Towards Effective Developer Recommendation in Software Crowdsourcing

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Abstract—Crowdsourcing has attracted increasing attention from both industry and academia since it was proposed. Now a lot of work is finished by crowdsourcing, such as logo design, website promotion, industrial design, copywriting, software development, translation and image annotation. Although software crowdsourcing achieves positive results in practice, we still face a challenge of assigning suitable developers to specific tasks. In this paper, we propose a novel approach that recommends developers. In particular, our approach supports: comprehensively measuring the tasks and developers in software crowdsourcing, and recommending developers on the basis of the developer-task competence, task-task similarity, and soft power.

Keywords: software crowdsourcing; developer recommendation; developer model

I. INTRODUCTION

Crowdsourcing is the act of taking a job traditionally performed by a designated agent (usually an employee) and outsourcing it to an undefined, generally large group of people in the form of an open call [1]. It has attracted great attention from both industry and academia. Now a lot of work is finished by crowdsourcing, such as logo design, website promotion, industrial design, copywriting, software development, translation and image annotation. Meanwhile, when employing crowdsourcing to accomplish software development tasks, we face a challenge of assigning suitable developers to specific tasks. Up to now, most development tasks are assigned in a form of bidding or competition. As a result, much human effort is wasted. Although many attendees would compete for the tasks, some tasks are not well accomplished, since they are not assigned to the most suitable developers.

To the best of our knowledge, most crowdsourcing platforms still rely on crowdsourcers to assign tasks. As a result, crowdsourcers have to spend much time in matching the tasks and the developers. To make things worse, a crowdsourcer is usually biased, since he or she may not have a thoroughly understanding of all developers.

To address the above problem, in this paper, we propose a novel approach that recommends suitable developers to tasks in software crowdsourcing. In particular, our approach uses two models to measure tasks and developers, respectively. For given tasks and developers, our approach computes their developer-task competences, task-task similarities, and soft powers, and recommends the best candidate(s) to each task.

II. RELATED WORK

Most research on crowdsourcing is concentrated on several topics, including how to apply crowdsourcing [2, 3], how to control the quality of crowdsourcing [4, 5], how to allocate crowdsourcing tasks.

Few researchers discuss how to recommend workers. In particular, I. Boutis and V. Kalogeraki [6] present REACT that schedules tasks for the crowd under time constraints. It collects worker profiles (e.g., real-time computational capabilities) and dynamically assigns tasks to suitable workers. Research [7] advocates replacing “pull” with “push” for task allocation to achieve higher quality. They analyze the social network of the crowd to gain better performance. E. Simpson and S. Roberts [8] present an information-theoretic approach to assigning workers to specific tasks in crowdsourcing using a Bayesian method. Research [9] proposes to use auctions to map tasks to workers. They organize auctions taking into account price and the suitability of workers estimated based on generated user profiles.

Meanwhile, the existing researches mainly focus on simple tasks, e.g., image annotation, and most researchers just do theoretic research or provide their frameworks. In addition, most of their researches are not domain specific and not complete. They are not able to be applied to software crowdsourcing. We provide an approach to recommend suitable developers to software development tasks.

III. TASK MODEL AND DEVELOPER MODEL

Our approach first abstracts software development tasks and developers with two models. The models measure the tasks and developers quantitatively and thus help establish matching relations between them.

A. Task Model

We model a task as [ID, software category, software size, ability requirement(s), enrolled deadline, task deadline, budget, location].

Each task is associated with one or more ability requirements, and each ability is composed of three sub-attributes: “type” and “name” are the type and name of an

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ability requirement; and “level” represents the required degree of skills. For example, [coding language, Java, J] indicates that the task requires a Java programmer at a level of “3”.

A task has other attributes: “software category” is the kind of the software; “software size” is the size of the software, and it could be an estimated value given by the crowdsourcer for the developers to estimate a reasonable delivery time; “enrolled deadline” is the deadline for the enrollment; and “task deadline” is the deadline to complete the task. Each task is also associated with “budget”, working “location”.

