ABSTRACT

Although freelancing work has grown substantially in recent years, in part facilitated by a number of online labor marketplaces, traditional forms of “in-sourcing” work continue being the dominant form of employment. This means that, at least for the time being, freelancing and salaried employment will continue to co-exist. In this paper, we provide algorithms for outsourcing and hiring workers in a general setting, where workers form a team and contribute different skills to perform a task. We call this model team formation with outsourcing. In our model, tasks arrive in an online fashion: neither the number nor the composition of the tasks are known a-priori. At any point in time, there is a team of hired workers who receive a fixed salary independently of the work they perform. This team is dynamic: new members can be hired and existing members can be fired, at some cost. Additionally, some parts of the arriving tasks can be outsourced and thus completed by non-team members at a premium. Our contribution is an efficient online cost-minimizing algorithm for hiring and firing team members and outsourcing tasks. We present theoretical bounds obtained using a primal–dual scheme proving that our algorithms have logarithmic competitive approximation ratio. We complement these results with experiments using semi-synthetic datasets based on actual task requirements and worker skills from three large online labor marketplaces.

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KDD 2018, August 19–23, 2018, London, United Kingdom.

ACM ISBN 978-1-4503-5552-0/18/08...
https://doi.org/10.1145/3219819.3220056

1 INTRODUCTION

Self-employment is an increasing trend; for instance, between 10% and 20% of workers in developed countries are self-employed [24]. This phenomenon can be partially attributed to business downsizing and employee dissatisfaction, as well as to the existence of online labor markets (e.g., Guru.com, Freelancer.com). This trend has enabled freelancers to work remotely on specialized tasks, and prompted researchers and practitioners to explore the benefits of outsourcing and crowdsourcing [14, 15, 17, 22, 25, 28].

Although crowdsourcing adoption was driven, at least in part, by the assumption that problems can be decomposed into parts that can be addressed separately by independent workers, crowdsourcing results can be improved by allowing some degree of collaboration among them [20, 26]. The idea of combining collaboration with crowdsourcing has led to research on team formation [2–4, 10–12, 16, 18, 19, 21, 27], in which a common thread is the need for complementary skills, and problem settings differ in aspects such as objectives (e.g., load balancing and/or compatibility), constraints (e.g., worker capacity), and algorithmic setup (online or offline).

Overview of problem setting and assumptions. We consider tasks that arrive in an online fashion and must be completed by assigning them to one or more workers, who jointly cover the skills required for each task. At any point in time, there is a team of hired workers who are paid a salary, independently of the work they perform. This team is dynamic: new members can be hired and existing members can be fired. Hiring and firing workers is expensive, which is why companies routinely keep on the payroll skilled workers even if they are temporarily idle; however, they also seek to maintain “benching” to a minimum [29]. Outsourcing provides additional flexibility as some parts of the incoming tasks can be completed by non-team members who are outsourced. In practice, outsourcing involves additional costs such as searching, contracting, communicating with, and managing an expert or specialist external to a company [6].

Deciding when to hire, fire, and outsource workers is a difficult online problem with parameters that depend on job market conditions and employment regulations. Intuitively: (1) if the cost of hiring or firing workers is too high, outsourcing becomes preferable to hiring; (2) if the cost of outsourcing work relative to salaries of hired workers is too high, hiring becomes preferable to outsourcing; and (3) if the workload consists of many repetitions of similar tasks, hiring becomes preferable to outsourcing.

In this paper, we formulate this as an online cost minimization problem, which we call Team Formation with Outsourcing (TFO).
We formally define this problem in Section 2 and solve it in Sections 3 and 4. Despite this being a model and hence not capturing every aspect of employment decisions in a company, we show how it brings formalism to the intuitions we have outlined, helps understand under which circumstances a combination of hiring and outsourcing can be cost effective, and motivates experimentation on semi-synthetic data allowing us to cover a broad range of cases, as we show in Section 5.

Algorithmic techniques. To the best of our knowledge, we are the first to consider this problem and study some of its variants. Our problem turns out to be an original generalization of online set cover and online ski rental, two of the most paradigmatic online problems. In fact TFO has elements that make it more complex; to solve it, an algorithm has to address its various characteristics: (1) it is also online, so decisions should be taken with limited information on the input, but at each step, an entirely new instance of the set-cover problem needs to be solved by using hired and outsourced workers; (2) hired and outsourced workers collaborate with each other, and this needs to be taken into account; and (3) workers can be hired, fired, hired again, and so on, so one has to keep track of their status at every point in time.

Several natural approaches inspired by online algorithms for the problems we mentioned previously, fail to provide solutions with theoretical guarantees. Therefore, we consider an approach introduced in the last years for studying complex online problems, the online primal–dual scheme [8]. The idea is to create a sequence of integer programs to model the online problem by incrementally introducing variables and constraints. We then consider their linear relaxations and their duals to design an online algorithm and we analyze it by comparing the costs of the primal and the dual programs as they evolve over time with the arrival of new tasks. This is a powerful approach, which has so far been applied with success to several classical online problems: packing and covering problems, ski-rental, weighted caching, k-server among others [5]. We refer to [5, 8] for a survey of the applications of the online primal-dual method.

Our analysis results in polynomial-time algorithms that have logarithmic competitive approximation ratios. This means that despite the fact that our algorithms work in an online fashion and they do not have any knowledge of the number and the composition of future tasks, we can guarantee that the cost they will incur will be, at every time instance, only a logarithmic factor worse than the cost incurred by an optimal algorithm that knows the set of requests a priori.

Contributions. The key contributions of our work are:

- We formalize TFO: the problem of designing an online cost-minimizing algorithm for hiring, firing and outsourcing.
- We design efficient and effective approximation algorithms for TFO using an online primal–dual scheme, and provide approximation guarantees on their performance.
- We experiment on semi-synthetic data based on actual task requirements and worker skills from three large online labor marketplaces, testing algorithms under a broad range of conditions.
- We provide experimental evidence of the quality of the performance of online primal–dual algorithms for a complex real-world problem. Prior work has performed theoretical analysis mostly for classical or practically motivated online problems [7, 9]. To the best of our knowledge, the empirical validation was previously addressed only for the Adwords matching problem [13]. We demonstrate that such approaches, even though they are based on heavy theoretical machinery, can be easily implemented and are efficient in practice.

