Towards Efficient Team Formation for Crowdsourcing in Non-Cooperative Social Networks

Wanyuan Wang, Jiuchuan Jiang, Bo An, Yichuan Jiang*, Senior Member, IEEE, Bing Chen

Abstract—Crowdsourcing has become a popular service computing paradigm for requesters to integrate the ubiquitous human-intelligence services for tasks that are difficult for computers but trivial for humans. This paper focuses on crowdsourcing complex tasks by team formation in social networks (SNs) where a requester connects to a large number of workers. A good indicator of efficient team collaboration is the social connection among workers. Most previous social team formation approaches, however, either assume that the requester can maintain information of all workers and can directly communicate with them to build teams, or assume that the workers are cooperative and willing to join the specific team built by the requester, both of which are impractical in many real situations. To this end, this paper first models each worker as a selfish entity, where the requester prefers to hire inexpensive workers that require less payment and workers prefer to join the profitable teams where they can gain high revenue. Within the non-cooperative SNs, a distributed negotiation-based team formation mechanism is designed for the requester to decide which worker to hire and for the worker to decide which team to join and how much should be paid for his skill service provision. The proposed social team formation approach can always build collaborative teams by allowing team members to form a connected graph such that they can work together efficiently. Finally, we conduct a set of experiments on real dataset of workers to evaluate the effectiveness of our approach. The experimental results show that our approach can 1) preserving considerable social welfare by comparing the benchmark centralized approaches and 2) form the profitable teams within less negotiation time by comparing the traditional distributed approaches, making our approach a more economic option for real-world applications.

Index Terms—Team formation, social networks, crowdsourcing, multiagent, non-cooperative, negotiation

1 INTRODUCTION

Driven by the requirement of massive human intelligence service-oriented applications, such as data sensing [1], language translation [2] and image classification [3], crowdsourcing has become a flexible service computing paradigm by making the ubiquitous human resources available to requesters on demand [4]. By using certain crowdsourcing platform (e.g., Upwork), the requesters can advertise their tasks (i.e., service requirement) to workers and the workers choose whether or not to participate in and complete the tasks in change for monetary reward [5]. Typical crowdsourcing applications include solving simple tasks that each worker can complete each task independently and complex interdependent tasks that need to be solved in multiple phases [6] (e.g., sentence spelling mistakes correction) or teamwork [7][8] (e.g., article editing in Wikipedia). In crowdsourcing environment, due to the diversity of workers’ skills on performing tasks, previous researches mainly focus on whether the hired workers are professional enough such that they can satisfy a task’s skill requirements [1-8].

In this paper, we concentrate on crowdsourcing an important class of complex tasks, where the success of completing such a complex task depends not only on the skills of the hired workers but also on how efficiently these workers can work together as a team [9]. For example, to develop a software product successfully, the product manager first needs to hire a group of professional software engineers with the necessary skills: Requirement Analysis, Architecture Design, Implementation, Testing, Deployment, and Maintenance. During software development, the engineer who performs Testing must communicate with the engineer who performs Implementation again and again to debug and optimize the software. Once the communication fails between the engineers due to language barriers or geographic distance, the product cannot be produced on time [10]. Therefore, the hired workers must also be able to cooperate with each other efficiently for team task completion. Now the manager’s problem is how to build such a professional and collaborative team of workers.

With the advent of online social networks (e.g., LinkedIn, linkedin.com and Github, github.com), social networks (SNs) provide good opportunities for the requester addressing this social team formation problem. On one hand, within SNs, the requester connects to a large number of social individuals and can collect these individuals’ public information (e.g., skill, salary requirement and working experience, etc.) by learning their profiles. This advantage will help the requester build professional teams [11][12]. On the other hand, social connections among social individuals might represent collaboration relationships [13][14] (e.g., collaborate on common task previously). The advantage of using these SNs is that the social individuals who have worked together previously are estimated to work effectively as a team without much coordination overhead [15][16]. Motivated by this advantage, we consider building collaborative teams in SNs where team members form a connected graph such that they can work together efficiently [17-19].

Although a number of social team formation approaches have been proposed to build professional and collaborative teams in SNs [15][16][20-23], from which we find a
couple of restrictive assumptions that we feel that are impractical. First, they assume that workers are cooperative, i.e., each worker is willing to join a team built by the requester to optimize the requester’s objective. However in practice, workers are always rational and their only incentive to join a team and provide skill services is to maximize their own benefits. A practical social team formation should consider the worker’s selfish nature. Second, they assume that the requester can maintain information of all workers and can directly communicate with them to build professional teams. However, because of privacy-preserving in SNs, the requester can only maintain limited information of its directly connected neighbors. Therefore, a practical social team formation should build teams in a natural distributed manner with partial information of socially-close partners.

To address these issues, this paper first models each individual as a selfish entity, where the requester aims to hire a collaborative team of inexpensive workers to minimize expense and the worker aims to join a profitable team and provide skill services to earn a considerable payment. Within the non-cooperative SNs, we then present a distributed negotiation-based social team formation approach by allowing the requester to negotiate with the team members’ neighbor workers only. As the main contribution of this paper, we rigorously design the negotiation mechanism for the requester and worker to make agreement on skill provision and payment for their own profit maximization. This negotiation-based social team formation mechanism mainly consists of the following three phases: i) offer: the requester interacts with the worker and sends an offer to the worker on skill provision and payment; ii) Respond: the worker responds (e.g., accept, reject or propose skill payments improvement) to the requester on this offer and iii) Confirm: the requester makes the final confirmation on the received response and updates the team’s profile.

Our theoretical analyses show that the requester can always find the most beneficial skills from the workers. Finally, we also conduct a set of experiments on real dataset to evaluate the proposed social team formation approach. The experimental results show that 1) compared to the ideal centralized approach [17][18][22], our approach can preserve considerable social welfare and 2) compared to traditional distributed contract-net approach [31] and the greedy approach [28], our approach forms desirable teams by spending less budget and team formation time.

The remainder of this paper is organized as follows. In the next section, we provide a brief review of related work on crowdsourcing and team formation in SNs. In section 3, we give a formal definition of the social team formation problem. In Section 4, we present the framework of negotiation-based social team formation approach. In section 5, we discuss the negotiation mechanism employed by the requester and worker in detail. In Section 6, we conduct a set of experiments to evaluate the proposed approach’s effectiveness. Finally, we give a conclusion of our paper and discuss the future work in Section 7.

2 RELATED WORK

2.1 Crowdsourcing for Task Allocation

Crowdsourcing is a useful paradigm for requesters to harness the ubiquitous human resources on solving tasks that are difficult for computers. To motivate workers to contribute their personal resources, the workers should gain certain economic benefit from the task completion. However, because of the limited budget, the requester should decide how much should be paid to the workers. To address this issue, Azaria et al. [32] develop an agent-based reward determination mechanism by allowing agents to determine each worker’s reward autonomously. To capture the dynamic characteristics of online labor markets, Singer and Mitta [33] introduce a truthful pricing mechanism which in addition is budget balanced. Unfortunately, due to the openness and dynamics of the online markets, workers might vary greatly in the quality of task completion [34]. Therefore another key challenge in crowdsourcing is to guarantee the quality of task completion. To address this issue, a novel multi-armed bandit approach is devised for the requester to spend the first $c B$ budget of its total budget $B$ to derive workers’ quality estimates and spend the remaining $(1-\epsilon)B$ budget to maximize the task quality based on those estimates [34].