### B. Developer Model

A developer model defines the attributes of developers. As shown in Table I, the developer model has the key attributes of a developer in software crowdsourcing.

“Base information” includes personnel information of a developer: “address” determines whether a developer can be assigned when a task has the location requirement; “education background” and “work experience” are strong reference; “service range” indicates what kinds of software a developer is able to develop.

The “ability and development experience” attribute helps crowdsourcer decide whether or not a developer is competent for a task: “ability” is similar to the ability requirement in the task model; “development experience” shows the history of a developer in completing software tasks in the crowdsourcing platform.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Sub-attribute</th>
<th>Field</th>
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<tbody>
<tr>
<td>ID</td>
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<tr>
<td>Base information</td>
<td></td>
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<tr>
<td>Address</td>
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<tr>
<td>Education background</td>
<td>Degree</td>
<td>Major</td>
</tr>
<tr>
<td>Work experience</td>
<td>Job</td>
<td>Duration</td>
</tr>
<tr>
<td>Service range</td>
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<tr>
<td>Ability and development experience</td>
<td>Ability</td>
<td>Name</td>
</tr>
<tr>
<td>Development experience</td>
<td>Date</td>
<td>Task</td>
</tr>
<tr>
<td>Credit and guarantee</td>
<td>Credit</td>
<td>Guarantee</td>
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<tr>
<td>Task-specific information</td>
<td>Task-ID</td>
<td>/</td>
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<tr>
<td></td>
<td>Bid price</td>
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<td></td>
<td>Delivery time</td>
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</table>

“Guarantee” is the guarantee provided by the developer. It is measured by the security deposit of a developer. “Credit” shows the status of development credits; after completing each crowdsourcing task, the developer is evaluated by the crowdsourcer. When calculating the credit of a developer, we consider these factors: if two developers have the same credit value (e.g., four stars), the one with more earnings is preferred (reward-related); the credit changes over time, thus a credit that is gained a long time ago has a weak effect (time-related).

The task-specific information is associated with the task that the developer is enrolled in. It includes task-ID, bid price, and promised delivery time.

### IV. Developer Recommendation

After a task is released, the crowd can browse and enroll for the task. We recommend the suitable developers among the candidates to tasks. The crowdsourcer selects developers to accomplish tasks according to recommendation list.

Employing our task model and developer model, we calculate the developer-task competence \((com_{dt})\), the task-task similarity \((sim_t)\) and the soft power of developers \((sfpwr)\), when recommending developers. In particular, the developer-task competence is used to measure whether a developer is competent for a task; the task-task similarity measures whether a developer has good similar work experience; and soft power reflects personal inner qualities, e.g., the credit of the developer. The three factors complement each other and are useful to match tasks and developers comprehensively. Based on them, we calculate recommendation index \((recindex)\) of a developer by (1). The larger \(recindex\) is, the higher the developer will be in the recommendation list.

\[
recindex = \alpha \times com_{dt} + \beta \times sim_t + \gamma \times sfpwr \tag{1}
\]

where \(\alpha + \beta + \gamma = 1\).

Next, we will introduce how to calculate the developer-task competence, the task-task similarity and the soft power.

### A. Developer-task competence

The developer-task competence \((com_{dt})\) measures whether a developer satisfies the requirements of a task. We calculates this value by

\[
com_{dt} = \frac{com_{dtc_1} \times com_{crg} \times (com_{bgt} + com_{loc} + com_{dbt})}{3} \tag{2}
\]

It is calculated from the software category competence \((com_{crg})\), the ability competence \((com_{dbt})\), the task deadline competence \((com_{dbt})\), the budget competence \((com_{bgt})\), and location competence \((com_{loc})\). The requirement of task deadline and category is compulsory, so in (2), \(com_{dbt}\) and \(com_{crg}\) act as multipliers. The formula of \(com_{dtc_1}, com_{crg}, com_{bgt}, com_{loc}\) and \(com_{dbt}\) are defined in Table II.

