Coverage-Oriented Task Assignment for Mobile Crowdsensing

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Abstract—Crowdsensing tasks are usually described by certain features or attributes, and the task assignment essentially performs a matching w.r.t. worker or user’s preference on these features. However, existing matching strategy could lead to an misaligned task coverage problem, i.e., some popular tasks tend to enter workers’ candidate task lists, while some less popular tasks could be always unsuccessfully assigned. To ensure task coverage after the assignment, the system may have to increase their bidding costs to reassign such tasks, which causes a high operational cost of the crowdsensing system. To address this problem, we propose to migrate certain qualified workers to the less popular tasks for increasing the task coverage and meanwhile optimize other performance factors. By doing this, other performance factors, such as the task acceptance and quality, can be comparably achieved as recent designs, while the system cost can be largely reduced. Following this idea, this paper presents cTaskMat, which learns and exploits workers’ task preferences to achieve coverage-ensured task assignments. We implement the cTaskMat design and evaluate its performance using both real-world experiments and dataset driven evaluations, also with the comparison with the state-of-the-art designs.

Index Terms—Mobile crowdsensing; Task assignment; Task coverage; Preference

I. INTRODUCTION

DUE to the increasing popularity of mobile devices, crowdsensing [7] emerges as an important technique to coordinate a group of individuals to complete certain tasks collectively. It can serve as a powerful weapon to collect a large volume of useful data to enable many useful applications. For instance, in the urban traffic engineering [18][38], the concurrent multi-source data (e.g., pedestrian mobility, bus traffic, metro statistics, etc.) need to be collected for a metropolitan-scale human mobility exploring [37]. In this case, each type of data collection can be organized as a task, and workers (i.e., users) then participate according to their choices on certain data type(s). Finally, crowdsensing helps complete the data collection from the crowd. Besides, other typical applications include environment monitoring [31], event detection [20][21], traffic monitoring [16], social analysis [34], etc.

In general, crowdsensing assigns a set of tasks to a group of workers according to their preferences, and leverages the sensing and/or computing abilities from the workers’ mobiles to complete these tasks. Of course, the crowdsensing system will pay each worker as their returns [36]. During this process, one key metric to assess the performance of crowdsensing systems is the overall system cost [40]. Basically, each task can be described by certain features or attributes and each worker has her preferences to different task attributes, based on which the system can assign tasks. However, if we directly borrow the task assignment design from the recommender system domain [1], it could lead to an misaligned task coverage, i.e., some popular tasks tend to enter workers’ candidate task lists (the list usually has a limited size to display the most matched tasks), while some less popular tasks could be unsuccessfully assigned. To ensure the task coverage, the system may have to increase their bidding costs (cost can be one attribute) to reallocate the tasks.

For those unassigned tasks, purely from the feature’s matching point of view, there may already exist sufficient workers who likely accomplish them. In other words, these tasks can be potentially assigned, but the challenge is that popular tasks could lead to better matchings, e.g., higher matching scores, so as to exclude less-popular tasks from the candidate lists. Thus, our key idea is to migrate certain suitable workers to those less popular tasks (still satisfying their preferences yet) for increasing the task coverage and meanwhile also strive to optimize other performance factors. In this paper, we find that with a careful coverage-oriented task assignment design, other performance factors, like the task acceptance rate and quality, can be comparably achieved as recent designs [35], while the system cost can be largely reduced, which can dramatically improve the overall benefit of the design and also make mobile crowdsensing systems much more practical.

To this end, this paper presents cTaskMat, with the following two main steps. To facilitate the cTaskMat design, in addition to worker’s preferences to each potential task attributes, denoted as positive attributes, we also introduce negative attributes that indicate the worker’s disliking of certain attributes.

1) We exploit and promote existing techniques to achieve an initial task assignment, which may cause the misaligned task coverage issue. Then, we leverage workers’ negative attributes to exclude certain popular tasks from the candidate task lists, if possible, and supplement with less popular tasks (still satisfying their preferences). Thus all workers’ candidate...
lists together could achieve a good coverage for the entire task set. To this end, we propose worker profiling and worker-attribute model based task assignment method.

2) Rather than blindly raising task rewards to attract workers, just as previous methods do, to assign the unsuccessfully assigned tasks, we categorize available workers according to their preferences and attitudes on rewards, and then differentially raise rewards of the remaining tasks according to the worker types. Such a cost-efficient remedy method not only enhances the overall task coverage, but also ensures task acceptance and saves system cost.

We implement cTaskMat system with the designs above and evaluate its performance extensively. We first recruit volunteers to complete a series of traffic monitoring tasks. We further leverage an existing dataset [8] to understand cTaskMat’s performance under a larger-scale setting. Compared with the state-of-the-art approaches [15][25][30], experimental results show that cTaskMat can reduce system cost by 28% at least, while sacrificing matching quality by 7% at most. In summary, the contributions of this paper can be summarized as follows.

- We identify an misaligned coverage problem in the task assignment for the mobile crowdsensing that could largely increase the system operation cost.
- We propose a coverage-oriented solution, which formulates this problem and achieves a good trade-off between performance related factors and task coverage.
- We implement the cTaskMat design, and conduct a real-world crowdsensing experiment as well as dataset driven evaluations to examine the performance of cTaskMat.

The rest of this paper is organized as follows. Section II presents the problem statement and motivation. We introduce the cTaskMat design in Section III and evaluate its performance in Section IV. Related works are reviewed in Section V and we conclude in Section VI.