2 PRELIMINARIES

In this section, we formally describe our setting and problem, and provide some necessary background.

2.1 Notation and Setting

Skills. We consider a set $S$ of skills with $|S| = m$. Skills can be any kind of qualification a worker can have or a task may require, such as video editing, technical writing, or project management.

Tasks. We consider a set of $T^*$ tasks (or jobs), $J = \{J_t ; t = 1, 2, \ldots, T^*\}$, which arrive one-by-one in a streaming fashion; $J^t$ is the $t$th task that arrives. Each task $J \in J$ requires a set of skills from $S$, therefore, $J \subseteq S$. We use $J^t$ to refer to both the task and the skills that it requires.

Workers. Throughout we assume that we have a set $W$ of $n$ workers: $W = \{W_r; r = 1, \ldots, n\}$. Every worker $r$ possesses a set of skills ($W_r \subseteq S$), and $P_r$ denotes the subset of workers possessing a given skill $\ell$: $P_r = \{r; \ell \in W_r\}$. Similarly to the tasks, we use $W^t$ to denote both the worker and his/her skills.

We partition the set of available workers $W$ into the set of workers who are hired at time $t$, denoted by $H^t$, and the set of workers who are not hired, denoted by $F^t$ (we sometimes refer to these workers as freelancers, and they can be outsourced for $J^t$), so that $H^t \cup F^t = W$.

Coverage of tasks. Whenever task $J^t \subseteq S$ arrives, an algorithm has to assign one or more workers to it, i.e., a team. We say that $J^t$ can be completed or covered by a team $Q \subseteq W$ if for every skill required by $J^t$, there exists at least one worker in $Q$ who possesses this skill: $J^t \subseteq \bigcup_{W \in Q} W$. We assume that for every skill in the incoming task there is at least one worker possessing that skill, so all tasks can be covered.

Costs. Every worker $W^t$ potentially can charge the following non-negative, worker-specific fees: (1) an outsourcing fee $\lambda_r$, (2) a hiring fee $C_r$, and (3) a salary $\sigma_r$. Outsourcing fees $\lambda_r$ denote the payment required by a (non-hired) worker when a task is outsourced to him/her. Note that $\lambda_r$ depends on the worker but does not depend on the task. Hiring fees $C_r$ reflect all expenses associated to hiring and firing a worker, such as signup bonuses and severance payments. Given that any algorithm commits to pay the firing costs the moment in which it hires a worker, we follow a standard methodology used in online algorithms for caching [8] and account for both hiring and firing costs when the worker is hired. Once a worker $r$ is hired, s/he is paid a recurring salary $\sigma_r$, which recurs for every step $t$ that the worker is hired. The above notation is summarized on Table 1.

Assumptions. To avoid making the model overly complicated, we assume that the salary periods are defined by the arriving tasks, this is, there is one task per salary period, and task completion takes one salary period. A further assumption will be that $\sigma_r <
λ_r, as in practice requesting a single task from an external worker involves extra costs [6], which are reduced when the worker is hired (or when an outsourcing arrangement for an external group of workers to perform a specific recurring task is done, which is different from the individual outsourcing we discuss here). Finally, we assume λ_r < C_r + σ_r, because otherwise workers were hired and fired for every task.

### 2.2 Problem Definition

We now define the problem that we study:

**Problem 1 (Team Formation with Outsourcing - TFO).** There exists a set of skills S. We have a pool of workers W, where each worker W_r ∈ W is characterized by a subset of skills W_r ⊆ S, an outsourcing cost λ_r ∈ R ≥ 0, a hiring cost C_r ∈ R ≥ 0, and a salary cost σ_r ∈ R ≥ 0. Given a set of tasks J = {J_1, J_2, ..., J_T}, with J_t ⊆ S, which arrive in a streaming fashion, the goal is to design an algorithm that, when task J_t arrives, decides which workers to hire (paying cost C_r + σ_r), keep hired (paying cost σ_r), and outsource (paying cost λ_r), such that all the tasks are covered by the workers who are hired or outsourced and the total cost paid over all the tasks is minimized.

TFO is an online problem: J_t is revealed one task at a time. Our goal is to guarantee that for any input stream J_t the total cost of our online algorithm, ALG(J_t), is at most a small factor greater than the total cost of the optimal (offline) algorithm that knows J in advance, OPT(J). This factor, max_J ALG(J_t)/OPT(J), is called the competitive ratio of the algorithm.

We solve the TFO problem in Section 4. Because neither the algorithm nor its analysis are trivial, we introduce them gradually by first solving a simplified version of TFO, which we describe and solve in Section 3.

### 2.3 Background Problems

Two special cases of TFO are SetCover and SkiRental.

**SetCover: the single-task, multiple-skill case.** The set cover problem is an instance of our problem when there is a single task J ⊆ S and for each worker W_r, C_r = ∞. Then, as soon as the task J arrives, the algorithm needs to cover all skills in J by selecting a set of workers Q ⊆ W such that Q covers J and ∑_r∈Q λ_r is minimized. In this case, our problem can be solved using the greedy algorithm for the set-cover problem (see [30, Chapter 2]).

**SkiRental: the single-skill, single-worker case.** The ski rental problem is an instance of our problem when the sequence of tasks J_t consists of a repetition of the same single-skill task J and the workforce W consists of a single worker W_r who possesses the same one skill, and has σ_r = 0 and some C_r, λ_r. In this ski rental version of our problem [23], the question is the following: without knowledge of the total number of tasks that will arrive, when should worker W be hired so that the total cost paid to him/her in outsourcing plus hiring fees is minimized?

