLoad accommodates for the different values of $\lambda$ by creating $R$ solutions; one after each assignment round. Then, given a specific value of $\lambda$, it returns the solution that has the corresponding smallest cost.

The runtime complexity of the first step of BestLoad depends on the method used to solve the LP relaxation of the algorithm. State-of-the-art LP solvers require running time polynomial in the number of constraints of the problem \[7, 19\]. For the coverage of all skills, $O(nkm)$ constraints are required. The second step of the algorithm requires $O(Tnk)$ time.

Observation 1. The performance of BestLoad is at least as good as the performance of Load for the BalancedTA problem.

Clearly, Observation 1 holds since one of the solutions considered by BestLoad is the one returned by Load.

Improving the running time of ExpertGreedy and TaskGreedy: For any value of the trade-off parameter $\lambda$, continually adding more workload to the experts will increase the value of $B(Q, J, \lambda)$ in two cases: (i) when all task requirements have been covered, and (ii) when the benefit from decreasing the incompleteness cost is significantly smaller than the cost of increasing the maximum load. In these two cases, we expect the first part of the objective function to grow, while the second part remains approximately constant. This observation allows us to improve the runtime complexity of ExpertGreedy and TaskGreedy by setting a maximum possible value for $\ell$, namely $\ell_{\text{max}}$, with $\ell_{\text{max}} < |J|$. The appropriate selection of $\ell_{\text{max}}$, is a trade-off between the running time, and the quality of the results.

Solving the R-BalancedTA problem: Here, we present how we can extend the above algorithms to solve the R-BalancedTA problem. This extension is based on a pre-processing stage that accounts for the required skills that need to be covered.

Solving the R-BalancedTA problem is essentially the same as adding a pre-processing step to the algorithms discussed in the previous paragraph. This pre-processing step makes sure that all required skills from all tasks are covered, with a relatively small maximum load among the experts. More specifically, in this step, we deploy the Load algorithm proposed in [1] with inputs the set of experts $P$ and the set of tasks $J^r$. Then, we remove from each task those skills that are covered by the corresponding team members – in this way we remove all required skills and some of the optional ones that are now covered. On this new input, we run the algorithms we designed to solve BalancedTA.

The running time of the pre-processing step is dominated by the method used to solve the linear programming relaxation of the algorithm Load. As described above the state-of-the-art LP solvers require time polynomial in the number of constraints \[7, 19\].

5 Experiments

This section explores the practicality of our algorithms using data from three major online labor markets. Specifically, (i) we evaluate and compare the performances of our three methods, ExpertGreedy, TaskGreedy and BestLoad, to multiple baselines for the BalancedTA and R-BalancedTA problems, (ii) we showcase the impact of the trade-off parameter $\lambda$ on the load and incompleteness cost of the solution, (iii) we provide a running time analysis of our algorithms.
### Dataset Statistics

| Dataset   | Freelancer | Guru  | Upwork |
|-----------|------------|-------|--------|
| # experts | 1212       | 6120  | 1500   |
| # tasks   | 993        | 3195  | 3000   |
| # avg. skills/expert | 1.46 | 13.07 | 6.2   |
| # avg. skills/task   | 2.86       | 5.24  | 39.9   |

Table 1: A summary of the dataset statistics.

For all our experiments we use a single process implementation of our algorithms on a 64-bit MacBook Pro with an Intel Core i7 CPU at 2.6GHz and 16 GB RAM. We use the Gurobi optimizer [17] for linear programming. We make the code, the datasets and the chosen parameters available online \(^1\).

### 5.1 Datasets

We use data from the online labor marketplaces, freelancer.com, guru.com, and upwork.com. We refer to these datasets as Freelancer, Guru, and Upwork, respectively.

Table 1 exhibits statistics on the different sizes and skill properties of these datasets.