Although the above approaches are efficient in crowdsourcing simple tasks, there is a need to consider crowdsourcing a complex task that requires to be solved in multiple phases [6] or by teamwork [7][8]. A popular method for solving a complex task is to decompose such a complex task into a flow of simple sub-tasks, allocate them to workers subsequently and finally combine the partial results of sub-tasks together to get the final solution [6]. These methods only focus on hiring professional workers [6-8]. In comparison, this paper not only crowdsources complex tasks by hiring professional workers but also guarantees the hired workers can collaborate with each other effectively. Being aware of the fact that teamwork can produce higher product quality than individuals alone, Rokicki et al. [35] allow workers to build teams to improve the cost efficiency of crowdsourcing. On the other hand, Woolley et al. [36] empirically show that a number of factors (e.g., social sensitivity and conversation democracy) are correlated with team performance and Kittur and Kraut [8], Lykourentzou et al. [9] and Dow et al. [37] further verify that timely task-specific feedback, flexible coordination tools and personality similar can improve team performance. Complementary to these works [8][9][37], we aim to build the collaborative team with socially-close workers in social networks. Recently, being aware of the social influence and similar attributes among socially-close users, social networks have also been used in recommendation systems to improve the quality of recommendations [38-40]. To predict the rating of an item for a particular user, these methods [38-40] aggregate the ratings of a set of direct or indirect connected users on that item and then perform the recommendation based on the predicted ratings. These concepts (e.g., trust/influence propagation) proposed in the social network-based recommendation can inspire to form the collaborative team for social network-based crowdsourcing.

2.2 Team Formation in Social Networks

Wolf et al. [10] first realize that social networks play an important role in team collaboration. Meantime, Lappas et al. [15] first formally formulate the problem of team formation in social networks. They model each social network as a weighted and undirected graph $G(V,E)$, where $V$ represent individuals, $E$ represent social connections and the weights on the connections represent the communication cost between connected individuals. Given a social network $G$ and a task $J$, Lappas et al. [15] target to find a team of individuals $V^* \subseteq V$ such that $V^*$ not only meets all of the skill requirements of $J$ but also incurs the least team communication cost. Following [15] are other social team formation variants with different application constraints and objectives, such as online dynamic settings where
tasks arrive to the system dynamically [20]; expertise query settings where each required skill needs to be satisfied by adequate number of experts [21]; load balancing where the workers' assigned tasks should not exceed their capacity [16]; and budget minimization where the workers need to be paid for their skill contribution [22]. Rangapuram et al. [23] propose a more generalized social team formation problem where team size, team budget and team communication cost are considered. Noticing that all of these problems are NP-hard, the previous researches [15][16][20-23] focus on developing centralized approximations with rigorous quality guarantees. These centralizations, however, are impractical for real-world applications where many SNs do not involve such a central coordinator and individuals are always building or joining teams in a self-organized manner [25-28]. In comparison, our work aims to design a distributed team formation approach for the requester to build teams and for workers to join teams.

Negotiation is a very effective distributed problem solving technique, which can be utilized to build social teams [40-44]. For example, Jiang et al. [41][42] present a contextual based team formation model, where the requester negotiates resources from nearby individuals to faraway individuals. Recently, Wang and Jiang [43] propose a game-theoretic team formation model by modeling each subtask as a cooperative mobile agent and then each agent targets to move to the individual that has the least workload. On the other hand, being aware of that the network has a dramatic effect on team performance [44], Gaston and Desjardins [45] develop a dynamic structural adaption team formation method by allowing individuals to delete costly connections and rewire to professional individuals. Moreover, to improve team collaboration efficiency, system designer can facilitate social relationships to increase system social welfare [46][47]. All of these proposals [41-45][48] assume that social individuals are cooperative, i.e., each individual is willing to join the specific team built by the requester. In contrast, this work mainly focuses on building social teams in non-cooperative social networks, where individuals are selfish with the aim of maximizing their own profit. Wang et al. [49] recent propose a reverse auction-based truthful team formation in social networks that consider the individuals' selfish nature. This work mainly focuses on maximizing social welfare (i.e., the aggregate utility of the requester and worker), while this work attempts to maximize the requester and worker's utilities simultaneously.

Weerd et al. [31], Ye et al. [28] and Wang and Jiang [27] have made great effort on team formation in non-cooperative systems. For example, Weerd et al. [31] propose a greedy neighbor-aware team formation model, where workers contribute their resources to the most desirable neighbor requester with the most profitable task. Although this model is easy to implement, its efficiency is limited due to its greedy nature. Ye et al. [28] consider a market-based team formation problem, where requesters have incomplete information (e.g., working cost) of workers. To address this issue, they propose an efficient bilateral bargaining-based negotiation mechanism, where workers negotiate with each other until they reach an agreement on working cost. However, computing equilibrium strategies for such complex negotiation problem is difficult even impossible [26]. Thus, this paper proposes a set of negotiation strategies to compensate for these disadvantages. In addition, compared to [27][28][31], our approach also considers forming social collaborative teams such that team members can work together efficiently.

### 3 Problem Description

In this section, we define the problem of team formation for crowdsourcing complex tasks in social networks. Table 1 gives a summary of notations used in this paper.

**Social Networks.** Each social network $SN=\langle A, E \rangle$ is an unweighted and undirected graph, where $A=\{a_1, a_2, \ldots, a_n\}$ is the set of agents (hereafter, we use the terms "agent", "worker" and "freelancer" interchangeably). $\forall (a, a) \in E$ represents the existence of a social connection between agents $a$ and $a$. Those connections can provide high collaboration efficiency during task execution. Moreover, we assume that there are $l$ type skills $S=\{s_1, s_2, \ldots, s_k\}$ available in a SN. We can transform any weight network to unweighted network by removing the low social collaborations and regarding all of the remaining collaborations as the unweighted social relationships with high collaboration efficiency.

**Agents.** Each agent $a \in A$ is defined by a 3-tuple $<Q(a), C(a), N(a)>$, where $Q(a) \subseteq S$ indicates the set of skills that agent $a$ owns and if $s \in Q(a)$, agent $a$ can provide the skill $s$; $C(a)=\{c_1(a, s_1), \ldots, c_1(a, s_k)\}$ indicates agent $a$'s working cost of providing its skill $s \in Q(a)$ (where $X$ denotes the number of elements in the set $X$); and $N(a)$ indicates the direct social neighbors of $a$, i.e., $N(a)=\{a|a, a) \in E\}$. Furthermore, we assume that each agent cannot join more than one team at a time. However, as a member of a team it can provide more than one skill to team task. This assumption is rea-

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<td>$as(a, R\kappa)$</td>
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sonable since each individual has limited energy and participating in multiple teams will degrade the performance of each team it joins [17][46].

Tasks. We consider a set of tasks $K=\{κ_1, κ_2, \ldots, κ_n\}$ initiated by these agents $A$ independently. Then, each task $κ \in K$ can be defined by a tuple $\langle Ω_κ, R_κ, I_a(κ), D_l(κ), W_t(κ)\rangle$, where $I_a(κ) → A$ indicates the agent that initiates task $κ$. In this paper, we consider a practical scenario that at each time step, tasks are initiated by agents independently with certain probability $R$. $Ω_κ$ is the set of skills required by $κ$ and if $s \in Ω_κ$, task $κ$ needs the skill service $s$. $I_a(κ)$ is the initialization time of $κ$, i.e., at time $I_a(κ)$, $κ$ is generated by $I_a$. $D_l(κ)$ is the deadline (the latest execution start time) of $κ$ and $W_t(κ)$ indicates the working time it will take to execute $κ$ (note that $κ$ must be executed completely before $D_l(κ)$). Finally, $v_t(κ)$ represents the value associated with the task $κ$, which is a function of time $t$. Here, referring to the related definition in [26], we define the value function as:

$$v_t(κ) = \begin{cases} \frac{W_t(κ)}{D_l(κ) - I_a(κ)} & , t ≤ D_l(κ) + W_t(κ) \\ 0 & , t > D_l(κ) + W_t(κ) \end{cases}$$

$v_κ$ is the value associated with $κ$, set by its initiator $I_a$. $v_κ$ at the initialization time $I_a: δ (0≤ δ≤ 1)$ is the parameter modeling how task value decreases with the elapse of time $t$. If task $κ$ starts execution before its deadline $D_l(κ)$, $v_t(κ)$ has the maximum value at time $D_l(κ) + W_t(κ)$ and the minimum value at time $D_l(κ)$.