A well-known algorithm for this problem is the following: for every instance of J_t that arrives, outsource J_t to worker W_r as long as: ∑_r J_t ≥ C_r. Then, hire the worker when ∑_t J_t ≥ C_r. The above algorithm achieves a competitive ratio of 2.

### 3 THE LUMPSUM PROBLEM

First, we solve a simplified version of the TFO problem, where for every worker W_r the salary is equal to 0 (σ_r = 0). In this version of the problem, which we call LumpsSum, a hired worker W_r is paid a lump sum of C_r the moment s/he is hired and this amount is assumed to cover all future work done by the worker. Instead, when a worker W_r is outsourced, a payment of λ_r is done every time s/he performs a task.

#### 3.1 The LumpSum-Heuristic Algorithm

A natural algorithm for solving the LumpSum problem combines ideas from SetCover and SkiRental as follows: first, it starts with no worker being hired and each worker W_r is associated with a variable δ_r initially set to 0.

For any t ∈ {1, ..., T}, when task J_t arrives, the algorithm proceeds as follows: first, it identifies J_t as the set of skills of J_t that cannot be covered by already-hired workers. Then, it covers the skills in J_t using the greedy algorithm for SetCover. This way it finds Q^t ⊆ W such that ∑_r Q^t λ_r is minimized. Finally, for each worker W_r ∈ Q^t, it updates δ_r ← δ_r + λ_r. Worker W_r is hired when δ_r ≥ C_r. Clearly, since there are no salaries there is no motivation to fire a worker once s/he is hired.

**LumpSum-Heuristic has arbitrarily bad competitive ratio.** Although our experiments (Section 5) demonstrate that the above algorithm, which we call LumpSum-Heuristic, performs quite well in many practical cases, we can show that its competitive ratio can be arbitrarily bad. For this, consider an example where W = {W_1, W_2} and both workers have the same skill: W_1 = W_2 = {ℓ}. Further assume that λ_1 = 1, λ_2 = 1 + ε and C_1 = M, C_2 = 2, where M is a large value and ε a small one. For a sequence of tasks J_t = J_2 = ... = J_T = {ℓ}, it is clear that LumpSum-Heuristic will always outsource to W_1 until hiring him/her and will incur worst-case cost 2M, whereas the optimal algorithm pays just C_2 = 2.

#### 3.2 A Primal–Dual Algorithm

The above discussion illustrates that to obtain an algorithm with bounded competitive ratio, we need to take into account both the outsourcing and hiring costs of all workers. To do so, we deploy an online primal–dual scheme, which drives our algorithm design.

**The integer and linear programs.** The first step of the primal–dual approach, is to define an integer formulation for the problem,
for each step $T \in \{1, \ldots, T^*\}$. We assume that the current task is the $T$th task and we use the following variables:

- $x_r = 1$ if worker $W^r$ is hired when task $J^T$ arrives; otherwise $x_r = 0$.
- $f_{rt} = 1$ if worker $W^r$ is outsourced for performing task $J^t$; otherwise $f_{rt} = 0$.

Using this notation, LUMP SUM can be formulated as follows:

\[
\text{Linear program for LUMP SUM:}
\]

\[
\begin{align*}
\min & \quad \sum_{t=1}^{T} \left( C_r x_r + \lambda_r \sum_{t=1}^{T} f_{rt} \right) \\
\text{subject to:} & \\
\forall t = 1, \ldots, T, \ell \in J^t : & \sum_{W^r \in P_{r}} (x_r + f_{rt}) \geq 1 \quad (1) \\
\forall t = 1, \ldots, T, r = 1, \ldots, n : & x_r, f_{rt} \geq 0
\end{align*}
\]

The above, in addition to the integrality constraints $x_r, f_{rt} \in \mathbb{N}$, form the integer program for LUMP SUM. In this formulation, the objective function sums over all workers the hiring costs (paid if the corresponding worker has been hired by time $t$) and the outsourcing cost for the tasks for which the worker has been outsourced. This is the total cost of the solution until the current task $J^T$. Note that in this formulation of the problem there is no motivation for a worker who is hired to be fired. Therefore, once $x_r$ is set to 1, it does not change its value to become 0 again.

The first constraint (1) in the above program is the covering constraint: it simply enforces that for every skill required for each task, there exists a hired or outsourced worker who has this skill. This guarantees that the team selected for each task $J^t$ covers all the required skills. The nonnegativity and the integrality constraints, ensure that the solutions that we obtain from the integer-program formulation can be transformed to a solution to our problem: eventually, every variable will take the value 0 or 1.

To apply the online primal–dual approach, we first consider the linear relaxation of the integer program, which simply drops the integrality constraints $x_r, f_{rt} \in \mathbb{N}$. In a solution to this linear program (LP) each variable takes values in $[0, 1]$. Given this LP, we can write its dual as follows:

\[
\text{The dual of the linear program for LUMP SUM:}
\]

\[
\begin{align*}
\max & \quad \sum_{t=1}^{T} \sum_{\ell \in J^t} u_{\ell t} \\
\text{subject to:} & \\
\forall r = 1, \ldots, n : & \sum_{t=1}^{T} \sum_{\ell \in J^t \cap W^r} u_{\ell t} \leq C_r \quad (2) \\
\forall t = 1, \ldots, T, r = 1, \ldots, n : & \sum_{\ell \in J^t \cap W^r} u_{\ell t} \leq \lambda_r \quad (3) \\
\forall t = 1, \ldots, T, \ell \in J^t : & u_{\ell t} \geq 0
\end{align*}
\]

Note that at every time $t \in \{1, \ldots, T\}$ we have such a pair of primal–dual formulations. We are now going to use these two formulations for designing and analyzing our algorithm.

The LUMP SUM algorithm: Next, we present the LUMP SUM algorithm, which is designed and analyzed using the primal and the dual linear programs. We assume that task $J^T, T \in \{1, \ldots, T^*\}$, has just arrived and the algorithm must act before task $J^{T+1}$ arrives (or the stream finishes if $T = T^*$).