II. PROBLEM STATEMENT AND MOTIVATION

In this section, we introduce the task assignment problem in prior crowdsensing systems (Section II-A), analyze the misaligned task coverage problem of mobile crowdsensing through a motivation example (Section II-B), and highlight our design with cTaskMat (Section II-C).

A. Problem Statement

A crowdsensing system involves two major parts: tasks and workers. It assigns unfinished tasks to a set of registered workers by matching the attributes of tasks and the preferences or interests of workers to complete with the best matching, according to certain criteria, e.g., system cost, task acceptance, quality, latency, etc. Next we introduce the task and worker models to facilitate our following discussions, and the key notations are summarized in Table I.

Task model. The crowdsensing system maintains a task set $\mathcal{T}$, involving many different task category $C$. Therefore, each specific task is denoted as $t_i^c$, where $i = 1, 2, \ldots, |\mathcal{T}|$ and $c \in C$. For instance, in the multi-source data collection example (stated in Section I) for the urban traffic monitoring, traffic sensing and road surface condition sensing can be two categories, where specific tasks may need to sense: bus traffic, taxi traffic, potholes, construction spots, etc.

In addition, to facilitate the task assignment, each task category has some attributes, e.g., describing its potential costs and requirements on different aspects. For each task category $c$, we denote its attributes as a vector with $m$ items:

$$\tilde{\mathbf{a}}^c = \langle a_1^c, a_2^c, \ldots, a_m^c \rangle,$$

and each $t_i^c$ has a concrete instance of this attribute vector. In particular, the reward that pays a worker after the completion of one task is also an attribute.

Back to the urban data collection example, one task category could be “Check the road surface condition at a specific location”, which requires the workers to travel to the specific location and then measure different types of traffics. Such tasks have potential costs on traveling distance along target roads and energy consumption of mobile devices for taking and uploading pictures. In addition, this task category is not time-sensitive and could be finished within a short time with small duration. Therefore, a possible attribute vector for this category of tasks could be $<\text{traveling distance}, \text{urgency}, \text{duration}, \text{data type}, \text{reward}>$. It is clear that these task attributes will influence the choices of workers to select tasks.

Worker model. There are a set of human workers, denoted as $w_i \in W$, who have registered to the system for accepting tasks. Each worker may prefer different categories of tasks and such preference information can be directly provided by the workers at the beginning and could be further refined from their historical selected tasks. To ensure the task completion quality, each worker can only undertake a limited number, $n_{\text{max}}$, of tasks concurrently. However, to provide each worker with more choices, when the system assigns tasks, it will not just display the top $n_{\text{max}}$ tasks, instead it will display more, e.g., top $n_{\text{and}}$ candidate tasks (after the preference matching) for the worker to pick. After the worker finishes each task $t_i^c$, she will receive $r_{i}^{c_j}$ reward as the return.

Task assignment problem. With the notations above, prior task assignment designs could convert the matching between task attributes and worker preferences into a score, $S_{\text{match}}$, and conducts the assignments by the following optimization:

$$\max S_{\text{match}},$$

with certain constraints, like each task is undertook by certain number of workers at most. Note that the calculated matching score $S_{\text{match}}$ can be purely based on the preference matching or weighted by some other performance indicators [35], e.g., latency, task completion quality, etc.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
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<tbody>
<tr>
<td>$t_i^c$</td>
<td>Task $i$ in category $c$</td>
</tr>
<tr>
<td>$a_j^c$</td>
<td>$k$-th attribute for the task category $c$</td>
</tr>
<tr>
<td>$n_{\text{max}}$</td>
<td>Maximum tasks can be undertook by a worker</td>
</tr>
<tr>
<td>$n_{\text{and}}$</td>
<td>Number of candidate tasks for a worker to pick</td>
</tr>
<tr>
<td>$S_{\text{match}}$</td>
<td>Matching score</td>
</tr>
</tbody>
</table>
As the assignment is essentially a score matching problem, solving it directly will lead to an \textit{misaligned task coverage problem}, \textit{i.e.}, some popular tasks tend to enter workers' candidate task lists (with higher matching scores), while some less popular tasks could be unsuccessfully assigned. As the task reward $r_{ij}$ is usually one task attribute, to encourage these tasks being undertook on time, the system may have to increase their bidding costs to realign the tasks, which essentially increases the overall costs of crowdsensing systems. Next, we detail this issue through one concrete example.

\subsection*{B. Motivation Example}
In this example, we consider the four task categories for the urban traffic monitoring with multi-source data collections.

- \textit{Category c1}: measuring vehicle traffic flow at a specific intersection, denoted as \{t$_1^{c1}$, t$_2^{c1}$, \ldots \};
- \textit{Category c2}: measuring the passenger flow at a specific bus stop, denoted as \{t$_2^{c2}$, t$_3^{c2}$, \ldots \};
- \textit{Category c3}: checking whether there is any traffic accident or construction at a specific region, denoted as \{t$_3^{c3}$, t$_4^{c3}$, \ldots \};
- \textit{Category c4}: checking the surface condition of a specific road, denoted as \{t$_4^{c4}$, t$_5^{c4}$, \ldots \}.

For simplicity, these categories share the same attribute vector $\tilde{\alpha}$ with the following five attributes:

- $a_1$: traveling distance for completing the task (in km);
- $a_2$: the latest beginning time from now (in hour);
- $a_3$: duration for completing the task (in hour);
- $a_4$: type of the desired sensing data;
- $a_5$: reward for completing a task. In this example, we adopt a simple reward formula, \textit{e.g.}, $r_{ij} = (a_1 + 2 \times a_3) \times a_5$, where $a_5$ (\textit{\geq} 1) is an augment factor when more rewards are needed to attract workers to complete the tasks.