### B. Task-task similarity

If a developer has the development experience of similar tasks in the crowdsourcing platform, it will be an important
reference. As a result, we take the task-task similarity into account, and here defines a task as $T = \{\text{cat, typ, nam, lev, bgt}\}$. The $i$-th done task of a developer is presented with $T_i = \{\text{cat}_i, \text{typ}_i, \text{nam}_i, \text{lev}_i, \text{bgt}_i, \text{evl}_i\}$, where $\text{Cat}$, $\text{typ}$, $\text{nam}$, $\text{lev}$ and $\text{bgt}$ represent category, ability type, ability name, ability level, and budget, respectively; and $\text{evl}$ is the evaluation of a developer gotten from the crowdsourcer on this task.

We use Soft Jaccard’s Coefficient to measure the task-task similarity. Suppose that the evaluation value is an integer from 1 to 5, and the developer has $n$ finished tasks in total, $\text{sim}_{t_i}$ is calculated as follows:

$$\text{sim}_{t_i} = \max \left\{ \frac{|T \cap T_i|}{|T \cup T_i|} \cdot \frac{\text{evl}_i}{5} \right\} (i = 1, \cdots, n) \quad (3)$$

For $\text{cat}$, if $\text{cat} = \text{cat}_i$, they are regarded as intersected. Otherwise they are disjoint. So are $\text{typ}$ and $\text{nam}$. For $\text{lev}$, if the name of the $i$-th finished task is same with the task, and $\text{lev}_i$ is not lower than $\text{lev}$, they are regarded as intersected. Otherwise, they are disjoint. For $\text{bgt}$, if $1/5 \leq \text{bgt}_i \leq 5$, they are regarded as intersected. Otherwise, they are disjoint. When judging whether they are intersected or not, the condition is relaxed but not just depending on whether they are the same, so we call it Soft Jaccard’s Coefficient.

Although a developer has experience on a similar task, she/he may not do the task well. Considering this issue, when calculating the task-task similarity, our approach introduces the crowdsourcer’s evaluation, $\text{evl}_i$. All the similar tasks of a developer are calculated one by one, and we select the maximum value as $\text{sim}_{t_i}$.

C. Soft power

Some information of a developer are not reflected in $\text{com}_{dt}$ and $\text{sim}_{\text{dt}}$, e.g., the education background, work experience (not in software crowdsourcing), the credit, the guarantee of a developer, and the recent performance. We call these factors soft power. The composition of soft power is in Fig. 1. “$\text{sftpwr}$” is calculated by

$$\text{sftpwr} = \text{Bas} \times \text{Bas}_w + \text{CreGua} \times \text{CreGua}_w + \text{Rec} \times \text{Rec}_w \quad (4)$$

where $\text{Bas}_w + \text{CreGua}_w + \text{Rec}_w = 1$.

Now we will focus on “$\text{Bas}$”, “$\text{CreGua}$” and “$\text{Rec}$”.

1) “$\text{Bas}$”

The base information includes education background and work experience. The original “$\text{Bas}_0$” is calculated by (5).

Suppose that $\text{BASE}$ is the maximum value among all the enrolled developers, we divide “$\text{Bas}_0$” by $\text{BASE}$ to get “$\text{Bas}$”.

$$\text{Bas}_0 = \text{Edut} \times \text{Eduw} + \text{Wor} \times \text{Worw} \quad (5)$$

where $\text{Edut} + \text{Worw} = 1$.