All the variables used in our algorithm are initialized to 0 before the arrival of the first task. When task $J^T$ arrives the following steps are done:

1. Let $\tilde{F}^T$ and $\tilde{H}^T$ represent the workers who are not hired and hired, respectively, at the time that $J^T$ arrives. Clearly, when the first task arrives ($T = 1$), $\tilde{F}^T = \emptyset$ and $\tilde{H}^T = \emptyset$. For $T > 1$, the values of $\tilde{F}^T$ and $\tilde{H}^T$ are updated in the last step (step 10) of the previous round.

2. Let $J^T_{\tilde{H}} = J^T \cap \bigcup_{W^r \in \tilde{H}^T} W^r$ be the skills from $J^T$ that are covered by already-hired workers and $J^T_{\tilde{F}} = J^T \setminus J^T_{\tilde{H}}$.

3. For every skill $\ell \in J^T_{\tilde{F}}$ let $P^F_{\ell} = P_{\ell} \cap \tilde{F}^T$ be the set of workers in $\tilde{F}^T$ such that every worker in $P^F_{\ell}$ has skill $\ell$. Also let $P^T_{\ell} = \bigcup_{W^r \in \tilde{H}^T} P^T_{\ell r}$ be the set of unhired workers who possess at least one skill that is required and not covered by already-hired workers.

4. For each $W^r \in P^F_{\ell}$ set $\tilde{x}_r \leftarrow x_r$.

5. For each skill $\ell \in J^T_{\tilde{F}}$:

\[
\text{while } \sum_{W^r \in P^F_{\ell}} (x_r + f_{rt}) < 1:
\]

\[
\quad \text{for each } W^r \in P^F_{\ell}: \tilde{x}_r \leftarrow x_r + \frac{1}{\lambda_r} + \frac{1}{\lambda_r} f_{rt}
\]

\[
\quad \text{for each } W^r \in P^F_{\ell}: \tilde{x}_r \leftarrow x_r + \frac{1}{\lambda_r} f_{rt}
\]

6. For each $W^r \in P^T_{\ell}$ set $\Delta x_r \leftarrow x_r - \tilde{x}_r$.

7. Set $\tilde{H}^T \leftarrow \emptyset$.

8. Repeat $p_1$ times:

\[
\text{for each } W^r \in P^F_{\ell}:
\]

\[
\quad \text{with probability } \Delta_x:
\]

\[
\quad \text{hire worker } W^r \text{ (set } x_r \leftarrow 1, \tilde{H}^T \leftarrow \tilde{H}^T \cup \{r\})
\]

\[
\quad \text{with probability } f_{rt}:
\]

\[
\text{outsourcer worker } W^r \text{ (set } f_{rt} \leftarrow 1)
\]

9. For each skill $\ell \in J^T_{\tilde{F}}$:

\[
\text{if skill } \ell \text{ is not covered:}
\]

\[
\quad \text{hire worker } W^r \in P^F_{\ell} \text{ with minimum cost } C_r
\]

\[
\text{ (set } x_r \leftarrow 1, \tilde{H}^T \leftarrow \tilde{H}^T \cup \{r\})
\]

10. $\tilde{H}^{T+1} \leftarrow \tilde{H}^T \cup \tilde{H}^T, \quad \tilde{F}^{T+1} \leftarrow \tilde{F}^T \setminus \tilde{H}^T$.

For $T = 1$, the LUMP SUM starts with no worker being hired. Intuitively, as tasks arrive, the algorithm tries to gauge two quantities: (1) the usefulness of every worker for the task at hand $J^T$ and (2) the overall usefulness of every worker for tasks $J^1, J^2, \ldots, J^T$. This is done in step 5, via variables $\tilde{f}_{rt}$ (for (1)) and $\tilde{x}_r$ (for (2)). In particular, the more useful $W^r$ proves over time, the larger the value $\tilde{x}_r$. Subsequently, in step 8 every worker is outsourced or hired based on the increase in the values of $\tilde{f}_{rt}$ and $\tilde{x}_r$ observed in step 5. Finally, for every skill that remains uncovered after step 8 (which is randomized), LUMP SUM hires worker $W^r$ with the minimum $C_r$ that covers the skill. Note that the increase of the variables $u_{\ell t}$ in

\footnote{A solution in which some variables take values greater than 1, can be transformed to another feasible solution with lower cost by setting these variables to 1.}
step 5 is not required for solving the LUMP SUM, but it is used in our analysis and thus we leave it in the description above.

Our analysis requires to set the value of \( p_1 \) in step 8 to \( p_1 = \ln m + \ln C^* \), where \( C^* = \max_{W \in W} C_r \).

Although one may think that an additive update of variables in step 5 would seem more natural, such an update would introduce a \( \Theta(m) \) factor in the competitive ratio. On the other hand, the multiplicative update that we adopt, has the property that the more a worker \( W^* \) is required over time the higher the increase of the corresponding variable \( \hat{x}_r \). This fact, leads us to Theorem 3.1 below.

**Theorem 3.1.** LUMP SUM is an \( O(\log n (\log m + \log C^*) \) - competitive algorithm for the LUMP SUM problem, where \( C^* = \max_{W \in W} C_r \).

**Running time.** The running time of LUMP SUM per task is determined by the execution of steps 5 and 8. For step 5, using binary search, the algorithm can determine in \( O(\log C^*) \) the minimum increase of \( \hat{x}_r \) and \( f_{rt} \) that makes false the condition of the while loop for at least one uncovered skill \( \ell \). Therefore, the running time of step 5 is \( O\left(\left| J^T \right| n \log C^* \right) \). Step 8, using a hash table to store hired workers, can be executed in expected time \( O(n t^2) = O(n (\log m + \log C^*)) \). Therefore, the expected time required for processing task \( J^T \) is \( O\left(\left| J^T \right| (\log C^* \left| J^T \right| + \log m) \right) \).