In all datasets, skills acquired by experts that are never required by any task have been removed, since these are never used. Note that, Freelancer (1212 experts, 993 tasks) and Guru (6120 experts, 3195 tasks) have more experts available than posted tasks, while the reverse is true for Upwork (1500 experts, 3000 tasks). An interesting observation is that the ratio of expert skills to task skills is different in each of the three datasets.

**Task skills:** The Freelancer and Guru datasets include a random sample from a large pool of real tasks posted by users in these marketplaces. The Upwork dataset is a synthetic dataset obtained through a data-generation procedure similar to that used in the past [2]; a small number of experts (10\%) is removed from the pool of experts in the dataset, and then subsets of their skills are repeatedly sampled to create tasks, by interpreting the union of their skills as task requirements.

**Expert skills:** All expert datasets used in this work are acquired from anonymized profiles of members registered in the three marketplaces. A profile itself includes a self-defined set of skills.

### 5.2 Baseline algorithms

We compare the performance of our algorithms to the following baselines:

**SetCover:** A simple variation of the well-known greedy algorithm for SetCover [20]; for each task, the algorithm iteratively assigns to each team the expert whose skills overlap the most with the uncovered skills of the task and then removes these skills from the task. The algorithm stops, either when all skills have been covered, or when none of the experts overlap with the remaining uncovered skills. The running time of this algorithm is $O(knm^2)$.

**BestCostGreedy:** This is a variant of SetCover that takes into account the workload. The difference is that instead of selecting the expert overlapping the most with the task, BestCostGreedy assigns the expert that improves the objective function the most. The algorithm stops when the cost cannot be further decreased. The running time of this algorithm is $O(knm^2)$.

**PairGreedy:** PairGreedy is another intuitive greedy algorithm, which finds in each iteration the (task, expert) pair that improves the objective the most, and assigns the expert to the corresponding team. The drawback of this baseline is its runtime complexity, which is $O(k^3n(n+m))$, thus prohibiting us from evaluating it on real datasets. As such, we do not report its performance. Nevertheless, even when tested on smaller datasets, its performance is always outperformed by the proposed algorithms.

---

\(^1\)https://www.dropbox.com/sh/8zpsi1etvvv/vJk/AACU5GEJwUibO1P_UtOPk5Ha?dl=0
5.3 Performance evaluation for BalancedTA

This section demonstrates the performance of the proposed algorithms compared to the baselines, for the BalancedTA problem.

In these experiments, we vary the trade-off parameter $\lambda$ to take values in $\{0, 2, \ldots, 10\}$. We select this specific range of $\lambda$ values because it makes the impact of the trade-off parameter clear application-wise. However, we also show the performance of our algorithms for values of $\lambda$ for which we showed that BalancedTA is NP-hard. Furthermore, we set the parameter $\ell_{\text{max}}$ (the maximum number of $\ell$ iterations) to 80 for all experiments, because we saw that in real applications it generally leads to reasonable solutions and runtime performances.

We present the results for BalancedTA for all three datasets in Figure 1. The $y$-axis represents the team-assignment cost ($B$) of each algorithm, and the $x$-axis corresponds to the value of the trade-off parameter $\lambda$. Smaller values of cost correspond to a better solution.

We observe that the performances of our algorithms and the baselines follow a similar trend, which is consistent among the different datasets. Furthermore, the baseline algorithms are clearly outperformed by our proposed approaches, with SetCover performing the worst – the only exception is for $\lambda = 0$, i.e., the case that completely ignores the load of the experts. This is because SetCover always returns a team that covers all the task requirements and ignores the load of the experts. BestCostGreedy is also outperformed by our proposed algorithms. Note that for $\lambda = 0$, BestCostGreedy is able to find solutions where no requirement is left uncovered. However, as $\lambda$ increases, the algorithm continues covering all of the task requirements without decreasing the workload, which leads to the linear increase of the total cost. The only exception is for the dataset Upwork, Figure 1(c), where for $\lambda = 4$ the algorithm begins compromising incompleteness cost for less workload, but the total cost remains significantly larger compared to the other algorithms. The performance of BestCostGreedy is followed by BestLoad. One observation is that BestLoad performed significantly better than the original algorithm Load. We do not present these results because as explained in Observation 1 BestLoad always performs at least as good as Load. Recall that Load finds a single solution that optimizes the workload, while it covers all the task requirements and its final solution is completely independent of the trade-off parameter $\lambda$. Therefore, since the load of the solution is constant and the coverage is 0 the team-assignment cost increases linearly with the coefficient $\lambda$.