In this example, we assume the attribute vector instances of tasks of the four categories are $< 1, 1, 0.5, \text{numeric}, 2 \times a_5 >$, $< 0, 1, 1, \text{numeric}, 2 \times a_5 >$, $< 2, 0, 1, \text{numeric}, 4 \times a_5 >$, $< 1.5, 3, 1, \text{image}, 3.5 \times a_5 >$, respectively. Assuming we have 5 tasks for each category, and thus there are totally 20 tasks for assignments. Meanwhile, 4 workers are available and each can undertake 5 tasks at most, \textit{i.e.}, $n_{max} = 5$.

Given an instance of each worker's preferences to each attribute, as illustrated in Table II, existing approaches \cite{15,25} firstly derive the task preference scores for each worker, based on which the task assignment can be conducted. Table II shows that \textit{Category c4} is the most popular task among workers and its tasks are recommended to $w_1$, $w_2$, and $w_4$ at the same time. Although traditional methods can guarantee a high matching score (since it assigns the most preferred tasks to each worker), we find that some tasks could be never recommended at all, \textit{i.e.}, tasks of \textit{Categories c1} and \textit{c2}. As a result, it is expected that more rewards are needed to attract workers to accept those tasks, \textit{e.g.}, doubling their rewards by changing $\alpha$ from 1 to 2. Therefore, the traditional methods can only achieve 50\% of task coverage and costs will be increased for the coverage. In this case, the overall cost needs to increase to 77.5 (we omit the details due to page limit), so that all tasks can be covered.

However, for those unassigned tasks, purely from the feature’s matching point of view, there already exist sufficient workers who likely accomplish them. In other words, these tasks can be potentially assigned. In this example, we demonstrate an alternative way to accomplish the task assignment, as shown in the last column of Table II, which may achieve a better trade-off between the task coverage and the matched scores. In particular, we can assign tasks of \textit{Category c4} to $w_2$, tasks of \textit{Category c2} to $w_3$, tasks of \textit{Category c1} to $w_1$. Such an assignment achieves 100\% coverage with overall cost only 57.5, while the matched score is still as high as 185 (compared with the original score 200).

\subsection*{C. Design Overview of cTaskMat}
Inspired by this example, we propose the \textit{cTaskMat} design in this paper. The key idea behind is that we migrate certain workers from their most popular tasks to the less popular ones (but still with sufficiently high preference scores), so that the overall task coverage can be increased and thus potential cost can be saved. Fig. 1 illustrates the system architecture with three major components: \textit{worker profiling}, \textit{coverage-ensured task assignment}, and \textit{cost-efficient remedy}.

At first, \textit{worker profiling} module implicitly learns each worker $w_i$‘s task preferences from historical records and thus produces a primary task list ordered by $w_i$‘s task preference scores. Then \textit{coverage-ensured task assignment} module further infers $w_i$‘s attitudes on task attributes and filters out these
tasks containing attributes disliked by \( w_i \) to derive top \( n_{\text{cand}} \) candidate tasks for \( w_i \). At last, to assign remaining tasks, the \textit{cost-efficient remedy} module classifies workers and differentially raises task rewards according to each worker type. The final outputs of \textit{cTaskMat} are the assigned task lists for all workers.

## III. DESIGN OF cTaskMat

In this section, we elaborate design detail of each component of \textit{cTaskMat} in the previous three subsections respectively and present the discussions in the last subsection.

### A. Worker Profiling

We characterize each worker \( w_i \)'s preferences on tasks and then make use of such information to generate a primary task list for \( w_i \). To this end, we exploit \( w_i \)'s historical task selection information in an implicit manner, due to the lack of worker's explicit feedback (e.g., rating, like or dislike). Specifically, we infer workers’ task preferences by comprehensively considering the task attributes, task similarity and latent factor between workers and tasks.

1) Attributes based preference inference: Each task is described by an attribute vector \( \bar{a}_i \), which covers the aspects of traveling distance, duration, reward, and etc. For a given task \( t_j \) recommended by the system, a worker's decision (i.e., select or not) can be viewed as the result through implicitly scoring on the attributes of \( t_j \). Therefore, we can encode each worker's historical task selection records, including the decisions and corresponding task attributes, as the training samples to build some machine learning models to capture each worker's attribute based preferences. For a given task \( t_j \), we take its attribute vector \( \bar{a}_i \) as input of the learned model for worker \( w_i \) to derive a probability \( p_{ij} \), which indicates how likely \( w_i \) will select task \( t_j \). Indeed, there exist multiple candidate models, e.g., k-means, SVM, logistic regression [11] or Bayesian classifier [23], for this learning task. Previous studies [2][9][24] find that the Bayesian classifier model is less likely to be over-fitting and can achieve a better generalization. Hence, we adopt the Bayesian classifier in our implementation.