4 THE TFO PROBLEM

In this section, we provide an algorithm for the general version of TFO (Problem 1). In contrast with LUMP SUM, now after hiring a worker we must pay a salary \( \sigma \geq 0 \), complicating the problem significantly as it may now be cost-effective to fire workers.

**The integer and linear programs for TFO.** Given that workers can be hired, then fired and potentially hired again, and so on, we introduce in this new LP the notion of intervals. Those intervals are used to model periods in which workers are hired \( I = \{ (a, b) \mid a, b \in \mathbb{N}, a \leq b \} \). Intuitively, an interval is a subset of time steps during which an algorithm decides to hire a given worker. The new LP, (omitted) uses the following variables:

- \( x(r, I) \) with \( I \in I \) : \( x(r, I) = 1 \) if worker \( W^* \) is hired during the entire interval \( I \); otherwise \( x(r, I) = 0 \).
- \( f_{rt} \): \( f_{rt} = 1 \) iff worker \( W^* \) is outsourced for performing \( J^t \).

It turns out that it is hard to design an approximation algorithm with proven guarantees using this program, mostly because it is hard to keep track of the costs being paid for every worker when the intervals of him/her being hired, outsourced, or idle are of variable length. Therefore, we resort to a different overall strategy. First, we define the ALT-TFO problem, in which the solutions are restricted such that every worker is hired for fixed-length (worker-specific) intervals (Section 4.1). Then, we design an algorithm for ALT-TFO with good competitive ratio (Section 4.2). Finally, we prove that a solution to ALT-TFO can be transformed to a solution for TFO, and that any solution of TFO can be transformed to a feasible solution of ALT-TFO that is a factor of at most 3 times higher (Section 4.3), obtaining an approximation algorithm for TFO.

**4.1 The ALT-TFO Problem**

The difference between ALT-TFO and TFO is that we restrict the solutions of the former to have a specific structure; whenever worker \( W^* \) is hired s/he is then fired after \( \eta_r \hat{x}_r \geq [C_r / \sigma_r] \) time units—independently of whether s/he is used or not in tasks within those \( \eta_r \) time units.

In this case, every worker \( W^* \) is associated with a new hiring cost \( \tilde{C}_r \), which is the summation of his/her original hiring cost \( C_r \) plus the salaries paid to him/her for the \( \eta_r \) time units he is hired. Thus, the total hiring cost and salary for an entire interval is \( C_r + \eta_r \cdot \sigma_r \leq C_r + \left( \frac{\eta_r}{\sigma_r} + 1 \right) \cdot \sigma_r \leq 3C_r \). We will use \( \tilde{C}_r = 3 \cdot C_r \).

We can now write the LP for ALT-TFO. In addition to the notation we discussed in the previous paragraph, we use \( I^t \in I \) to denote the interval that starts at time \( t \). Worker \( W^* \) has \( x(r, I^t) = 1 \) iff s/he is hired during the entire interval \( I^t \). All intervals \( I \) for which \( x(r, I) = 1 \) are of fixed length \( \eta_r \).

**Linear program for ALT-TFO:**

\[
\min \sum_{r=1}^{n} \left[ \sum_{I \in I} \tilde{C}_r x(r, I) + \sum_{t=1}^{T} \lambda_r f_{rt} \right] \quad \text{subject to:}
\]

\[
\forall t = 1 \ldots T, \forall \ell \in J^t: \sum_{W^* \in P_r} \left( f_{rt} + \sum_{I \in I} x(r, I) \right) \geq 1 \quad (4)
\]

\[
\forall t = 1 \ldots T, r = 1 \ldots n, I \in I: \quad x(r, I), f_{rt} \geq 0
\]

**4.2 Solving the ALT-TFO Problem**

In this section, we design and analyze an algorithm for the ALT-TFO problem. The similarity between the LPs for ALT-TFO and LUMP SUM (Section 3) translates into a similarity in the algorithms (and their analysis) of the two problems. The key difference now is that we need to take care of the firings.

Our algorithm for ALT-TFO differs from the algorithm for LUMP SUM in steps 1, 5, 8, and 9, which are changed as follows:

1’. Let \( F^T \) and \( H^T \) represent the workers who are not hired and hired, respectively, at the time that \( J^T \) arrives. Clearly, when the first task arrives \( (T = 1) \), then \( F^T = W \) and \( H^T = \emptyset \). For \( T > 1 \), the values of \( H^T \) and \( F^T \) are updated in the last step (step 10) of the previous round and then we remove workers whose hiring interval finished in the previous step:

\[
F^t \leftarrow \{ r \in W \mid x(r, I^T \cap \eta_r) = 1 \}
\]

\[
H^T \leftarrow H^T \setminus F^T
\]

\[
\forall W^* \in F^T: \quad \text{set } \tilde{x}_r = 0
\]

5’. For each skill \( \ell \in J^T \):

\[
\text{while } \sum_{r \in P_r} (\tilde{x}_r + \tilde{f}_{rt}) < 1:
\]

\[
\text{for each } r \in P_r: \quad \tilde{x}_r \leftarrow \tilde{x}_r \left( 1 + \frac{1}{\tilde{C}_r} \right) + \frac{1}{n \tilde{C}_r}
\]

\[
\text{for each } r \in P_r: \quad \tilde{f}_{rt} \leftarrow \tilde{f}_{rt} \left( 1 + \frac{1}{\tilde{C}_r} \right) + \frac{1}{n \tilde{C}_r}
\]

8’. Repeat \( p_2(T) \) times:

\[
\text{for each } r \in P^T_f: \quad \text{with probability } \Delta \tilde{x}_r:
\]

\[
\text{hire worker } W^* \text{ (set } x(r, I^T) = 1, \text{ } H^t \leftarrow H^t \cup \{ r \})
\]

\[
\text{with probability } \tilde{f}_{rt}
\]
4.3 Solving TFO Using ALT-TFO

Note that any solution output by ALT-TFO can be transformed into a feasible solution to the original TFO problem by setting $g_{rt} ← 1$ for each $r, t \in I$ for which $x(r, t) = 1$, and $g_{rt} ← 0$ otherwise. We call the algorithm that runs ALT-TFO and subsequently does this transformation a final step, the TFO algorithm.