Now, we illustrate the performance of our algorithms for values of $\lambda$ for which we showed that the BalancedTA problem is NP-hard. The corresponding performances for the three datasets can be seen in Figure 1 as subplots. As expected, the closer $\lambda$ is to 0 the closer the algorithmic performances are, but as $\lambda$ increases the difference in the performance of our proposed algorithms and the baselines also increases. Overall, we observe that our algorithms, namely ExpertGreedy, TaskGreedy and BestLoad, outperform the baseline algorithms and we discuss their individual trade-off and efficiency differences below.

5.4 Performance evaluation for R-BalancedTA

We perform another set of experiments to demonstrate the performances of the algorithms for the R-BalancedTA problem. In these experiments, we vary the fraction of required skills in the tasks as follows; with probability $p_s$ we independently define each skill of every task to be a required skill otherwise it is considered optional. In Figure 2, we study how the algorithms and baselines perform for a range of $p_s$ values and a fixed $\lambda = 4$. We see that the observations for the algorithmic comparisons are similar to the ones made in the previous experiment for the BalancedTA problem. Note that for $p_s=0$ no skill is required and therefore the algorithms perform exactly as in the BalancedTA problem, while for $p_s=1$ all skills are required and the performance of all algorithms is the same and equal to the result of the pre-processing stage.
We study the behavior of our proposed algorithms for different load and incompleteness cost trade-off values. We begin by setting $\lambda = 0$, i.e., we ignore the workload and ensure complete coverage (incompleteness cost is 0), and increase $\lambda$ to observe how the trade-off between load and incompleteness cost changes. The results are shown in Figure 3. The $y$-axis shows the load cost, and the $x$-axis the incompleteness cost for the specific load.

As expected, for $\lambda$ close to 0, our algorithms yield solutions with low incompleteness cost and high workload, while increasing $\lambda$ changes this balance accordingly. Note that BestLoad lacks trade-off capabilities, compared to ExpertGreedy and TaskGreedy. This is because the first step of the algorithm, which creates the optimal fractional solution for the balanced task covering problem [1], is oblivious to the parameter $\lambda$. Thus, even though the second step of the algorithm weighs the trade-off parameter $\lambda$ the trade-off capabilities are restricted by the assignment probabilities created in the first step. Therefore, what we see in Figure 3 is that for our datasets and the examined range of $\lambda$ the values of load and incompleteness achieved by the algorithm are the same except from the solution for $\lambda = 0$. A quality of ExpertGreedy and TaskGreedy is that improving the cost in one of the two components is achieved by paying a moderate price for the other component. For instance, assume a customer using guru.com...
that considers task requirements to be important. By observing Figure 3(a) we can set $\lambda = 2$ to create teams that would satisfy both, the customer and the experts, as for a reasonable maximum load $\sim 20$ \textit{ExpertGreedy} and \textit{TaskGreedy} induce very small incompleteness cost $\sim 5$. Now, if another customer prefers hiring few people at the cost of incompleteness, we can set $\lambda = 4$ to achieve load $\sim 15$ for an incompleteness cost of $\sim 30$, thus weighing differently the two components, yet always reasonably.