2) Task similarity based preference inference: In addition to detailed attributes of each individual task, we could infer worker's task preferences by exploiting the similarity between tasks. The intuition behind is that tasks similar with already completed tasks by worker \( w_i \) may be preferred by \( w_i \) in the future. Therefore, item-based collaborative filtering [25] can be used to predict \( w_i \)'s preferences on those tasks. Here tasks are viewed as the items. For any two tasks, \( t_j \) and \( t_k \), we calculate their similarity \( \theta_{jk} \) using the following equation:

\[
\theta_{jk} = \frac{|W_j \cap W_k|}{|W_j \cup W_k|},
\]

where \( W_j \) and \( W_k \) represent the worker sets having selected task \( t_j \) and task \( t_k \) in the past, respectively. Different from correlation or cosine based similarity functions used in previous works [25], Eq. (1) measures the task similarity from the perspective of workers' practical choices. It is worthy to note that item-based collaborative filtering allows us to compute the similarity of any pair of tasks in advance, which can speedup the online task assignments.

Denote \( U \) as the worker-task preference matrix, where each entry \( u_{ij} \) is worker \( w_i \)'s preference on task \( t_j \). Based on the similarity function in Eq. (1), we calculate \( u_{ij} \) using

\[
u_{ij} = \sum_{k \in (D_{w_i} \cap S^*_{j})} \theta_{jk}, \tag{2}\]

where \( D_{w_i} \) is the task set already completed by \( w_i \), and \( S^*_{j} \) is the top-\( e \) most similar tasks with \( t_j \).

3) Latent factor based preference inference: Compared to previous two inference methods, we further use the Latent Factor Model (LFM) to indirectly infer worker's interests on tasks. In recommender systems, LFM is widely used to group items into virtual clusters (i.e., latent factors) and explore the relations between clusters and users/items for recommendations. In our case, we can also leverage latent factors to link the worker’s preferences and tasks. Similarly, we construct a worker-task preference matrix, whose elements \( l_{ij} \), indicating worker \( w_i \)'s preference on task \( t_j \), is set as:

\[
l_{ij} = \begin{cases} N/A & \text{if } w_i \text{ did not browse } t_j; \\ -1 & \text{if } w_i \text{ browsed but not selected } t_j; \\ 1 & \text{if } w_i \text{ browsed and selected } t_j. \end{cases}
\]

The LFM aims to infer the missing elements in the worker-task preference matrix through matrix factorization, which decomposes the worker-task preference matrix into two matrices, \( P \) and \( Q \). We can infer the missing workers' task preferences by minimizing the following loss function:

\[
L = \sum_{(i,j) \in K} (l_{ij} - \hat{l}_{ij})^2
= \sum_{(i,j) \in K} (\sum_{k=1}^{K} (p_{ik} \times q_{jk}))^2 + \lambda \|p_i\|^2 + \lambda \|q_j\|^2, \tag{2}\]

Where \( \hat{l}_{ij} \) is the predicted value by LFM. \( K \) is the specific number of latent factors, \( p_i \) is the \( i \)-th row of \( P \) that captures the relations between worker \( w_i \) and latent factors, and \( q_j \) is the \( j \)-th column of \( Q \) that captures relations between task \( t_j \) and latent factors. \( \lambda \) is a regularization parameter to avoid over-fitting. We set \( \lambda = 5 \) in our implementation.

### Comprehensive task preference score

The above three inference results estimate worker’s task preference from three different aspects, which allow us to compound a more comprehensive task preference score. Specifically, we combine these inferences to derive \( w_i \)'s preference score on task \( t_j \) (denoted as \( s_{ij} \)) using a weighted linear model, i.e.,

\[
s_{ij} = \mu_1 \times p_{ij} + \mu_2 \times u_{ij} + (1 - \mu_1 - \mu_2) \times \hat{l}_{ij}, \tag{3}\]

where \( \mu_1 \) and \( \mu_2 \) are both user-defined parameters. Based on our empirical testing, we set \( \mu_1 = 0.24 \) and \( \mu_2 = 0.38 \) in our current implementation.

By calculating the preference scores of all tasks with respect to worker \( w_i \), \textit{cTaskMat} sorts these tasks in descending order based on their preference scores and regards the sorted list as \( w_i \)'s primary task list.
B. Coverage-ensured Task Assignment

Traditional task assignment methods usually adopt the task acceptance rate as an important metric to evaluate the performance of crowdsensing systems [14], which is defined as:

$$\text{Acceptance rate} = \frac{1}{|W|} \sum_{w_i \in W} \frac{|R_{w_i} \cap T_{w_i}|}{|R_{w_i}|},$$

(4)

where $R_{w_i}$ and $T_{w_i}$ are the assigned task set and truly selected task set, respectively, for worker $w_i$.

As motivated in Section II-B, although traditional methods can achieve high acceptance rate, they fail to guarantee task coverage, which may introduce extra costs for assigning the less popular tasks. Formally, we define task coverage rate as

$$\text{Coverage rate} = \frac{|\bigcup_{w_i \in W} R_{w_i}|}{|T|}.$$

(5)

According to above definitions, we find the assigned task list $R_{w_i}$ is the key that will decide both task acceptance rate and task coverage rate. Typically, a larger set $R_{w_i}$ can benefit the improvement of Coverage rate. However, for a crowdsensing system, the number of assigned tasks, i.e., $n_{cand}$, is fixed. As a result, we can only adjust the tasks in each $R_{w_i}$ to optimize the performances of both task acceptance rate and task coverage rate, which is formally stated as:

$$\max \{ \text{Acceptance rate}, \text{Coverage rate} \}.$$

To achieve this goal, we will explicitly mine workers’ preferences on task attributes and exploit such information to process the primary task list to derive the suitable $n_{cand}$ tasks for each worker. Specifically, we make use of worker’s favorite task attributes (i.e., positive features) to enhance task acceptance rate, and meanwhile exploit worker’s dislike task attributes (i.e., negative features) to filter out tasks owning the disliked attributes from primary task list. The latter operation will increase the recommendation chances for the less popular tasks, and thus potentially improve task coverage rate.