The question is whether TFO provides a solution with bounded competitive ratio for the TFO problem. We answer this question affirmatively by showing (1) that the solution of TFO for the TFO problem is feasible and has a cost bounded by the cost of ALT-TFO for the ALT-TFO problem, and (2) that any solution for the TFO problem can be turned into a feasible solution to the ALT-TFO problem at the expense of a small loss in the approximation factor.

These two suffice to prove that the solution produced by TFO is a good solution for the TFO problem. We have the following result (proof omitted due to space constraints):

**Theorem 4.1.** ALT-TFO is an $O(\log n(\log m + \log \lambda^* + \log T^*))$-competitive algorithm for the ALT-TFO problem.

4.4 The TFO-Heuristic

Similarly to LumpSum, we also consider the heuristic TFO-Heuristic, which is a generalization of LumpSum-Heuristic, for general values of $\sigma$. Specifically, the difference is that worker $W^T$ is hired when $\delta_t ≥ C_r + \eta_t \cdot \sigma$, and is fired after $\eta_t$ tasks (see Sections 3.1 and 4.1 for definitions of $\delta_t$ and $\eta_t$). Note that theoretically TFO-Heuristic may perform arbitrarily bad: the example of Section 3.1 holds for TFO-Heuristic for small $\sigma$. Yet, in Section 5 we observe that even though it does not offer the theoretical guarantees of TFO, it performs well in practice.

4.5 The TFO-Adaptive algorithm

As we will see in Section 5, although TFO gives theoretical guarantees for the worst-case performance, in practice some of our other algorithms for the TFO problem may perform better under some input parameters. Given the low running time of all our solution approaches to TFO, we implemented the TFO-Adaptive algorithm. This algorithm runs in parallel all the presented methods for solving the TFO problem (TFO, TFO-Heuristic, Always-Outsource and Always-Hire), and selects at each time the current minimum-cost algorithm to apply to solve the current task, switching between algorithms when it is advantageous. The asymptotic worst-case results hold for the TFO-Adaptive algorithm as well. Furthermore, our experiments (see Section 5) show that it is beneficial to change the hiring policy even if we pay switching costs.

5 EXPERIMENTS

Our experiments seek to compare the total cost that would be incurred by companies using different algorithms to assign workers to a stream of incoming tasks. We use synthetic datasets representing possible workloads, built using actual task requirements and worker skills from three large online marketplaces. Synthetic data, while having the limitation of not reflecting the particular conditions of a specific company, allows us to evaluate the effectiveness of our algorithms under a broad range of conditions. Section 5.1 introduces our datasets, Section 5.2 presents results on the LumpSum problem, and Section 5.3 on the TFO problem.

5.1 Datasets

We start by introducing our datasets and discussing our choice of cost parameters for experimentation.

**Source datasets.** To create a large pool of tasks from which to sample workloads, we use datasets obtained from three large online marketplaces for outsourcing: UpWork, Freelancer and Guru (the authors are not associated with any of these services). All three are in the top-30 of traffic in their category ("consulting marketplaces") according to data from Alexa (Feb. 2018), indeed, Freelancer and Guru are respectively number 1 and number 3. General statistics of these datasets are shown on Table 2.

**Worker skills.** The input data that we obtained contain anonymized profiles for people registered as freelancers in these marketplaces.

### Table 2: Characteristics of the three source datasets used to generate workloads for our experiments. Numbers in italics correspond to tasks generated for the Upwork dataset, as explained in Section 5.1.

| Dataset       | UpWork | Freelancer | Guru |
|---------------|--------|------------|------|
| **Skills (m)**| 2,335  | 175        | 1,639|
| **Workers (n)**| 18,000 | 1,211      | 6,119|
| **Tasks (T)** | 50,000 | 992        | 3,194|
| **– distinct**| 50,000 | 600        | 2,939|
| **– similarity (Jaccard)** | 0.095  | 0.045      | 0.018|
| Average Skills/worker | 6.29   | 1.45       | 13.07|
| Average Skills/task | 41.88  | 2.86       | 5.24 |
The latter diverges rapidly due to salary costs. Parameters for both Freelancer and Guru we have access to a large number of tasks. Our online algorithm, its heuristic version \((TFO-Heuristic)\) and the \(TFO-Adaptive\) have smaller cost than \(Always-Outsource\) and \(Always-Hire\). The latter diverges rapidly due to salary costs. Parameters \(C_r = 4\lambda_r, \sigma_r = 0.1\lambda_r\) and \(T = 40K\).

These include their self-declared sets of skills, as well as the average rate that they charge for their services. There is a large variation in the number of skills per worker among datasets, as can be seen in Table 2. Data have been cleaned to remove skills that were not possessed by any worker and skills that were never required by any task. The numbers in Table 2 refer to the clean datasets.

Tasks, For both Freelancer and Guru we have access to a large sample of tasks commissioned by buyers in the marketplace; they are included as tasks on Table 2. They correspond to actual tasks brought to these marketplaces by actual users. These samples are anonymized: we do not know the name of the company commissioning them, and there are no timestamps in this data. In the case of Upwork, we generate synthetic tasks following a data-generation procedure used in previous work \([4]\): we remove a small number of workers (10%), who are excluded from the pool of workers in the dataset, and then repeatedly sample subsets of them to create tasks, by interpreting the union of their skills as task requirements.

Workloads, Marketplaces for online work cover a broad range of tasks from graphic design and web development to accounting, administrative assistance, and legal consulting. Except for huge conglomerates, most firms will not outsource work across all categories at the same time. The workload-generation process that we use has a single parameter \(p\), which we call the coherence parameter of the workload, and works as follows. First, we start with a random task, which we select as pivot. To select the next task, with probability \(1/p\) we select a random task from the pool of distinct tasks in the dataset and make this task the new pivot, and with probability \(1 − 1/p\) we select another task with Jaccard similarity at least 0.5 to the pivot. The expected length of a sequence of “similar” tasks is \(p\). Each workload stream that we create has 10K tasks. We also experimented with streams of up to 100K tasks, but we observed that 10K tasks suffice to expose the trends of the algorithms that we compare. We believe that in general a large value of \(p\) is realistic for a company, as customers would probably procure from it services exhibiting a certain coherence; we also evaluate our algorithms for a broad range of values for \(p\).