Teams. Each team $T_κ$ is responsible for a task $κ$ and is denoted by a 3-tuple $\langle Ω_κ, Cont(Ω_κ, κ), P_κ, us(κ)\rangle$, where $Ω_κ$ is the set of agents that join $T_κ$, i.e., the team members of $T_κ$. $Cont(Ω_κ, κ, P_κ) = \{a | s(a, p_κ(a, s)) \in Ω_κ\}$ is the skill contribution function indicating that which team member contributes what skill service and how much will be paid. In other words, the tuple $(a, s, p_κ(a, s))$ means that team member $a$ contributes skill $s$ and in return, team manager $I_a$ pays $p_κ(a, s)$ for $a$’s skill provision of $s$. Finally, $us(κ)$ is the set of skills that are not satisfied by the team members $Ω_κ$, i.e., $us(κ) = R_κ \setminus \{s | (a, s, p_κ(a, s)) \in Cont(Ω_κ, κ, P_κ)\}$. A team $T_κ$ is called a complete fulfilled team if each skill has been satisfied by one team member, i.e., $∀s \in R_κ, \exists a ∈ Ω_κ: (a, s, p_κ(a, s)) \in Cont(Ω_κ, κ, P_κ)$. Otherwise, $T_κ$ is a partial fulfilled team.

Social Team Formation Problem. Given a task $κ$ and a social network $SN=\langle A, E, Ω_κ, Cont(Ω_κ, κ, P_κ), us(κ)\rangle$, the team manager $I_a$ first wishes to build a feasible team $T_κ = Cont(Ω_κ, κ, P_κ)$. A feasible team $T_κ$ must satisfy the following three constraints:

- The team $T_κ$ must be professional. Each skill of $κ$ must be satisfied by one team member, i.e., $∀ s \in R_κ, \exists a ∈ Ω_κ: (a, s, p_κ(a, s)) \in Cont(Ω_κ, κ, P_κ)$.
- The team $T_κ$ should not include any redundant workers. Each team member must provide at least one skill service, i.e., $∀ a \in Ω_κ, \exists s \in R_κ: (a, s, p_κ(a, s)) \in Cont(Ω_κ, κ, P_κ)$.
- The team $T_κ$ must be collaborative. The subgraph induced by the team members $Ω_κ$ must be connected.

Besides satisfying the feasibility property, the requester’s ultimate objective is to form the optimal feasible team with the cheapest workers as soon as possible, i.e., maximize $v_t(κ)$ subject to $\sum_{a \in Ω_κ} \sum_{s \in R_κ} \sum_{p_κ(a, s) \in P(κ)} p_κ(a, s)$ subject to $∀ a \in Ω_κ, \sum_{s \in R_κ} (a, s, p_κ(a, s)) \in Cont(Ω_κ, κ, P_κ)$. This is because the task profit is discounted over time, and the earlier the team formed, the earlier the task can be completed, thereby the more profit will be produced for the requester.

4 Sketch of The Social Team Formation

Before describing the social team formation model, we first define three roles of agents used throughout the team formation process, i.e., Manager, Contractor and Freelancer.

Definition 1. Manager, Contractor and Freelancer. Given a team $T_κ$ for task $κ$, the agent who initiates $κ$ is called the Manager, the agents who join the team $T_κ$ are called the Contractor of team $T_κ$ and other agents are called the Freelancer that the team manager $I_a$ can negotiate with.

The social team formation model employed by the team manager $I_a$ to find a set of beneficial freelancers is presented in Algorithm 1.

Algorithm 1. Social Team Formation Model $(κ, I_a)$
1. Initialize $Ω=I_a, R_κ=\emptyset, Q(I_a), Cont \cap Ω_κ, κ, I_a \cap Ω_κ=\emptyset$.
2. Initialize $V_e<Ω, Cont \cap Ω_κ, κ, I_a∧ R_κ$. All tasks are not assigned.
3. While $B \subseteq E_κ$
4. For each contractor $a ∈ Ω_κ$.
5. For $a ∈ N(a)$.
6. Negotiate $(I_a, a, a, I_a)$ and update team $T_κ$.
7. If $∀s_i \in R_κ, \exists a_i ∈ Ω_κ: (a_i, s_i, p_κ(a_i, s_i)) \in Cont(Ω_κ, κ, I_a)$.
8. Terminate team formation.
9. End for
10. End for
11. End while

In Step 1, as the initiator of task $κ$, agent $I_a$ is responsible for contributing all of its available skills to $κ$ and is responsible for building a team $T_κ=I_a, Q(I_a), Ω_κ, κ, I_a∧ R_κ$ to manage team contractors and recruit new freelancers (Step 2). Before the deadline of task $κ$ (Step 3), each team contractor $a_i ∈ Ω_κ$ is responsible for introducing its neighboring freelancers $N(a_i)$ to the team manager $I_a$. After team contractor $a_i$’s introduction, in Step 6, the team manager $I_a$ is able to negotiate with the freelancer $a_i ∈ N(a_i)$. The negotiation protocol adopted to make a contract between the team manager $I_a$ and the freelancer $a_i$ about which skills to contribute and how much to be paid for $a_i$’s skill provision will be discussed in Section 5. Finally, if the team manager $I_a$ has recruited enough contractors such that they can satisfy all of the skill requirements of $κ$, $I_a$ will terminate the team formation process and start task execution (Steps 7–8). It should be noted that this social team formation model can always form a connected sub-graph of SNs, which satisfies collaboration objective of social team formation.

5 Negotiation Mechanism

The negotiation mechanism, adopted in the team formation model, extends the traditional contract net protocol [31] by allowing a team manager $I_a$ and a freelancer $a$ to reach an agreement on skill provision and skill provision payment. This mechanism mainly consists of three phases: i) Offer. $I_a$ sends an offer to $a$ on skill provision and skill provision payment; ii) Respond: $a$ responds to $I_a$’s offer, such as accept, reject this offer or propose payment improvement and iii) Confirm: $I_a$ confirms a final contract with $a$ on skill provision and skill payment. Because of system dynamics, uncertainty, team competition and time factor, it is almost impossible to compute the best strategies of the requesters and workers. Therefore, inspired by the evidence for these factors in the performance of real-world applications e-commerce [25][26][28], the proposed negotiation mechanism connects these influential factors indirectly and develops a set of heuristics to approximate agents’ optimal strategies. The main contribution of this paper is the strategies designed for the manager to build beneficial feasible teams and for the worker to join the profitable teams, rather than only implementing the contract-net framework. In the following, we will describe these three phases in detail in Section 5.1 (i.e., Offer), Section 5.2 (i.e., Respond) and Section 5.3 (i.e., Confirm), respectively.
5.1 Team Manager Makes Offer to the Freelancer

Before presenting the offer strategy, it is necessary to discuss the definition of the estimated profit that team manager aims to maximize. Due to the dynamics and uncertainties during social team formation, there are many factors correlated with the manager’s estimated profit, such as:

- The estimated value $E_v$ attached to task $\kappa$ at time $\tau$, which is given by the average completion time $(\tau + W_t)$ and the latest completion time $(D_t + W_t)$, i.e.,
  \[
  E_v(\kappa, \tau) = \int_{t=0}^{\tau+w} v(t) dt \quad (2)
  \]

- The success rate $S_r$ of forming a complete team, which is given by the fraction of task $\kappa$’s skills that have been satisfied by team contracts, i.e., $S_r(T_i) = \frac{n - |\mathcal{R}_i|}{|\mathcal{R}_i|}$. The larger fraction of skill requirement has been satisfied, the higher possibility a complete team will be formed.

- Team contractors’ remuneration $R_e$ for performing task $\kappa$, where
  \[
  R_e(T_i) = \sum_{p(a,s)}{p(a,s)}(a, s, p)\quad (3)
  \]
  $p(a,s)$ is the payment that $a$ requires for providing skill service $s$. In practical applications, the worker’s working costs for providing skills are often public and from a worker’s perspective, letting the requesters know its true information may help them get a beneficial occupation [25]. Therefore, in the offer phase, the skill payment $p(a,s)$ is equal to the public skill working cost $c(a,s)$.