**Empirical survey result.** We have conducted a questionnaire survey (see more details in Section IV-A), and one of the question is “Will you directly reject one task when it owns some task attributes you do not like?” The statistical result indicates that most respondents (around 82%) choose “Yes” and will directly reject the task. Such a result implies that it is feasible and necessary to mine workers’ preferences on task attributes and adjust the assigned task list accordingly.

**Worker-attribute model.** To capture workers’ preferences on task attributes, we construct a tensor $\mathbf{A} \in R^{(|W| \times m \times v)}$ with the three dimensions standing for workers of size $|W|$, task attributes of size $m$, and attribute values of size $v$, respectively.

An entry $\mathbf{A}_{(i,j,k)}$ denotes the preference of worker $w_i$ on the $k$-th possible value of the $j$-th task attribute. The top-left of Fig. 2 demonstrates a worker-attribute model, and the bottom-left of this figure shows an instance of task attribute preferences for worker $w_j$. The color of a box (i.e., an entry) in Fig. 2 indicates worker $w_j$’s attitude on the given value of a specific task attribute. In this example, the redder a box is the more disliked by the worker. Next we will introduce how to initialize and update this model.

**Initialization.** To initialize the model $\mathbf{A}$, a common approach is to assign the entries with random weights, while we aim to boost the model initialization by exploiting previously derived results. To this end, we reduce the 3-dimensional tensor $\mathbf{A}$ to a 2-dimensional matrix $\mathbf{A} \in R^{(|W| \times (mv))}$ by stacking all attribute values of all attributes sequentially. Then we can reuse the LFM technique in Section III-A3 to decompose the worker-task preference matrix and derive two matrices $\mathbf{P}$ and $\mathbf{Q}$. In principle, we can set the size of matrix $\mathbf{P}$ as $|W| \times (mv)$. Recall that $\mathbf{P}$ captures the relations between workers and latent factors, and we thus could initialize $\mathbf{A}$ as matrix $\mathbf{P}$ by implicitly viewing each latent factor in $\mathbf{P}$ as a specific task attribute value. By mapping the items in $\mathbf{A}$ back to the entries of $\mathbf{A}$, we obtain the initial worker-attribute model.

Since matrix $\mathbf{P}$ has been calculated in the prior step, it can be reused directly for the initialization without introducing additional computation overhead. More importantly, the items in matrix $\mathbf{P}$ are meaningful on capturing the relations between workers and task attributes. Therefore, compared with random initialization, our initialization can greatly accelerate the convergence of the worker-attribute model updating.

**Update.** We update the worker-attribute model $\mathbf{A}$ continuously with the the latest task assignment results. Since there are no direct feedback from workers on task attributes and attribute values, e.g., ratings, we can only implicitly learn the preferences through workers’ historical behavior on task selections. Fortunately, a crowdsensing system could log workers’ behaviors. Such records include which tasks the worker had browsed, selected, and finally completed. Note that workers can only browse the tasks recommended by the system. We regard the tasks in records as training samples and classify them into two groups:

- **Positive samples:** when task $t_j$ was browsed, selected, and completed by worker $w_i$;
- **Negative samples:** when task $t_j$ was browsed but not selected by worker $w_i$.

We use the accumulated positive and negative samples to update the worker-attribute model $\mathbf{A}$ by exploiting the idea of attention mechanism. Recently, attention mechanism has been successfully applied in many domains, e.g., recommender system [4], information retrieval [39], and computer vision [5], and has demonstrated remarkable performance improvements. The key idea of attention mechanism is to distribute different
weights to each part of a vector of interest based on a similarity function that can predict attention score [29]. Here, we make use of the attention mechanism to explore the influences of different attributes and their values on the acceptance or rejection of a task for a given worker. Specifically, we use the following similarity function to calculate an attention score vector when assigning task $t_j$ to worker $w_i$:

$$s_{ij} = w_i \odot t_j \oplus |\min(w_i \odot t_j)|,$$  

(6)

where $w_i$ is a worker-attribute vector that describes the workers interest on each task attribute, and $t_j$ is a vector that describes the relations between this task and attribute values. In addition, the operator $\odot$ denotes element-wise product of two vectors, function $\min()$ returns the minimum value of a given vector, and the operator $\oplus$ denotes to add the right value to each element of the left vector.

The result $s_{ij}$ of Eq. (6) indicates the attention scores of the worker with respect to the attribute values of the given task. Each item in vector $s_{ij}$ implies to what degree the worker will prefer the corresponding attribute value. Such information can be used to update the worker-attribute model. In our design, rather than directly applying $t_j$ to update the worker-attribute model, we further utilize Eq. (7) to calculate an updated weight vector. For each attention score $s_{ij} \in s_{ij}$, its corresponding weight $g_z \in g_{tij}$ is computed by the following equation:

$$g_z = \frac{\exp(s_z)}{\sum s \in s_{ij} \exp(s)}.$$  

(7)

Based on the weight score vector $g_{tij}$, we then update $w_i$ of the worker-attribute model given the task $t_j$ is a positive sample or a negative sample, using the following equation:

$$w_i = w_i + (-1)^I g_{tij} \odot t_j,$$  

(8)

where $I = 0$ if the task $t_j$ is a positive sample and $I = 1$ if task $t_j$ is a negative sample. Therefore, we exploit an attention-based mechanism to explore the worker’s preferences on task attributes and attribute values, and update the worker-attribute model pertinently.