Note, that the baseline algorithms are omitted from this plot. This is because \textit{BestCostGreedy} always maintains the incompleteness cost very low, which requires workload that is much larger than the ones induced by the proposed algorithms. On the other hand, \textit{SetCover} lacks trade-off capabilities, since its solution is always independent of $\lambda$ with 0 incompleteness cost and constant load.

Figure 3 allows us to further investigate the properties of our algorithms for \textsc{BalancedTA}. A first observation is that all algorithms demonstrate a smooth transition on the load and incompleteness cost as the trade-off parameter changes. Note in Figures 3(a) and 3(b) that assigning a maximum workload of 80 is enough to achieve complete task coverage. In fact, for the same datasets, even if the load decreases to $\sim 20$, the incompleteness cost increases by little. However, this is not the case for Figure 3(c) (\textit{Upwork}), where it is clear that the load should be more than 80 ($\ell_{\text{max}}$) to reach complete coverage (0 incompleteness cost). This occurs because, in the specific dataset, both the experts and the average number of skills acquired by them are significantly less than the tasks and the skills required by the tasks, respectively, which requires creating large teams and utilizing the same experts many times to achieve full coverage. Even the baseline \textit{Load} that guarantees complete coverage with minimum workload cost, needs minimum load 548 for the specific dataset to accomplish full coverage.

To showcase the differences of the algorithms as depicted in this experiment, we compare \textit{TaskGreedy} with \textit{ExpertGreedy} and \textit{BestLoad}, for the \textit{Upwork} dataset (Figure 3(c)). Recall that the \textit{TaskGreedy} algorithm assigns experts to tasks, based on how suitable they are for the task individually, and not within a team. Therefore, for datasets such as \textit{Upwork}, where there are fewer experts and expert skills compared to tasks and task requirements, the algorithm becomes less effective as it cannot evaluate a newly-added person is the best option for the whole team. However, in a dataset such as \textit{Guru} (Figure 3(b)) where the experts acquire on average more and a larger variety of skills than the tasks require, we observe that \textit{TaskGreedy} performs slightly better, or the same compared to the other two algorithms. This is because the skill “surplus”, leaves to the algorithm room for seemingly wrong local choices, as it will be able to compensate for them by using the skills of some other of the remaining experts.
5.6 Runtime analysis

Finally, we investigate the running time efficiency of our algorithms. Figure 4 shows the average running times for all algorithms and datasets when setting the parameter $\lambda = 4$. The running time complexities of the algorithms are independent of $\lambda$ so its selection does not affect the running time results. The times are averaged over 5 runs for the \textsc{BalancedTA} problem – the results for \textsc{R-BalancedTA} are similar and omitted.

We use the baselines \textsc{SetCover} and \textsc{BestCostGreedy} as indicators of how well our algorithms perform in terms of running time because they have the best runtime complexity. Even though their asymptotic complexity is the same, \textsc{BestCostGreedy} is slower than \textsc{SetCover}. This is because the two algorithms have different stopping criteria, the former depending on the improvement of the team-assignment cost, and the latter on the coverage of the skills. Note that simply comparing the asymptotic running times of the different algorithms (see Section 4) is not sufficient. In fact, there are multiple factors we need to consider, such as constants, dominating factors that depend on the properties of the datasets, efficient implementations, etc.

In Figure 4 datasets \textit{Freelancer} and \textit{Guru} show that \textsc{ExpertGreedy} is much faster than \textsc{TaskGreedy} and \textsc{BestLoad} for datasets $k < n$ (the y-axis is in logarithmic scale). Yet, for the dataset \textit{Upwork}, where $n < k$, we see that even though \textsc{ExpertGreedy} remains the fastest algorithm, the running time of \textsc{TaskGreedy} is also very close. One possible explanation is that having fewer experts than tasks, with fewer skills on average allows \textsc{TaskGreedy} to find teams faster in this dataset; yet \textsc{TaskGreedy} is consistently slower than \textsc{ExpertGreedy} for all datasets. Thus, we can conclude that overall \textsc{ExpertGreedy} is the most efficient of our algorithms.