As the manager of task $\kappa$, $la.$ prefers to employ a freelancer $a$ if $a$’s participation increases the success rate of forming a complete team and $a$ asks for low skill service provision payment. Then, the estimated profit of team manager can be defined as follows.

Definition 2. Estimated Profit of Team Manager. For a partial fulfilled team $T_i = \langle \Omega_i, \text{Cont}(\Omega_i, T_i, P_i), \mathcal{U}_i, \mathcal{R}_i \rangle$ at the time step $t$, the team manager $la.$’s estimated profit is:
  \[
  E_p(T_i, \tau) = S_r(T_i) \cdot E_v(\kappa, \tau) - R_e(T_i) \quad (4)
  \]
  The meanings of terms $S_r, E_v$ and $R_e$ are defined above.

Given the freelancer $a$, that team manager $la.$ is negotiating with, $la.$ should consider all of $a$’s available skills $as(a, R)$ to compute the optimal skill provision. Different freelancers might have different kinds of available skills, with whom the team manager should negotiate with different strategies. Next, we first divide the freelancers into two different categories (i.e., fresh freelancer and redundant freelancer) according to his available skills and then present different offer strategies for the requester to negotiate with the two kinds of freelancers in Section 5.1.1 and 5.1.2, respectively.

Definition 3. Fresh Freelancer and Redundant Freelancer.

Given a freelancer $a$, that the team manager $la.$ is negotiating with, if $a$’s available skills $as(a, R)$ are exactly what team $T_i$ lacks, i.e., $as(a, R) \in \mathcal{U}_i$ then $a$ is called a fresh freelancer. These available skills of the fresh freelancer are called the fresh skills. Otherwise, if there exists certain available skill $s_\kappa \in as(a, R)$ that has been satisfied by certain team contractors $a_\kappa \in \Omega_i$, i.e., $as(a, R) \not\in \mathcal{U}_i$ then $a$ is called a redundant freelancer. These available skills that have been satisfied by certain team contractors are called the redundant skills.

5.1.1 Team Manager Makes Offer to a Fresh Freelancer

Suppose the team manager $la.$ is negotiating with a fresh freelancer $a$ whose available skills are just what the team $T_i$ lacks, $la.$ has to decide which skills to recruit such that these skills' contribution can maximize $la.$’s estimated profit. We propose a polynomial algorithm for $la.$ to select the optimal skills of $a$, shown in Algorithm 2.

Algorithm 2. Offer to Fresh Freelancer ($la., T_i, a, ns, \tau$)

/* $ns$: the set of skills that freelancer $a$ should provide; $\tau$: the current time. */

1. Initialize $th = E_v(\kappa, \tau)/|\mathcal{R}|$, $ns = \emptyset$. 
2. For $s \in as(a, R)$:
   1. If $c(a,s) \leq th$, then $ns = ns \cup s$ and $j = j + 1$.
3. End For

5. If $ns \neq \emptyset$, send the Offer $O = \langle la., T_i, ns \rangle$ to $a$.

In Step 1 of Algorithm 2, before negotiating with $a$, $la.$ first initializes some useful variables: the threshold value $th = E_v(\kappa, \tau)/|\mathcal{R}|$ represents how much will the estimated profit be improved by hiring a fresh skill $s \in \mathcal{U}_i$. This value is used to evaluate whether a skill is worth hiring or not. The set $ns$ stores the skills that $T_i$ would hire from $a$. In Step 2, $la.$ evaluates $a$’s available skills $as(a, R)$ one by one, and if the cost of skill $s$ is not larger than the threshold value $th$, the manager adds $s$ to the skill set $ns$ and proceeds to evaluate the next skill (Step 3). Finally, if $la.$ finds that it is beneficial to recruit $a$ by using its skills $ns$ (i.e., $ns \neq \emptyset$), $la.$ sends an offer $O = \langle la., T_i, ns \rangle$ to $a$ for skill acquisition (Step 5).

Besides its low $O(I)$ time complexity ($I$ is the number of available skills in the system), Algorithm 2 also guarantees that the selected skills $ns$ maximizes $la.$’s estimated profit.

Theorem 1. Given a fresh freelancer $a$ that the team manager $la.$ is negotiating with, Algorithm 2 returns the optimal skill provision of $a$ that maximizes $la.$’s estimated profit.

Proof: Before the negotiation, assume that the team $T_i$’s current team profile $T_i = \langle \Omega_i, \text{Cont}(\Omega_i, T_i, P_i), \mathcal{U}_i, \mathcal{R}_i \rangle$ and the team manager $la.$’s current estimated profit is:
  \[
  E_p(T_i, \tau) = S_r(T_i) \cdot E_v(\kappa, \tau) - R_e(T_i) \quad (5)
  \]
  where the threshold value $th$ represents the estimated profit improvement per skill, i.e., $th = E_v(\kappa, \tau)/|\mathcal{R}|$. Then we can derive that the marginal benefit from adding a fresh skill is exactly the threshold and adding a skill that has larger cost than $th$ will definitely decrease $la.$’s estimated profit. Now we can conclude that for a given fresh freelancer $a$, Algorithm 2 always returns $a$’s optimal skill provision.

5.1.2 Team Manager Makes Offer to a Redundant Freelancer

For a redundant freelancer $a$ that agrees to contribute a redundant skill $s$ that has been satisfied by the certain team contractor $a \in \Omega_i$, $la.$ needs to remove $a$’s skill contribution of $s$. If removing $a$’s contribution of skill $s$ makes $a$ do not contribute skills any more, $la.$ then will break the contract with $a$. Moreover, if $a$ is only connected with the team contractor $a$ and removing $a$ from team $T_i$ makes other team contractor $a \in \Omega_i$ be isolate, $a$ will also depart from $T_i$, which further degrades the estimated profit of team $T_i$.

Thus, given a redundant freelancer $a$, on one hand, even if $a$’s available skill $s \in as(a, R)$ has been satisfied by certain team contractor $a \in \Omega_i$, $a$ still needs to be accounted for. This is because the freelancer $a$ might require a lower payment for providing $s$. On the other hand, even if the available skill $s$ requires a lower payment than that of the existing team contractor (e.g., $a$) for providing $s$, team manager $la.$ should not replace the existing skill contribution $(a, s)$ by the cheaper skill contribution $(a_\kappa, s)$. This is because this kind of replacement might make existing team contractors depart. At first glance, $la.$ needs to consider all of the exponential $O(2^{\text{nr}(a, R)})$ possible skill combinations to
identify the optimal skill contribution of a. In the following, we propose an efficient polynomial algorithm (i.e., Algorithm 3) to find the optimal skill contribution of a that produces the maximal estimated benefit for \( l_a \).

**Algorithm 3. Offer to Redundant Freelancer** \((l_a, T, a_i, n, s, \tau)\)

1. Initialize \( q=1, H=\emptyset, \max = \text{Ep}(T, \tau), \text{th} = \text{div}(s, \tau)/|R_s|\).
2. Rank \( s_i \in \text{as}(a, R_s) \) such that \( c(a, s_i) \leq \cdots \leq c(a, s_{\text{max}}(a, R_s)) \).
3. While \( q < \text{ns}(a, R_s) \)
   4. If \( \text{Ep}(T, \tau) \leq \text{max} \)
      \( ns = \text{ns}(a, s) = \text{Ep}(T, \text{ns}(a, s), \tau) \).
   5. Else
      6. If \( c(a, s_i) \leq \text{th}, \text{then} H = \text{HU}(s_i) \).
      7. End for
      8. If \( \text{Ep}(T, \tau) \leq \text{max} \), then \( ns = \text{ns}(a, s) \).
      9. End Else
   10. \( q = q + 1 \).
   11. End while

If \( ns = \emptyset \), send \( O = \text{las}(T, a_i, n, s, \tau) \) to \( a_i \).