In practice, we can train the worker-attribute model $\mathcal{A}$ with historical records, and this model can be continuously updated when more worker behaviors are logged. Therefore, even a worker changes her preferences in the future, model $\mathcal{A}$ will also be updated according to her latest task selection choices.

**Process primary task list using $\mathcal{A}$**. The derived model $\mathcal{A}$ can be used to process each worker $w_i$’s primary task list by filtering out the tasks containing $w_i$’s obviously dislike attributes and attribute values. In theory, when an entry $\hat{a}_{(i,j,k)}$ has an negative value, it means that worker $w_i$ does not like this task since $w_i$ has an negative preference on its $j$-th attribute with $k$-th value. In practice, we adopt a more strict rule by setting a threshold $\eta$ below 0 (e.g., -0.5 in our implementation). When $\hat{a}_{(i,j,k)} < \eta$, $cTaskMat$ considers that worker $w_i$ dislikes the task which has an attribute $a_j$ with value equaling to $v_k$. For each task in primary task list, $cTaskMat$ checks its attribute values by comparing with the worker-attribute preference in $\mathcal{A}$. $cTaskMat$ simply filters out the task once it has a low attribute preference for the worker. By doing so, $cTaskMat$ adjusts the primary task list and pick the top $n_{cand}$ (or all when there are not enough) tasks in the list as the assigned task list for each worker.

**C. Cost-efficient Remedy**

After worker-attribute model based task assignment in previous subsection, there may be still some remaining tasks that are not assigned yet. The traditional methods usually raise the rewards of remaining tasks to attract potential workers. Such a method, however, is not cost-efficient and may not guarantee the system performance, e.g., task acceptance rate, when tasks are not recommended to the right workers.

Therefore, we propose a cost-efficient remedy method to reassign the remaining tasks to these available workers, whose candidate task lists are not full (with the number of already assigned tasks $< n_{cand}$). Specifically, our method exploits the worker-attribute model $\mathcal{A}$ to categorize the workers and uses different strategies to reassign remaining tasks to the workers of each group. We firstly compute an average worker-attribute profile $A_{ave}$ by averaging the preferences of each attribute value for all workers, i.e., $A_{ave}^{ij} = mean(h(i,j,k))$. From model $\mathcal{A}$, we can also extract worker $w_i$’s attribute preference profile $A^i$. By comparing $A^i$ with $A_{ave}$, we can derive the preference difference $A^{i/ave}$ of worker $w_i$ against the average attribute preferences of all workers, and classify $w_i$ as:

- **rigorous worker**, when there are at least $n$ elements in $A^{i/ave}$ larger than a threshold $\gamma$ (we empirically set $n = 20$ and $\gamma = 0.5$ in our implementation). Rigid workers have strong preferences and significantly dislikes some task attributes.

- **Otherwise, non-rigorous worker**, who have relatively broad interests on all task attributes. We further classify non-rigorous workers according to their attitudes on the task rewards. Specifically, for a non-rigorous worker $w_i$, we compare her attribute preference profile $A^i$ with $A_{ave}$ only on the attribute of task reward, and regard $w_i$ as:
  - **lucrative worker**, who prefers high task rewards, e.g., task rewards of 80% prior completed tasks are higher than the average task reward computed from $A_{ave}$.
  - **normal worker**, who does not care task rewards too much and the rewards of prior completed tasks are uniformly distributed.

By categorizing all workers according to their attitudes on task attributes, we can differentially recommend tasks to them while guaranteeing task acceptance rate and saving the cost. Specifically, we do not reassign a task $t_j$ to a rigorous worker $w_i$ when $t_j$ contains attributes strongly disliked by $w_i$, and we only largely increase the reward of task $t_j$ when it is recommended to a lucrative worker. For each remaining task $t_j$, it is reassigned to workers as the following orders and reward raising strategies:

1) $t_j$ is firstly reassigned to rigorous workers if possible. For a rigorous worker $w_r$, if $t_j$ does not contain attribute values disliked by $w_r$, it is recommended to $w_r$. The task reward is not raised.

2) otherwise $t_j$ is reassigned to possible normal workers, and its reward is slightly raised, e.g., increasing by 25%.
Algorithm 1: Task assignment algorithm of cTaskMat

Input: worker set $W$, tasks set $T$, historical records
Output: assigned task list for each worker

1. foreach worker $w_i$ do
2.   Retrieve $w_i$’s historical records;
3.   foreach task $t_j$ in historical records do
4.     Calculate $s_{ij}$ using Eq. (3);
5.   end
6.   Create primary task list for $w_i$ by sorting all tasks according to their $s_{ij}$ in descending order;
7. end
8. Construct the worker-attribute model $\hat{A}$;
9. foreach worker $w_i$ do
10.   foreach attribute $a_j$ with $k$-th value $v_k$ do
11.     if $\hat{A}_{(i,j,k)} < \eta$ then
12.       Filter out tasks having attribute $a_j$ and its value equaling to $v_k$ from $w_i$’s primary task list;
13.     end
14.   Pick the top $n_{cand}$ tasks to form assigned task set for $w_i$;
15. end
16. Categorize worker $w_i$ based on $A^i$ and $A^{ave}$.
17. Reassign remaining tasks to rigorous, normal, and lucrative workers sequentially;
18. return assigned task list for each worker $w_i$;

3) at last $t_j$ is recommended to lucrative workers, and the task reward is largely raised, e.g., increasing by 50%.