For each dataset and for each coherence parameter that we use, we generated 100 workload streams; the costs that we report in our experiments are averages over these 100 workloads.

Cost parameters, We have data about the rates charged by workers in each marketplace, which we directly interpret as their outsourcing costs \(\lambda_r\). However, we do not have their hiring or salary costs, so we experiment with different values for these costs.

For hiring costs, which are characterized by \(C_r > \lambda_r\), we assume they are a multiplicative factor larger than the hiring cost, \(C_r = \alpha \lambda_r\). We performed extensive experiments in which \(C_r\) varied between \(4 \lambda_r\) and \(20 \lambda_r\), either as a fixed value, or setting \(\alpha\) to be a random variable distributed uniformly in a small range.

For salary costs, we assume that they are a fraction of outsourcing costs, experimenting with values from \(\sigma_r = \lambda_r/100\) to \(\sigma_r = \lambda_r/4\). Salaries \(\sigma_r\) are smaller than outsourcing costs \(\lambda_r\) because the latter includes many costs in which a company incurs when outsourcing \([6]\), including: (i) outside-hired consultants are usually more highly paid per hour/day than regular employees for a company; (ii) there are transaction costs involved in locating and contracting and outsourced worker that do not exist for regular employees, and (iii) there are communication and management costs of handling someone external to a company.

5.2 Experiments with LUMP\textsc{Sum}

Baselines, We consider two baselines. The \(Always-Hire\) baseline solves the \textsc{SetCover} problem for finding a low-cost set of workers that cover the task’s uncovered skills and hires them. The \(Always-Outsource\) baseline never hires, instead it outsources to workers that cover the required skills for the task, by solving a \textsc{SetCover} problem instance.

\[
\begin{array}{l}
\text{(a) LUMPSum UpWork} \\
\text{(b) TFO UpWork} \\
\text{(c) LUMPSum Freelancer} \\
\text{(d) TFO Freelancer} \\
\text{(e) LUMPSum Guru} \\
\text{(f) TFO Guru}
\end{array}
\]
Results. Figure 1 (Left) summarizes our results for \texttt{LumpSum} for workloads generated with the UpWork, Freelancer and Guru datasets, depicting total cost as a function of the number of tasks.

We observe that under all these workloads the algorithms behave similarly. \texttt{Always-Outsource} has cost proportional to the number of tasks and is not competitive, its cost is mostly outside the range of Figure 1 (Left). As expected, \texttt{Always-Hire} performs the best in the long run, because if the number of tasks is large, hiring is a dominant strategy; however the online algorithm does not know the number of tasks. Experimentally, the \texttt{LumpSum} algorithm has a cost that does not exceed that of \texttt{Always-Hire} by more than a factor of 2, across all the scenarios we tested. We note that for short sequences \texttt{LumpSum} has lower cost; this difference in the cost can sometimes be an order of magnitude smaller (plots omitted for brevity). We also note that although \texttt{LumpSum-Heuristic} can, theoretically, perform arbitrarily bad, in our experiments it performs quite well—although worse than the theoretically justified \texttt{LumpSum}.

Variations (plots omitted for brevity). Figure 1 (Left) is obtained with $C_r = 4\lambda_r$. We do not observe dramatic variations in the results when varying this parameter in the studied range ($1\lambda_r$ through $30\lambda_r$): \texttt{LumpSum} has a smaller cost than \texttt{Always-Outsource}. In general, higher hiring costs mean the number of tasks required before hiring a worker is larger, the costs of \texttt{LumpSum} and \texttt{Always-Hire} are higher, and the advantage for \texttt{LumpSum} over \texttt{Always-Hire} for a small number of tasks holds for a longer period of time.

In all plots of Figure 1 we use coherence parameter $p = 100$, which means we expect the input stream to be composed, on average, of runs of 100 similar tasks (i.e., having Jaccard coefficient of at most 0.5 between consecutive ones). In this setting, even if the workload is not coherent (experimentally, even for $p = 1$), \texttt{LumpSum} is still better than \texttt{Always-Outsource}.

5.3 Experiments with TFO

Baselines. As in \texttt{LumpSum}, we consider baselines \texttt{Always-Hire} and \texttt{Always-Outsource}. Additionally, we consider \texttt{TFO-Heuristic}, and \texttt{TFO-Adaptive} have the smallest total cost, followed by \texttt{Always-Outsource}. In contrast, the \texttt{Always-Hire} strategy has much higher cost due to mounting salary costs. We also observe that while \texttt{TFO-Heuristic} does not offer the theoretical guarantees of \texttt{TFO}, it performs well in practice.

Variations. Similarly to \texttt{LumpSum}, varying $C_r$ does not bring dramatic changes, but as $C_r$ increases while maintaining workload coherence and salary to outsource cost ratios constant, the advantage of \texttt{TFO} over \texttt{Always-Outsource} decreases, and for large hiring costs \texttt{Always-Outsource} has the smallest cost (plots omitted for brevity). Concretely, for $p = 100$ and $\sigma_r = \lambda_r/10$, if we vary the hiring cost $C_r$ (from $1\lambda_r$ to $30\lambda_r$), the total cost of \texttt{TFO} remains less or equal than the total cost of \texttt{Always-Outsource} until $C_r = 16\lambda_r$, when the cost of \texttt{TFO} becomes larger than the cost of \texttt{Always-Outsource} for the workload generated using the Guru dataset. The corresponding values of $C_r$ for workloads generated with Freelancer and Upwork data are $C_r = 18\lambda_r$ and $C_r = 26\lambda_r$ respectively. As expected, if the hiring costs are sufficiently large, \texttt{Always-Outsource} becomes a dominant strategy.