In Algorithm 3, Step 1, before negotiating with the redundant freelancer \( a_i \), the manager \( l_a \) first initializes some useful variables, such as \( \text{max} \), denoting the current team \( T \)’s estimated profit and the threshold \( \text{th} \), denoting how much will be improved on current team’s estimated value by contributing each fresh skill. This variable \( \text{th} \) is used to evaluate whether \( a_i \)’s skill is profitable. In Step 2, \( l_a \) first sorts \( a_i \)’s available skills \( \text{as}(a, R_s) \) in increasing order of working cost and then evaluates these skills in the order of their rank (Steps 3-15). In Step 4, we use \( \text{Ep}(T, \tau) \) to represent \( l_a \)’s estimated profit after the redundant freelancer \( a_i \) contributes skills \( \text{ns}(a, s) \). In this case that \( a_i \) is a redundant freelancer, \( \text{Ep}(T, \tau) \) can be computed by Algorithm 4, where \( l_a \) first adds \( a_i \)’s each contributed skill \( s_i \in \text{ns}(a, s) \) to the current skill contribution function \( \text{Cont}(\Omega, \kappa) \) (Step 1 of Algorithm 4). And then \( l_a \) updates team configuration \( T \) by removing existing team contractors’ overlapping skill contribution (Step 2 of Algorithm 4), removing the team contractors that do not contribute any skill after removing their overlapping skill contribution (Step 3 of Algorithm 4), and finally removing the team contractors that are isolate from the team \( T_i \) (Step 4 of Algorithm 4). If the estimated profit produced by the updated team \( T \) in not less than that of the previous team \( T \) with the estimated profit \( \text{max} \) (Step 4), add \( s_i \) to \( \text{ns} \) (Step 5). Otherwise, if \( a_i \)’s working cost for \( s_i \) is not greater than the minimum between the value \( \text{th} \) and the skill payment \( p(a, s_i) \) of the team contractor \( a_i \) (Step 7), then the only reason for the updated team \( T \) to \( \text{ns}(a, s) \) provides a lower estimated profit than that of the previous team \( T \) is that \( a_i \)’s skill contribution of \( s_i \) will make the contractor \( a_i \) and other contractors (if any) depart. These team contractors’ departure will make their contributed skills removed in \( T_i \), thereby decreasing the estimated profit of team \( T \) (\( \text{ns}(a, s) \)). Therefore, in the following steps (Steps 8-11), we try to compensate for these removed skills by using the remaining available skills \( \bigcup_{\text{sp}(a, R_s)} \text{sp}(a) \) of \( a_i \). First, in step 8, denoted by \( r_s \in \{ T \setminus \{ T \} \} \) as the removed skills because of \( a_i \)’s skill contribution of \( s_i \) and by \( \text{cs}(a_i, \text{ns}(a, s)) \) as the remaining available skills of \( a_i \) that can be used to compensate for the removed skills \( r_s \). Here, we can derive that \( \text{cs} \) is exactly what the current team \( T \) lacks. Then be similar to the scenario of negotiating with a fresh freelancer, we can utilize the idea of Algorithm 2 to identify the optimal compensation skills (i.e., \( \tilde{H} \)) from the available compensation skill set \( cs \) (Steps 9-11). If the value of \( \text{Ep}(T, \tau) \) by contributing the compensation skills \( H \) to team \( T \) is not less than \( \max \), \( l_a \) will consider hiring \( a_i \)’s skill \( s_i \) together with the compensation skills \( H \) (Step 12). Finally, if \( l_a \) finds it is beneficial to hire \( a_i \) by using its skills \( ns \) (i.e., \( ns \neq \emptyset \), \( l_a \) then sends an offer to \( a_i \) for skill acquisition (Step 16).

**Algorithm 4. Function (T, \text{cs})**

\( \text{cs} \): the set of skills that the team \( T \) hires and this function returns the team configuration after team \( T \) hires skill set \( cs \).

1. Manager \( l_a \) adds \( a_i \)’s each contributed skill \( s_i \in cs \) to the current skill contribution function \( \text{Cont}(\Omega, \kappa, \phi) \).
2. Remove the team contractor \( a_i \)’s overlapped skill contribution \((a_i, s_i))
3. Remove the team contractor \( a_i \) that does not contribute any skill after removing its skill contribution of \( s_i \).
4. Remove the team contractors (as well as their contributed skills) that are isolate in the team \( T \) after removing certain team contractors removed in Step 3.

Before presenting the optimization of Algorithm 3 (which is given in Theorem 2), we first give the following two lemmas that are useful to prove Theorem 2.

**Lemma 1.** Given a team \( T \) and a redundant freelancer \( a_i \) with the available skills \( Z = X \cup Y \) (\( X \neq \emptyset \) and \( Y \neq \emptyset \)), then \( \text{Ep}(T, \tau) = \text{Ep}(T, \tau) + \text{Ep}(T, Y) - \text{Ep}(T, X) \), where \( \text{Cont}(\Omega, \kappa) \) is the updated team of \( T \) by contributing the skills \( X \) to \( T \) (defined in Algorithm 4).

**Proof:** Based on the definitions of team manager’s estimated profit (i.e., \( \text{Ep} \)) and team updating function \( T \) (i.e., Algorithm 4), we can derive the estimated profit by contributing the skill set \( X \) to \( T \).

\begin{equation}
\text{Ep}(T, \tau) = \text{Ep}(T, \tau) + \{ \{ X \} \} - \{ \{ Y \} \} - \{ \{ X \} \} + \{ \{ X \} \}
\end{equation}

Therefore, we can conclude \( \text{Ep}(T, \tau) = \text{Ep}(T, \tau) + \text{Ep}(T, Y) - \text{Ep}(T, X) \). Here for simplicity, we omit the symbol \( \tau \).

**Lemma 2.** Given a team \( T \) and a redundant freelancer \( a_i \) with the available skills \( Z = X \cup Y \) (\( X \neq \emptyset \) and \( Y \neq \emptyset \)), then \( \text{Ep}(T, \tau) = \text{Ep}(T, \tau) + \text{Ep}(T, X) \).

**Proof:** According to Lemma 1, we can derive

\begin{equation}
\begin{aligned}
\text{Ep}(T, \tau) &= \text{Ep}(T, \tau) + \text{Ep}(T, X) - \text{Ep}(T, X) \\
&= \text{Ep}(T, \tau) + \text{Ep}(T, X) - \text{Ep}(T, X)
\end{aligned}
\end{equation}

Summing all of the above \( n \)-1 equations in (8), we have

\[ \text{Ep}(T, \tau) = \text{Ep}(T, \tau) - \sum_{i=1}^{n-1} \text{Ep}(T, X) \]

Now we are ready to give the optimization of Algorithm 3.

**Theorem 2.** Given a redundant freelancer \( a_i \) that \( l_a \) is negotiating with, Algorithm 3 returns the optimal skill contribution of \( a_i \) that produces the maximal estimated profit for \( l_a \).
Proof. Suppose that the skill set returned by Algorithm 3 is $\text{Alg}$, and the skill set returned by the optimum is $\text{Opt}$. In the following, we will prove that $\text{Opt}=\text{Alg}$. Denoted by $\Theta$ as the common contributed skills between $\text{Alg}$ and $\text{Opt}$, i.e., $\Theta=\text{Alg}\cap\text{Opt}$, by $\theta$ as the skills contributed by $\text{Alg}$ only, i.e., $\theta=\text{Alg}\setminus\Theta$ and by $\psi$ as the skills contributed by $\text{Opt}$ only, i.e., $\psi=\text{Opt}\setminus\Theta$. To prove $\text{Opt}=\text{Alg}$, we only need to prove $\theta=\psi=\emptyset$.