Note that each worker can only be assigned $n_{cand}$ tasks. With the remedy assignments, cTaskMat can finally assign all tasks to suitable workers with few increases on system cost. In Section IV-B, our experimental result proves that cTaskMat can guarantee system performances while significantly reducing the system costs. Algorithm 1 summarizes the task assignment algorithm of cTaskMat.

D. Discussions

Handling the cold start issue. When cTaskMat is initially adopted, there are no historical records. As a result, we cannot learn workers’ task preferences and build the worker-attribute model from workers’ behaviors. To cope with such a common cold start problem, we can conduct a questionnaire survey for each new worker to rate a series of preference attributes and learn workers’ task preferences and build the worker-attribute model from workers’ behaviors. Therefore, the filtering process can follow the preferences varying better.

Impact of filtering primary task list. cTaskMat makes use of model $\hat{A}$ to filter out some tasks from each worker $w_i$’s primary task list, which thus increases the opportunity of recommending less popular tasks to $w_i$. For those filtered tasks, they still may be assigned to other workers, or reassigned with the cost-efficient remedy at last. Therefore, the filtering process will not affect the task completions.

Settings of system parameters. cTaskMat involves the settings of some system parameters to measure workers’ preferences on tasks and attributes. In general, these parameters can be empirically set according to the system’s requirements. Since we adopt the same parameters to evaluate each worker and task, their impact on system performance can be ignored.

IV. Evaluation

In this section, we implement cTaskMat and extensively evaluate its performances by comparing with baseline methods on the real-world experiment and data-driven evaluations.

A. Experiment Setup

We implement cTaskMat in Python and run the system in a powerful Linux server that has 3.6 GHz CPU with 8 cores and 8 GB memory. We use the data collected from a real-world questionnaire survey and MovieLens 100K dataset [8] to evaluate and compare the performances of cTaskMat and baseline methods on some widely used performance metrics.

By default, we initially set $\alpha = 1$ in the task reward formula and increase it if necessary to reassign the remaining tasks. Besides, we set $n_{cand} = 20$ and $n_{max} = 15$.

Questionnaire survey: We conduct a questionnaire survey and recruit 74 volunteers (47 males and 27 females) to participate in the experiment. Specifically, we manually create 5 task categories for urban traffic monitoring. Besides the four task categories mentioned in Section II-B, we add another task category as “Sharing your latest traveling trajectory.” We instantiate 140 tasks for each category and thus totally have 700 tasks for the 74 volunteers. All tasks share the same task category as "Sharing your latest traveling trajectory.” We instantiate 140 tasks for each category and thus totally have 700 tasks for the 74 volunteers. All tasks share the same system parameters. cTaskMat makes use of model $\hat{A}$ to filter out some tasks from each worker $w_i$’s primary task list, which thus increases the opportunity of recommending less popular tasks to $w_i$. For those filtered tasks, they still may be assigned to other workers, or reassigned with the cost-efficient remedy at last. Therefore, the filtering process will not affect the task completions.

cTaskMat uses model $\hat{A}$ to filter out some tasks from each worker $w_i$’s primary task list, which thus increases the opportunity of recommending less popular tasks to $w_i$. For those filtered tasks, they still may be assigned to other workers, or reassigned with the cost-efficient remedy at last. Therefore, the filtering process will not affect the task completions.
decide whether to accept a task based on his/her preferences on the task attributes. If a task is not selected by volunteer \( w_i \), the survey allows \( w_i \) to write down an anticipate reward that can persuade him/her to accept the task. Such a setting helps us to analyze workers’ attitudes on task reward and understand how to raise task rewards to attract workers. For the data collected from this questionnaire survey, we use 80% of all data to learn workers’ task preferences and build the worker-attribute model \( A_w \), and exploit the remaining 20% for testing.

**MovieLens 100K dataset**: In addition to our questionnaire survey dataset, we choose the publicly available MovieLens dataset [8] to examine the performances of our system in the large-scale application scenario. In this dataset, each movie (similar as “task” in our system) is associated with certain attributes and users select movies according to their preferences on these attributes. Therefore, the settings of movie scoring are similar as that in our system. Specifically, this dataset contains 100,000 ratings (1-5, the higher the better) from 943 users on 1,682 movies, and each user had rated at least 20 movies. We treat the 4-star and 5-star ratings as the positive feedback and treat other ratings as the unknown feedback. Similarly, we split the dataset into training data and testing data according to the 80%/20% rule. In the experiments, we assume each worker can score a movie through her smartphone and we would like to rate a number of movies by crowdsourcing to the workers.

**Baseline methods**: We compare cTaskMat with the following alternative task assignment methods:

- **Random assignment (RA)**: The method will randomly assign \( n_{\text{cand}} \) tasks for each worker.
- **Preference-only task assignment (Pre-only)**: This method assigns tasks to each worker based on their preferences merely, which is implemented based on the classical item-based collaborative filtering technique [25].
- **Cost-only task assignment (Cost-only)**: Linden et al. [15] proposed a cost-efficient collaborative filtering method, and we implement it for task assignments.
- **IRGAN** [30]: It is one of the state-of-the-art methods for item-based recommendation and can also be applied for task assignments. Since it needs a lot of data to train the Generative Adversarial Nets (GANs), we only compare it on the large MovieLens 100K dataset.

