Truthful Team Formation for Crowdsourcing in Social Networks

(Extended Abstract)

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ABSTRACT

We study complex task crowdsourcing by team formation in social networks (SNs), where the requester wishes to hire a group of socially close workers that can work together as a team. The workers are selfish that can manipulate the crowdsourcing system by providing unreal private information, which will discourage other workers from participation and is unprofitable for the requester. This paper develops two efficient truthful mechanisms for the small- and large-scale social team crowdsourcing applications, to guarantee each worker's profit is optimized by behaving truthfully.

Keywords

Mechanism design, team crowdsourcing, social networks

1. INTRODUCTION

This paper studies team/group crowdsourcing, where the requester wishes to hire a group of workers that can work together as a team for the complex task completion [1]. Social networks (SNs) provide good opportunities to address the team crowdsourcing problem, where the social connections among workers are often good indicator of effective collaboration [3]. This social team crowdsourcing can be implemented by a reverse auction model, where the requester, first announces his task's skill requirements and each worker then bids to sell his skill services associated with his working cost and social relationships. Based on the workers' bids, the crowdsourcing system aims to form the optimal feasible (i.e., professional and collaborative) team of workers that requires the minimal working cost for the requester. However, the workers are selfish that can lie about their private information [2], which will discourage other workers from participation and increase the requester's budget. Therefore, it is essential to design truthful social team crowdsourcing mechanisms, where each worker's optimal bidding strategy is to declare his private information truthfully [5].

Directly extending existing social team formation approach [3] is not applicable, because it cannot guarantee truthfulness. Moreover, the VCG type mechanism [4], well-known for guaranteeing truthfulness while maximizing social welfare, is not applicable neither, because this social team crowdsourcing problem is NP-hard. Against this background, we propose a novel fixed-parameter time truthful mechanism for the small-scale applications, which works by first transforming a social network to a binary tree network, and then a dynamic programming-based optimal mechanism is developed in the transformed tree, and a novel polynomial time mechanism for the large-scale applications, which works by selecting the team members greedily based on their social structure as well as on their skills and working cost.

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2. PROBLEM DESCRIPTION

There is a task T=<V_T,O_T>, where V_T is the profit of T and $O_T = \{s_1, s_2, \ldots, s_k\}$ is T's skill requirements. We model the team crowdsourcing paradigm as a reverse auction framework, where the requester announces its task skill requirements O_T and then each worker a_i submits its bid B_i=(R_i,$\tilde{c}_i$,N_i), consisting of the skills $R_i = \{s_1, s_2, \ldots, s_l\}$ it can provide, the working cost $\tilde{c}_i$, representing the minimum reward a_i wishes to be paid and its neighbors/collaborative partners N_i. After receiving these workers' bids, the crowdsourcing platform can determine the workers' social network SN=<A,E>, where A=$\{a_1, a_2, \ldots, a_n\}$ denotes the collection of agents/workers and $\forall(a_i, a_j) \in E$ represents the existence of a connection between a_i and a_j.

A mechanism $\mathcal{M} = (X, Pay)$ consists of a team formation function X and a payment function Pay. The team formation function $X = \{x_1, x_2, \ldots, x_n\}$ determines whether an agent a_i is selected as a winner (x_i=1) or not (x_i=0). Let $S = \{a_i | x_i = 1\}$ be the winner team. To complete task T successfully, the formed team S must satisfy 1) ***Professional*:** each skill $s_j \in O_T$ must be satisfied by at least one team member and 2) ***Collaborative*:** the subgraph induced by the team members S must be connected. The payment function $Pay = \{p_1, p_2, \ldots, p_n\}$ determines the reward paid to each winner. The utility u_i of each winner $a_i \in S$ then is u_i=p_i-c_i, equals p_i-$\tilde{c}_i$ under truthful bidding. The requester's utility then is $u_T = V_T - \sum_{a_i \in S} p_i$. The social welfare W_T of the crowdsourcing system is the sum of the requester's utility and the agents' aggregate utility, i.e., $W_T = V_T - \sum_{a_i \in S} p_i + \sum_{a_i \in S}(p_i - \tilde{c}_i) = V_T - \sum_{a_i \in S} \tilde{c}_i$. This paper considers maximizing social welfare.

Each agent is strategic for maximizing its own utility, such an objective of maximizing social welfare alone will encourage the strategic agents to lie about its working cost information [1]. This paper designs truthful mechanisms to elicit the agents to report their working cost truthfully.

[1]Regarding why workers cannot manipulate their skills and social relationships: Over-report the skills that a worker cannot provide might make task failure, which can be detected during task execution. Each social relationship depends on two workers and once a worker reports the nonexistent relationships, it can also be detected.

3. TRUTHFUL SOCIAL TEAM CROWDSOURCING MECHANISMS

Towards Small-Scale Applications. The small-scale-oriented mechanism consists of the following three phases.