**Conclusion 1** $\psi=\emptyset$. We achieve this conclusion by proving that if the skills contributed only by $\text{Opt}$ (i.e., $\psi$) increase the estimated profit of the team of $T\otimes\Theta$, the team manager $\text{lm}_a$ can always find the skills $\psi$ that increases the estimated profit of the team $T\otimes\text{Alg}$. As described in Algorithm 3, the skills $\psi$ are first sorted in increasing order of their working cost such that $c(a,s)\leq\cdots\leq c(a,s_0)$ and then are evaluated one by one in their order. For the first skill $s_1\in\psi$, if Algorithm 3 does not select $s_1$, we have $\text{Ep}(T\otimes\{\text{Alg}\cup s_1\})<\text{Ep}(T\otimes\text{Alg})$ (**Assumption 1**), otherwise, Algorithm 3 will identify this beneficial skill. According to Algorithm 3, we can derive that there are three possible cases to support Assumption 1. **Case 1** $s_1\in\text{us} \& & \& \& c(a,s_1)<c(a,s_0)$. This is impossible, because it is profitable for $\text{Opt}$ to select the unsatisfied skill $s_1$, where $c(a,s)<c(a,s_0)$. **Case 2** $s_1\in\text{us} \& & \& \& c(a,s_1)=\min_{h\in\text{us}} c(a,s_0)\{ a_a \text{ is the team contractor that has agreed to contribute} s_1 \}$, which means the fact that $\text{Opt}$ is the optimal skill contribution. And **case 3** $s_1\in\text{us} \& & \& \& c(a,s_1)=\min_{h\in\text{us}} c(a,s_0)$, in this case, the reason that contributing $s_1$ does not increase the team profit $\text{Ep}(T\otimes\text{Alg})$ is that the skill contribution of $s_1$ makes other satisfied skills $\text{rs} \otimes \text{Alg} \cup s_1$ removed, thereby decreasing the estimated profit of team $T \otimes \text{Alg}$. Next, we will prove that case 3 never happens. If the skill contribution of $s_1$ to team $T \otimes \text{Alg}$ makes other satisfied skills $\text{rs}$ removed, then by Steps 9-12, Algorithm 3 can always find the optimal compensation skills $\text{cs} \otimes \{\psi_1\}$ for team $T \otimes \{\text{Alg} \cup s_1\}$ (which has been proved in Theorem 1). By Assumption 1, this contributions of skill $s_1$ associated with the compensation skills $\text{cs}$ does not increase the estimated profit of team $T \otimes \text{Alg}$, i.e., $\text{Ep}(T \otimes (\text{Alg} \cup s_1))<\text{Ep}(T \otimes \text{Alg})$.

The inequality (9) is derived from Lemma 2. On the other hand, from the view of Opt, we have $\text{Ep}(T \otimes \Theta)$

$\text{Ep}(T \otimes (\Theta \cup \{s \in \text{us}\}))=\text{Ep}(T \otimes (\Theta \cup \{s \in \text{us}\}))=\text{Ep}(T \otimes (\{\psi \}|\text{us}))<\text{Ep}(T \otimes (\{\psi \}|\text{us}))=\text{Ep}(T \otimes (\{\psi \}|\text{us}))=\text{Ep}(T \otimes (\{\psi \}|\text{us}))<\text{Ep}(T \otimes (\{\psi \}|\text{us}))<\text{Ep}(T \otimes (\{\psi \}|\text{us}))=(\Theta \cup \{s \in \text{us}\})=\emptyset$, which contradicts inequality (11). Therefore, we can conclude that $\psi=\emptyset$.

**Conclusion 2**: $\theta=\emptyset$. The proof of this conclusion is similar to that for Conclusion 1 and due to the limitations of space, we omit the proof.

5.2 Freelancer Makes Response to the Team Manager

Once the freelancer $a$ receives the offer $O=\langle a, T_a, a, ns \rangle$ from team manager $\text{lm}_a$, $a$ assesses this offer and make a response to $\text{lm}_a$. Before describing $a$'s response strategy, we first define the states (i.e., Fully-contracted, Partially-contracted and Free) of $a$ during social team formation.

**Definition 4. States of Agents.** During social team formation, the agent who initiates a task or has been a member of a fulfilled team is in state Fully-contracted; the agent who has been a member of a partial team is in state Partial-contracted; and the agent who neither initiates a task nor has joined a team is in state Free.

Agents in different states might have different response strategies. In the following we will present $a$’s optimal response strategies within different states.

**Case 1** $a$ is Free. In this case, $a$ will accept team $T_a$’s offer. This is because joining a team to work on team task can obtain some financial remuneration, which is a rather economical option compared to state in Free where there is no payment. Moreover, in the Free state, the payment $p(a, s)$ required for providing $a$’s skill service $s$ is just his public working cost $c(a, s)$, i.e., $p(a, s)=c(a, s)$.

**Case 2** $a$ is Partial-contracted. Assume that $a$ has been a member of a partial team $T_a$ and now at time step $\tau$, $a$ receives a new offer $O=\langle a, T_a, a, ns \rangle$ from a new team $T_a$. A dilemma is faced by $a$: breaking the contract with the original team $T_a$ by joining this new team $T_a$ or staying with the original team $T_a$ by rejecting the new offer $O(T_a, \tau)$. Here, to quantify how much $a$ gains by accepting or rejecting, the measure of estimated remuneration (per unit time) is utilized. On one hand, staying in the original team $T_a, a$ will obtain the estimated remuneration:

$$Er(a, T_a, \tau) = \frac{\text{Sr}(T_a, \tau) \sum_{a, a_i (\tau)} p(a, s)}{W_i}$$

The formula (12) indicates that $a$’s estimated remuneration (per unit time) $Er(a, T_a, \tau)$ is 1) directly proportional to the success rate, $\text{Sr}(T_a, \tau)$ of forming a complete team $T_a$, which is further positively related to the skills that have been satisfied and the remaining time for building team, i.e., $\text{Sr}(T_a, \tau)=(1-\text{us} \cup [\text{rs}] \otimes \text{Dl} \otimes \tau)$; 2) directly proportional to the revenue achieved by providing his skill service, i.e., $\sum_{a, a_i (\tau)} p(a, s)$; and 3) inversely proportional to the working time, $Wi$, that is required to accomplish the task $\kappa'$.

On the other hand, joining the new team $T_a$ that sends the new offer $O=\langle a, T_a, a, ns \rangle$, $a$ will obtain the estimated remuneration (per unit time):

$$Er(a, T_a, ns, \tau) = \frac{\text{Sr}(T_a, \tau) \sum_{a, a_i (\tau)} c(a, s)}{W_i}$$

where $\text{Sr}(T_a, \tau)=(1-\text{us} \cup [\text{rs}] \otimes \text{Dl} \otimes \tau)$ indicates the success rate of the new team $T_a$ that will be formed completely if $a$ agrees to contribute the skills $ns$. The value $\sum_{a, a_i (\tau)} c(a, s)$ indicates the revenue $a$ will achieve by joining $T_a$. The meanings of other terms are similar to those discussed in Equation (12).

As a rational freelancer that aims to maximize his own payment, $a$ prefers to join the team that can achieve a high estimated remuneration. Now we are ready to discuss the corresponding response strategy of $a$ by comparing the values of $Er(a, T_a, \tau)\tau$ and $Er(a, T_a, ns, \tau)$.

- **If** $Er(a, T_a, \tau)\tau < Er(a, T_a, ns, \tau)$, in the case that $a$’s estimated remuneration achieved from the original team $T_a$ is not less than that of the new team $T_a$, $a$ prefers to stay in the original team $T_a$ and reject the offer of $T_a$.

