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.

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

and

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

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:

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

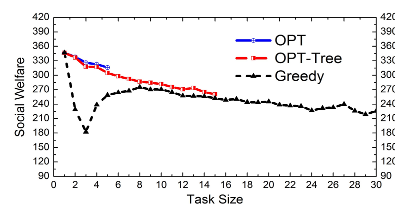
The value $W_{\Gamma^\beta_{r(a_i)}}$=$V_T$-$\sum_{a_j \in S_{\Gamma^\beta_{r(a_i)}}} \tilde{c}_j$ is the welfare of $S_{\Gamma^\beta_{r(a_i)}}$, where $S_{\Gamma^\beta_{r(a_i)}}$ is the optimal team returned from a_i's right subtree $\Gamma^\beta_{r(a_i)}$. The other terms have the similar meanings.

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., $\geq$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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