- **Tree Network Extraction**. We first extract a tree network Γ from the original network SN=<A,E> such that Γ preserves as much social connection information as that in SN. The proposed tree extraction algorithm is $\frac{1}{D}$-approximation on maximizing network closeness, where network closeness $CL(SN)$ is defined as how socially close these agents A connect with each other in network SN, i.e., $CL(SN)$=$\sum_{a_i \in A} \sum_{a_j \neq a_i} \frac{1}{d(a_i,a_j,SN)}$ and D is the diameter of the network SN.
- **Binary Tree Transformation**. We then transform the tree Γ to the binary tree Γ^{β}. We start from the root agent a_r of Γ. Suppose that a_r has l children $\{a_1, a_2, \ldots, a_l\}$ and we replace a_r and a_r's children with a binary tree of depth $\lceil log_2 l \rceil$+1, where the root agent still is a_r and the leaf agents are $\{a_1, a_2, \ldots, a_l\}$. The newly-added auxiliary agents between a_r and $\{a_1, a_2, \ldots, a_l\}$ in this binary tree neither have any skill nor require any working cost. Moreover, once their parent agent is selected as a winner, they will also be selected as winners. This transformation repeats recursively for all of the other none-leaf agents down a_r and finally the binary tree Γ^{β} is constructed.
- **Optimal Truthful Mechanism in Binary Tree**. For each agent a_i in Γ^{β}, let $S(a_i, 1, U)$ be the optimal team formed to satisfy the skills $U \subseteq O_T$ in the subtree $\Gamma^{\beta}_{a_i}$, where a_i is selected as a winner. Let $W(a_i, 1, U)$ be the welfare of $S(a_i, 1, U)$. Similarly, let $W(a_i, 0, U)$ be the welfare of the optimal team $S(a_i, 0, U)$ formed in $\Gamma^{\beta}_{a_i}$ without selecting a_i. Let $l(a_i)$ and $r(a_i)$ denote a_i's left and right child. The following dynamic programming is then implemented recursively for each agent a_i.

$$W(a_i,1,U) = \max \begin{cases} W(r(a_i),1,U \backslash R_i) - \tilde{c}_i; \\ W(l(a_i),1,U \backslash R_i) - \tilde{c}_i; \\ \max\limits_{U' \subseteq U \backslash R_i} W(r(a_i),1,U')+ \\ \quad W(l(a_i),1,U \backslash U') - \tilde{c}_i - V_T. \end{cases} \quad (1)$$

and

$$W(a_i,0,U) = \max \big\{ W(r(a_i),1,U), W(r(a_i),0,U), W(l(a_i),1,U), W(l(a_i),0,U) \big\}. \quad (2)$$

The initial conditions of this dynamic programming approach are: $W(\emptyset,0,\emptyset)$=V_T, and $\forall a_i \in A$, $W(a_i,1,\emptyset)$=V_T-$\tilde{c}_i$ and $\forall U \neq \emptyset$, $W(\emptyset,0,U)$=0. Finally, the optimal team formed in Γ^{β} is returned from function $\max\{W(a_r,0,O_T)$, $W(a_r,1,O_T)\}$. Denoted by the optimal team and its welfare as S_{Γ_β} and W_{Γ_β}, then the VCG-based threshold payment p_i for each winner agent $a_i \in S_{\Gamma^\beta}$ is defined as:

$$p_i = (W_{\Gamma^\beta} + \tilde{c}_i) - \max\{W_{\Gamma^\beta_{r(a_i)}}, W_{\Gamma^\beta_{l(a_i)}}, W_{\Gamma^\beta \backslash \Gamma^\beta_{a_i}}\} \quad (3)$$

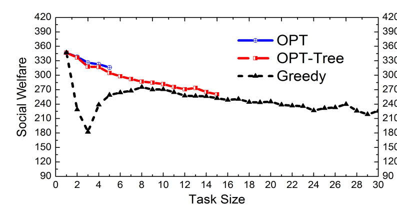
The value $W_{\Gamma^\beta_{r(a_i)}}$=$V_T$-$\sum_{a_j \in S_{\Gamma^\beta_{r(a_i)}}} \tilde{c}_j$ is the welfare of $S_{\Gamma^\beta_{r(a_i)}}$, where $S_{\Gamma^\beta_{r(a_i)}}$ is the optimal team returned from a_i's right subtree $\Gamma^\beta_{r(a_i)}$. The other terms have the similar meanings.

Towards Large-Scale Applications. We present a polynomial time truthful mechanism for the large-scale applications, which includes the monotonously greedy team formation algorithm and the threshold payment algorithm.

- **Greedy Team Formation**. We first locate the agent a_i that has the largest marginal contribution-per-cost value as team root, where agent a_i's marginal contribution-per-cost value with respect to the skill set $U \in O_T$ is $\epsilon(a_i, U)$= $|U \bigcap R_i|/\widetilde{c}_i$. Then, we select the team's best neighbor agent $a^* = \arg\max_{a_i \in I} \epsilon(a_i, O_T)$ with the largest marginal contribution-per-cost to join this team, where $I = \bigcup_{a_i \in Q} \{a_x | a_x \in N_i : \epsilon(a_x, O_T) > 0|\}$. We proceed to select the desirable team neighbors round by round until the team is professional.
- **Threshold Payment**. We adapt the threshold payment technique of Singer [5] to achieve the threshold payment p_{a_i} for each winner a_i such that p_{a_i} is the maximal value a_i can bid and still be selected by the greedy team formation.

4. EXPERIMENTS

We collect 928 workers data from a popular crowdsourcing website Guru. These workers are interconnected by the scale-free network structure. We also collect the tasks on Guru and observe that most of the tasks require less than 30 kinds of skills. For each task T, we assume its profit V_T is draw from the range [300, 400] randomly. We compare the proposed mechanisms, i.e., optimal mechanism in a tree network **OPT-Tree** and the greedy mechanism **Greedy** with the benchmark optimal mechanism **OPT** on social welfare.



The right figure shows the social welfare of the these mechanisms. For the small-scale applications where task size $k \leq 5$, OPT-Tree performs very close to OPT. Greedy performs worse when task size grows up from 1 to 3. However, as task size ranges from 3 to 8, the social welfare of Greedy grows up. Interestingly, when task size becomes larger further, i.e., ≥8, the social welfare of Greedy deceases again. Although OPT can always form the optimal team with the maximum social welfare, its exponential time complexity on task size limits itself to be applicable to the small-scale applications (i.e., $k \leq 5$) only, while Greedy scales well to various scale applications.

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