- **If** $Er(a, T_a, \tau)\tau > Er(a, T_a, ns, \tau)$, in this case, intuitively, $a$ should break the contract with the original team $T_a$ and join the new team $T_a$. However, the team contractor $a$’s departure will make the original team $T_a$ be disconnect. This disconnection will make other team contractors isolate and depart, which will degrade the estimated
profit of $T_e$. Therefore, when considering to terminate the contract with his joined team $T_e$, $a_i$ should attempt to propose whether the team manager $Ia_e$ is willing to improve the payments of the contributed skills to persuade him to stay with the team. Here, denoted by $cs$ as $a_i$'s contributed skills to his joined team $T_e$, i.e., $cs(a_i, T_e) = \{s_i|s_i \in Cont(T_e, \mathcal{K}_e')\}$. Then, to achieve as high estimated remuneration as that would be achieved from the new team $T_e$, $a_i$ will propose to improve the payment of each contributed skill $s_i \in cs$ to

$$ p(a_i, s_j) = \frac{W_{t, p, a}}{S_{r, T_e}} \cdot \frac{p(a_i, s_j)}{\sum_{s_k \in cs(a_i, T_e)}} $$

where $Er(a_i, T_e, ns, \tau)$ is the estimated remuneration that would be achieved from the new team $T_e$ computed by Equation (13). The values $p(a_i, s_j)$ and $p(a_i, s_j)$ are the original and adjusted skill payment, respectively. After computing the adjusted payment, $a_i$ will send a payment improvement response $R = \langle p(a_i, s_j) \rightarrow p(a_i, s_j)|s_i \in cs(a_i, T_e)\rangle$ to the original team's manager $Ia_e$.

**Case 3) $a_i$ is Fully-contracted.** If $a_i$'s joined team $T_e$ has hired enough contractors such that they can satisfy all of the skill requirements of team task $\kappa$ and has started task execution, $a_i$ will reject any new offer until task $\kappa$ has been finished. This is because each contractor can only make contract with one team and breach the current complete fulfilled team will suffer tremendous monetary penalty or reputation loss [18][47].

### 5.3 Team Manager Makes Confirmation to the Freelancer

As the manager of $T_e$, $Ia_e$ might receive two kinds of responses: 1) the payment improvement response from his team contractors because of other teams' competition; and 2) the acceptance or rejection response from the freelancer. Next we will discuss the corresponding confirmation strategy of $Ia_e$ when he confronts these two kinds of responses.

**Case 1) For the contractor $a_i$ that proposes to improve skill payment $\langle p(a_i, s_j) \rightarrow p(a_i, s_j)|s_i \in cs(a_i, T_e)\rangle$ (cs represents the skills that $a_i$ agrees to provide to his joined team $T_e$), the team manager $Ia_e$ will compare the estimated profit of team profile $Ep(T_e, \{p(a_i, s_j) \rightarrow p(a_i, s_j)|s_i \in cs(a_i, T_e)\}, \tau)$ by improving $a_i$'s skill payment and the estimated profit $Ep(T_e, \{\varnothing|a_i\})$ of the team profile $T_e \backslash \{a_i\}$ by removing the team member $a_i$. If $Ep(T_e, \{p(a_i, s_j) \rightarrow p(a_i, s_j)|s_i \in cs(a_i, T_e)\}, \tau) \geq Ep(T_e, \{\varnothing|a_i\}, \tau)$, $Ia_e$ will accept $a_i$'s proposal on skill payment improvement. Otherwise, he will reject $a_i$'s proposal.

**Case 2) For the freelancer $a_i$ that sends the acceptance or rejection response, the team manager $Ia_e$ needs to make some agreements for this response. On one hand, if $a_i$ accepts $Ia_e$'s offer $O = \langle Ia_e, T_e, a_i, ns \rangle$, $Ia_e$ first makes a tentative contract with $a_i$ on skill contribution $ns$ and skill payment. A tentative contract means that before $T_e$ is formed completely, team contractor $a_i$ can adjust its skill contribution to $T_e$ as well as can propose to improve the skill payment. Furthermore, if $a_i$'s skill contribution leads to a complete fulfilled team for task $\kappa$, all tentative contracts of this team will become a final contract such that team contractors cannot breach the contract unilaterally until $\kappa$ is finished successfully. After making the contract with $a_i$, $Ia_e$ then updates team configuration by adding the skill contributions $\bigcup_{a_i \in Ia_e(s, p(a_i, s_j))} Cont(T_e, \mathcal{K}_e, P_e)$, removing the overlapped skill contributions provided by other team contractors, removing the team contractors that do not contribute skills anymore and removing those isolate team contractors as well as these contractors' skills. On the other hand, if $a_i$ rejects $Ia_e$'s offer $O = \langle Ia_e, T_e, a_i, ns \rangle$, $Ia_e$ does nothing.

### 5.4 Negotiation Algorithm

Up to this point, we have described the negotiation process between a team manager and a freelancer. A formal description of this negotiation mechanism that makes an agreement on skill provision and skill provision payment between team manager $Ia_e$ and freelancer $a_i$ is shown in Algorithm 5. Algorithm 5 is implemented in a distributed manner such that each requester/worker invokes the negotiation mechanism independently.

**Algorithm 5. Negotiate($Ia_e, a_i, \alpha$)**

**Stage 1:** Manager $Ia_e$ calls Algorithm 2 (i.e., $a_i$ is a fresh freelancer) or Algorithm 3 (i.e., $a_i$ is a redundant freelancer) to generate the offer $O = \langle Ia_e, T_e, a_i, ns \rangle$ to $a_i$. 

**Stage 2:**

1) If $a_i$ is Free
2) Freelancer $a_i$ sends response $R = \langle \text{acceptance}\rangle$ to $Ia_e$.
3) If $a_i$ is Fully-contracted
4) Freelancer $a_i$ sends $R = \langle \text{rejection}\rangle$ to $Ia_e$.
5) If $a_i$ is Partially-contracted
6) If $Er(a_i, T_e, \tau) \geq Er(a_i, T_e, \kappa)$

**Stage 3:** If $R = \langle \text{acceptance}\rangle$, $Ia_e$ makes a contract (tentative or final) with $a_i$ and updates team configuration.

### 6 Experimental Validation and Analyses

In Section 6.1, we compare the proposed social team formation model with the traditional distributed models on social welfare and team formation time. In Section 6.2, we compare our model with the benchmark centralized model on social welfare.

#### 6.1 Comparing with the Traditional Distributed Social Team Formation Models

**6.1.1 Experiment Setting**

A Dataset. We collect the data on 764 workers registered in the crowdsourcing website Upwork, upwork.com. For each worker, we record two kinds of personal information: 1) the set of skills he owns and 2) the salary in dollars per hour he requires. Through analyzing these workers’ in-
formulation, we observe that there are 20 kinds of skills available by these workers, the skill number of each worker distributes in the range $[1, 13]$ and the cost of providing each skill service distributes in $[0.5, 90]$ randomly. These collected workers are interconnected by three typical social network structures such as Random network (Random), Small-World network (SMW) and Scale-Free network (SF).

B. Parameter setting. By referring to the related definition on parameter setting in [26], we range other parameters involved in the social team formation process as follows. At each time step, a task arrives at the system with a probability $\lambda=0.1-0.9$. The period required to accomplish a task (i.e., $W_{t}$) is drawn from $U(20,40)$ ($U(a,b)$ returns the value in the range $[a,b]$ randomly) and the deadline of each task (i.e., $D_{t}$) is distributed in $[It, It+50]$, which must be greater than the task’s initiation time $It$. The value associated with each task (i.e., $\omega_{t}$) is distributed in $U(200, 400)$ and the discount rate is $0.8$. The discount rate on time decay (i.e., $\delta$) is distributed in $[0.2, 1.6]$. For clarity, we give a detail description of the used variables in Table 2.

C. Comparison models and performance metrics. We compare the designed social team formation model (Our model) with other two distributed models, i.e., the greedy model (Greedy) and contract net model (CN).

- **Greedy Model (Greedy)** [28]. In this model, the task manager evaluates the skills of the negotiated worker $a$ one by one and once he finds $a$ has lower working cost of providing $s_i$ than that of certain team member $a\in\Omega$, i.e., $c(a, s_j) < c(a, s_i)$, the manager replaces the skill contribution $(a, s_j) \leftarrow (a, s_i)$ by using $a$’s skill service $s_i$. On the other hand, the workers only join the team where they can achieve high payment. Compared to this model, our model’s advantage of considering the combinational skill contribution could be revealed.