Figure 2 (Left) compares \texttt{TFO} and \texttt{Always-Outsource} experimentally by varying the coherence parameter $p$ from 20 to 200 and $\sigma_r$ from $\lambda_r/50$ to $\lambda_r/4$. We observe that less coherent workloads and high salaries make hiring more expensive; \texttt{Always-Outsource} then becomes a dominant strategy. Figure 2 (Right) shows the power of the \texttt{TFO-Adaptive} algorithm. We observe that it performs equal or better than \texttt{Always-Outsource} for all the range of parameters.

Performance. Our code, which will be released with this paper, is a relatively straightforward mapping of the algorithm to simple counters. Written in Java, it requires about 5 to 8 seconds on average to process 10K incoming tasks using commodity hardware.

![Figure 1](image1.png)

![Figure 2](image2.png)
We remark that, although our formulation is a linear program, the method does not involve solving the linear program, instead, we obtain the solution using the specific primal–dual method that we have described and analyzed.

6 RELATED WORK
To the best of our knowledge, we are the first to introduce and solve the Team Formation with Outsourcing (TFO) problem. However, our work is related to existing work on crowdsourcing, team formation, and online algorithms design, which we outline next.

Crowdsourcing. Among the extensive literature in crowdsourcing, the most related to ours is the work of Ho and Vaughan [13]. Their goal is to assign individual workers to tasks, based on the workers’ skills. Although Ho and Vaughan also deploy the primal–dual technique to solve the task-assignment problem, the tasks they consider can be performed by individual workers and not by teams. Thus, both their problem and their algorithm is different from ours.

Team formation. A large body of work in team formation considers the following problem: given a social or a collaboration network among the workers and a set of skills that needed to be covered, select a team of experts that can collectively cover all the required skills, while minimizing the communication cost between the team members [2, 4, 10, 11, 16, 18, 19, 27]. Other variants of this problem have also considered optimizing the cost of recruiting promising candidates for a set of pre-defined tasks in an offline fashion [12] and minimizing the workload assigned to each individual team member [3, 21].

Although the concept of set-cover is common between our work and previous work, the framework we propose on this paper is different in multiple dimensions. First, we do not focus on optimizing the communication cost; in fact we do not assume any network among the individual workers. Our goal is to minimize the overall cost paid on hiring, outsourcing, and salary costs. This difference in the objectives leads to different (and new) optimization problems that we need to solve. Secondly, most of the work above focuses on the offline version of the team-formation problem, where the tasks to be completed are a-priori known to the algorithm. The exception is the work of Anagnostopoulos et al. [3, 4]. However, in their setting they aim to distribute the workload as evenly as possible among the workers, while our objective is to minimize the overall cost of maintaining a team that can complete the arriving tasks. Moreover, the option of outsourcing that we propose is new with respect to the team formation literature. Finally, in the design of our online algorithms we use the primal–dual framework, which was not the case for previous work on online team formation.

Primal–dual algorithms for online problems. The algorithms we design for our problems use the primal–dual technique. A thorough analysis on the applicability of this technique for online problems can be found in the book by Buchbinder and Naor [8] and in [5]. Probably the most closely related to problem are the ski-rental and the set cover problems. We have already discussed the connection of TFO to ski-rental and set cover in Section 2. One can also draw the analogy with caching; one can think that bringing a page to the main memory is analogous to hiring a person. The main differences are that in the typical caching problem we do not have covering constraints, there are no recurring costs for keeping pages in the cache, and there is a fixed limit on the number of pages we can insert in the cache.

7 CONCLUSIONS
In this paper, we introduced and studied Team Formation with Outsourcing. We showed that hiring, firing, and outsourcing decisions can be taken by an online algorithm leading to cost savings with respect to alternatives. These cost savings are more striking when (1) the hiring and salary costs are low, because then hiring becomes an attractive option; (2) the tasks exhibit high coherence, i.e., consecutive tasks are similar to each other; and (3) the time horizon is long enough that we can find a core pool of workers to stay hired and satisfy a large fraction of the skills required by incoming tasks.

Technically, the problems we have analyzed in this paper involve embedding a set-cover problem in an online algorithm. Our main algorithms (LumpSum, TFO) are able to give results that are competitive in practice and, equally importantly, theoretically close to the best one can hope for. The design of our algorithms is based on the online primal–dual technique; we provide an experimental evidence of the goodness of this method even for a complex real-world problem. Furthermore, we present two heuristics which, although in theory are not competitive, perform well in practice. Future work may extend this by considering worker compatibility [4, 18], learning of new skills by hired workers, or other extensions.

Future work. As most problems, we can introduce further elements to introduce even more generality. For instance, the algorithms we have described assume one and only one task arrives per unit of time, can be extended trivially to cases in which task arrivals occur at arbitrary times.

As we noted in Section 6, there are also parallels with scenarios of caching and paging. Extending TFO when the number of hired workers is limited turned out to be a challenging combination of set cover, weighted caching and ski rental. We have begun to study these problems, our preliminary results show that we can achieve a \(O(\log k \log m)\) approximation, in which \(k\) is the maximum size of the worker pool. A more natural constraint could be that, for instance, the total cost paid per unit of time cannot exceed a certain budget, which would represent a cap in weekly or monthly personnel expenses. Another element we could incorporate is the possibility of not handling a task, but instead paying a penalty when a task is too difficult to handle with current workers and it is expensive to replace the worker pool with new workers. Other variants can include workers with different ability levels. We plan to study some of these variants in future work.

Additionally, we note that all the algorithms we have presented in this paper are deterministic. Just as randomized algorithms for paging can be defined in the primal–dual framework [8], it is of interest to introduce other update rules for the primal variables that allow us to describe a randomized algorithm.

Reproducibility. The code and data of this paper can be found at https://github.com/adrianfaz/Algorithms-for-Hiring-and-Outsourcing-in-the-Online-Labor-Market.
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