6 Conclusion

In this paper, we introduced \textsc{BalancedTA}, a team-formation problem where given a collection of tasks and a pool of experts, the goal is to form teams such that each team is associated with a task and it covers it as well as possible, while at the same time, the maximum workload of the chosen experts is also minimized. We also considered a variant of this problem where each task has some set of required skills that are required to be covered by the formed teams. To the best of our knowledge, we are the first to combine the coverage of tasks and the workload of experts into a single objective. We showed that our problems are NP-hard and designed efficient heuristics for solving them. Our experiments with three real-world datasets from online labor markets demonstrate the efficiency and the efficacy of our algorithms, and their superiority compared to other heuristics.
References

[1] A. Anagnostopoulos, L. Becchetti, C. Castillo, A. Gionis, and S. Leonardi. Power in unity: forming teams in large-scale community systems. In CIKM, 2010.

[2] A. Anagnostopoulos, L. Becchetti, C. Castillo, A. Gionis, and S. Leonardi. Online team formation in social networks. In WWW, 2012.

[3] G. Barnabò, A. Fazzone, S. Leonardi, and C. Schwiegelshohn. Algorithms for fair team formation in online labour marketplaces. In WWW, 2019.

[4] A. Bhowmik, V. Borkar, D. Garg, and M. Pallan. Submodularity in team formation problem. In SDM, 2014.

[5] C. Dorn and S. Dustdar. Composing near-optimal expert teams: a trade-off between skills and connectivity. In CoopIS, 2010.

[6] B. Golshan, T. Lappas, and E. Terzi. Profit-maximizing cluster hires. In SIGKDD, 2014.

[7] J. Gondzio and T. Terlaky. A computational view of interior-point methods for linear programming. Citeseer, 1994.

[8] M. Kargar and A. An. Discovering top-k teams of experts with/without a leader in social networks. In CIKM, 2011.

[9] M. Kargar, A. An, and M. Zihayat. Efficient bi-objective team formation in social networks. In ECML PKDD, 2012.

[10] M. Kargar, M. Zihayat, and A. An. Finding affordable and collaborative teams from a network of experts. In SDM, 2013.

[11] T. Lappas, K. Liu, and E. Terzi. Finding a team of experts in social networks. In KDD, 2009.

[12] C.-T. Li, M.-K. Shan, and S.-D. Lin. On team formation with expertise query in collaborative social networks. KAIS, 2015.

[13] L. Li and H. Tong. Network science of teams: Characterization, prediction, and optimization. In WSDM, 2018.

[14] L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin, and N. Bucher. Enhancing team composition in professional networks: Problem definitions and fast solutions. TKDE, 2017.

[15] L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin, and N. Buchler. Replacing the irreplaceable: Fast algorithms for team member recommendation. In WWW, 2015.

[16] A. Majumder, S. Datta, and K. Naidu. Capacitated team formation problem on social networks. In KDD, 2012.

[17] G. Optimization. Inc., gurobi optimizer reference manual, 2015, 2014.

[18] S. S. Rangapuram, T. Bühler, and M. Hein. Towards realistic team formation in social networks based on densest subgraphs. In WWW, 2013.

[19] D. A. Spielman and S.-H. Teng. Smoothed analysis of algorithms: Why the simplex algorithm usually takes polynomial time. Journal of the ACM (JACM), 51(3):385–463, 2004.

[20] V. V. Vazirani. Approximation algorithms. Springer Science & Business Media, 2013.
[21] X. Wang, Z. Zhao, and W. Ng. A comparative study of team formation in social networks. In DASFAA, 2015.

[22] X. Yin, C. Qu, Q. Wang, F. Wu, B. Liu, F. Chen, X. Chen, and D. Fang. Social connection aware team formation for participatory tasks. *IEEE Access*, 2018.