- **Contract Net Model (CN)** [31]. In this model, the task manager only selects the workers that have the skills the team lacks and the workers only join the team where they can achieve high payment. Since the negotiated workers always contribute the team’s lacked skills, there is no conflict between the negotiated worker and team contractors, therefore the formed team is always connected. Compared to this model, our model’s advantage of negotiating the working cost could be revealed.

- We evaluate the performance of these models through social welfare ($SW$) and the time used for team formation. $SW$ is defined as the sum of all managers’ profits, i.e.,

$$SW = \sum_{t \in CT} profit(I_{a_t}) = \sum_{t \in CT} (v_{\kappa}(c_t, Re(T_{t}))$$

where $CT$ denotes the set of tasks that are completed successfully and $c_t$ is the completion time of task $\kappa$ and $Re(T_{t})$ indicates the total remuneration paid to team workers. We perform a series of experiments to validate our model: we first test the effect of network degree and task discount rate on the distributed social team formation models’ social welfare and team formation time in Section 6.1.2A and 6.1.2B respectively. In Section 6.2, we test the social welfare of our model by comparing our model with the benchmark centralized model. Moreover, in Appendix A3 an A4, we also test the robustness and scalability of our model. All the results plotted in the figure are recorded by averaging over 50 instances.

6.1.2 Experimental Results

A. The Effect of Network Degree on Social Welfare and Team Formation Time

Fig. 1 shows the social welfare (Fig. 1a–Fig. 1c) and the team formation time (Fig. 1d–Fig. 1f) achieved by our model, CN and Greedy on network degree, where task discount rate is set to 0.8. The network degree is computed as the average degree of all workers. From Fig. 1, we have the following observations.

1) Within all network structures from Fig. 1a–Fig. 1c, our model produces larger social welfare than the other two distributed Greedy and CN models. This can be explained from two perspectives: i) As shown in Fig. 1d–Fig. 1f, our model uses less time on team formation. Because the task value is discounted over time, the less time used for team formation, the earlier the task will be completed, and then the larger task profit will be produced. ii) Compared to CN model, the team manager in our model negotiates with the workers on working cost, which can help the manager build team of inexpensive workers. Although the team manager in Greedy also evaluates the worker’s working cost, its large team formation time prevents Greedy producing high task profit.

2) The social welfare produced by Greedy performs much worse in the networks of Scale-Free (SF) compared to the social welfare in Random and Small-Word (SMW). This can be explained from the perspective of team formation time. Compared Fig. 1d and Fig. 1e with Fig. 1f, we
can observe that the team formation time of Greedy in SF is larger than the team formation time of Random (or SMW). However, why does Greedy generate larger team formation time in SF than that in Random (or SMW)? We can explain this phenomenon by the network property. Table 3 shows the three typical network properties, such as network diameter (Dia), average shortest path length (Aspl) and clustering coefficient (Clu) ([50]) gives a detail illustration of these properties. From Table 3, we can find that the SF network have shorter Dia and Aspl than those of Random (or SMW). The shorter Dia and Aspl indicate that the workers can interact with others more easily. Now we will explain why Greedy generates the larger team formation time in SF than that in Random (or SMW). On one hand, in Greedy, as long as a worker has the skills the team requires, the team manager would negotiate with the worker for skill provision, leading to the manager consume much time on making a contract with a freelancer and breaking a contract with certain existing contractor. And because of the shorter Dia and Aspl, this repetitive action of making and breaking contracts will happen more frequently, which will consume much more team formation time. While our model negotiates with the worker if and only if he can provide the available skills with cheaper working cost and CN only negotiates the worker that can provide the skills the team current lacks. Therefore, Dia and Aspl have not much effect on our model and CN model.

3) Within all the networks, as the network degree increases, our model, Greedy and CN will consume much more time on team formation (Fig. 1d–Fig. 1f). However, the social welfares of our model, Greedy and CN increase gradually. The potential reason is that on one hand, the larger the network degree, the managers will have more social neighbors, and then they will have higher probability to negotiate with the cheap workers, leading to an increase of their profit. On the other hand, the more social neighbors can make these managers access different kinds of skills, thereby increasing the success rate in task completion, which will also increase system social welfare.

### B. The Effect of Task Discount Rate on Social Welfare and Team Formation Time

Fig. 2 shows the social welfare (Fig. 2a–Fig. 2c) and team formation time (Fig. 2d–Fig. 2f) of these models on different task discount rates, where network degree is 8. From Fig. 2, we have the following two findings. 1) Within all the networks, the team formation time of Greedy and CN stay nearly invariable, while surprisingly, our model decreases with the increase of task discount rates (Fig. 2d–Fig. 2f). This can be explained as follows: on one hand, in our model, the manager’s decision on hiring workers depends on the remaining time for team formation. This means that when the task discount rate becomes larger, the threshold $\theta = E(T_k, \gamma)/|R_k|$ which is used to evaluate whether a skill is worth hiring, decreases as well. And this lower threshold will increase the probability of workers to be hired, thereby resulting in a fast team formation. While in CN and Greedy, the team manager’s decision on hiring a skill is time independent and when the task discount becomes larger, the team formation time stays invariable. 2) Within all the networks, the social welfare of our model, CN and Greedy is negatively proportional to task discount rate (Fig. 2a–Fig. 2c). This finding is intuitive because the larger the task discount rate, the less task profit will be produced.

### 6.2 Comparison with the Benchmark Centralized Optimal Approach

To test the efficiency of our model, we compare our model with the benchmark centralized model [17], where there exists a central controller maintaining information on all of the agents’ social connections and working costs. When a task submitted by a requester, the controller can build a team of connected workers that have the least working
costs. This is an ideal model, which is impractical, but it can be used as an upper bound of system performance.

Experiment setting. This experiment setting (including the workers and social network) is similar to the setting in Section 6.1, a notable exception is that because the benchmark centralized model does not consume any team formation time, here we set the task discount rate $\delta = 0$ for the correct comparison. Moreover, in this kind of experiment, we only consider the effect of network degree on our model and this centralized model’s social welfare performance.

Experiment results. The comparison results are shown in Fig. 3, from which we can observe that 1) both of the centralized model and our model’s social welfare increase with the network degree (Fig. 3a) and 2) In all of the experiments, although the benchmark centralized optimal model produces more social welfare than our model’s, our model preserves at least 70 percent of social welfare of the benchmark centralized optimal model (Fig. 3b), which can validate the efficiency of our model’s efficiency on producing social welfare to some extent.

7 CONCLUSIONS AND FUTURE WORK

In real-world social team crowdsourcing markets, the requester aims to build a professional and collaborative team for task completion, and the worker aims to join the desirable team for its own profit maximization. Being aware of the dynamics, uncertainty, heterogeneous working cost, team competition and time factor during social team crowdsourcing, we first develop a set of heuristics connecting these inter-dependent factors indirectly to approximate the requester’s and worker’s objective functions. Then to satisfy the requester and worker’s conflict objectives, we propose a decentralized team formation model for the requester to negotiate with the workers on skill provision and skill provision cost. These negotiation strategies are useful for real-world requesters, since this mechanism closely models real-world crowdsourcing markets (i.e., worker’s selfish nature). Theoretical analyses ensure that the requester can always recruit the worker’s optimal skill provision that can yield the maximal profit for the requester. Moreover, we also conduct a series of experiment to highlight the efficiency, robustness and scalability of the proposed social team formation model. The experimental results determine that compared to the optimal centralized model, our model can preserve desirable percentage of social welfare. Moreover, compared to the traditional decentralized approaches, the proposed team formation approach not only builds a feasible (i.e., professional and collaborative) team of inexpensive workers, but also reduces social team formation time.

In the current study, the requesters and workers are assumed to break the partial contract without suffering any penalty. However, in real-life scenarios, breaking a contract unilaterally will always suffer certain penalty such as monetary compensation or reputation loss [26][42]. Therefore, in the future, it is more practical to consider the decision penalty during negotiation and investigate how to optimize the penalty strategy.

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