The education background includes some [degree, major] tuples. “$\text{Edut}$” is calculated by (6). The work experience includes some [job, duration] tuples. “$\text{Wor}$” is calculated by (7). The score of degree (Degree) is 1, 2, 3 for bachelor, master, doctor respectively, and 0 for others. The score of major (Major) is 1 if the major is software-related, 0 otherwise, and so is the score of Job (Job). We divide the duration into several intervals, and the score of duration (Duration) is 1 if the

$$\text{Edut} = \text{Degree} \times \text{Degree} + \text{Major} \times \text{Major} + \text{Job} \times \text{Job} \quad (6)$$

$$\text{Wor} = \sum_{i=1}^{\text{Duration}} \text{Time}_i \times \text{Time}_i \quad (7)$$

$(\text{Time}_i)$ is the score of $\text{Time}_i$, and $(\text{Major})$ is the score of major.
developer’s work duration is in \([0, dura_1]\), 2 if it is in \([dura_1, dura_2]\), and so on.

\[
Edu = \sum_{i=1}^{n} Degree_i \times Major_i
\] (6)

\[
Wor = \sum_{i=1}^{n} Job_i \times Duration_i
\] (7)

2) “CreGua”

“CreGua” includes credit and guarantee. The original “CreGua” is calculated by (8). Suppose that CREGUA is the maximum value among all the enrolled developers, we divide “CreGua” by CREGUA to get “CreGua”.

\[
CreGua = Cre \times Cre_w + Gua \times Gua_w
\] (8)

where \(Cre_w + Gua_w = 1\)

“Cre” consists of two parts, good record and bad record. The weight of bad record \((Bad_{w})\) is greater than weight of good record \((Good_{w})\), because we punish those developers who have “bad” record, since employers would not deliver tasks to developers with bad credits. As the credit is time-related and reward-related, we introduce two parameters, \(T_{w}\) and \(Reward_{w}\). \(Time_{w}\) is calculated by (9), where \(T\) represents the months of age of the crowdsourcing platform, and \(\Delta\) represents the period (months) for the evaluation. This formula ensures that the longer from now, the less effect the credit record has. The effect won’t disappear. \(Reward_{w}\) is calculated using the similar method as “Duration” but the intervals are divided by reward. Since there can be many credit records, “Cre” of a developer is calculated by (10).

\[
Time_{w} = (T-\Delta) / T \times e^{-\Delta/T}
\] (9)

\[
Cre = \sum_{i=1}^{n} Good_{w_i} \times Time_{w_i} \times Reward_{w_i} \\
\approx \sum_{i=1}^{m} Bad_{w_i} \times Time_{w_i} \times Reward_{w_i}
\] (10)

“Gua” presents the guarantee of a developer. It is measured by the security deposit of a developer. “Gua” is calculated using the similar method as “Duration” but the intervals are divided by security deposit.

3) “Rec”

The recent performance often reflects the activeness of a developer. The more active a developer is, the more effort can be put in crowdsourcing. “Rec” is calculated by combing the number of finished tasks (“Tas”) of the developer, and earnings he/she has made (“Ear”) in the recent 3 months. The original “Rec_0” is calculated by (11), where “Tas” and “Ear” are calculated using the similar method as “Duration” but the intervals are divided by number of recent finished tasks and recent earnings, respectively. Suppose that REC is the maximum value of all enrolled developers, we divide “Rec_0” by REC to get “Rec”.

\[
Rec_0 = Tas \times Tas_w + Ear \times Ear_w
\]

where \(Tas_w + Ear_w = 1\)

V. EVALUATION PLAN

In the future, we will evaluate our approach in the three steps:

- Data preparation. We will fetch the most suitable data of accomplished software development tasks and do preprocessing.
- Parameter tuning. We will use greedy search to find the best value of the parameters in our approach.
- Precision comparison. We will recommend developers to tasks with our approach and compare the precision of our approach with a general approach.

VI. CONCLUSIONS

There exists a challenge of assigning the most suitable developers to specific tasks in software crowdsourcing. In this paper, we proposed an approach of recommending developers for software crowdsourcing. Firstly, our approach models the task and the worker comprehensively. Then our approach recommends developers for software crowdsourcing tasks based on their developer-task competence, task-task similarities and developer’s soft powers.

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