**Performance metrics**: We compare cTaskMat and baseline methods on task acceptance rate (i.e., \( \text{Accpet\_rate} \) defined in Eq. (4)) and task coverage rate (i.e., \( \text{Cover\_rate} \) defined in Eq. (5)). Besides, we define the \( \text{Cost} \) metric to evaluate system cost for completing all tasks, which is calculated as:

\[
\text{Cost} = \sum_{w_i \in W} \sum_{j \in T_{w_i}} r^c_j,
\]

where \( T_{w_i} \) means the selected task set of worker \( w_i \) and \( r^c_j \) is the reward for completing task \( t_j \) of category \( c \).

**B. Results of The Real-world Experiment**

To assign tasks to suitable workers, cTaskMat mainly takes two steps: (1) It firstly makes use of each worker \( w_i \)’s task preferences to derive a primary task list and then filters out these tasks, which contain dislike attributes by exploiting the worker-attribute model, from the list to obtain the top \( n_{\text{cand}} \) assigned tasks (denoted as the \( \text{core} \) step); (2) It then explores workers’ attitudes on task rewards to intentionally raise the reward of each unassigned task so that to minimize the overall system cost (denoted as the \( \text{remedy} \) step). We evaluate impacts of \( \text{core} \) step and \( \text{remedy} \) step on cTaskMat’s performances.

**Impacts on Accep\_rate and Cover\_rate**: We run baseline methods, cTaskMat, and cTaskMat-core (excluding the \( \text{remedy} \) step from the full version) on the testing dataset and present their performance results of \( \text{Accpet\_rate} \) and \( \text{Cover\_rate} \) in Fig. 3 and Fig. 4. Each method usually runs several rounds to assign all tasks, and may raise task rewards in the following rounds. We report the task acceptance rates of first round and final round for all methods in Fig. 3. We can see the acceptance rates of all methods in the first round are low, and will increase at the last round. Among all the methods, \( \text{Pre-only} \) method achieves the highest task acceptance rate (about 0.57 in the final round) since it only recommends the most preferred tasks to each worker, while \( \text{RA} \) and \( \text{Cost-only} \) have the worst performances, with the final \( \text{Accpet\_rate} \) less than 0.30. The task acceptance rate of \( \text{cTaskMat-core} \) is 0.39 and increase to 0.53 with the help of \( \text{remedy} \) step, with 36% improvement on \( \text{Accpet\_rate} \).

Fig. 4 shows the task coverage rates for different methods along with rounds of reward raising. In essence, to reassigned the remaining tasks, more and more task rewards are needed at last. \( \text{Pre-only} \) and cTaskMat achieve full task coverage with the fewest rounds, while \( \text{Pre-only} \) has the worst performance.
on Cover\_rate in the first round. As a result, Pre\_only has to raise rewards for a lot of remaining tasks in the next rounds. Although Cost\_only shows similar performance as cTaskMat in the initial stage, its low Accept\_rate causes more rounds (and thus more system cost) are needed. It is not surprise that RA achieves full task coverage with the most rounds. Since RA blindly assigns tasks to workers, which results in a low acceptance rate and more attempts are needed.

From the results in Fig. 3 and Fig. 4, we can see that among all the methods cTaskMat achieves the best performance with both high task acceptance rate and task coverage rate at the same time. Specifically, the core step helps cTaskMat assign workers with their most preferred tasks, and the remedy step reassigns remaining tasks to achieve full task coverage in a cost-efficient manner. In the next, we will study how remedy step helps cTaskMat save costs during the assignment of less popular tasks.

**Impacts on Cost.** To assign the remaining tasks to workers, a widely adopted strategy is to raise task rewards for attracting workers and such a raising increases along the rounds. In each round, previous methods equally raise the rewards of tasks for all available workers (e.g., raising by 50%), while cTaskMat firstly analyzes workers’ attitudes on task attributes and rewards, and then differentially raise task rewards for different workers. We report the task reassignment cost comparisons for all methods in Fig. 5, where blue bars represent the costs for original methods and red bars represent the costs if we apply our remedy step in those methods for task reassignments. From the experiment results, we can see the Cost\_only method introduces the fewest costs while Pre\_only has the most costs to reassign the less popular tasks. cTaskMat has an moderate cost about 2241. When we apply the remedy step to those methods, we can see obvious reductions on their costs, saving 32.3\%, 35.1\%, and 12.3\% costs compared to the original strategy for RA, Pre\_only, and Cost\_only, respectively. Although Cost\_only method is designed to save costs for task assignments, our remedy step can further reduce its costs.

The core step of cTaskMat will filter out some tasks from each worker’s primary task list, and we have tracked how these tasks are reassigned. According to our experiment, we find that although these tasks are removed from a worker’s primary task list, 74.0\% of them will be successfully reassigned to other workers. For the remaining tasks, remedy step reassigns them to suitable workers by carefully setting task rewards. Thanks to the analysis of workers’ attitudes on rewards, 20.5\% tasks are reassigned in the remedy step without raising rewards and only 5.5\% tasks are reassigned after bidding.

These results from real-world experiment demonstrate that cTaskMat can well balance various performance metrics than the alternatives. Specifically, cTaskMat could achieve high task coverage and largely saves the system cost on average by 28\% while sacrificing task acceptance by 7\% when compared to Pre\_only and Cost\_only, the state-of-the-art methods.

**C. Results of Data-driven Evaluations**

We make use of the publicly available Movielens dataset to examine cTaskMat’s performances in a large scale application scenario. Fig. 6 and Fig. 7 presents the performance comparisons of different methods when we vary the number of maximum assigned tasks, i.e., n\_card, from 3 to 20. Specifically, when we increase n\_card, task acceptance rates of all methods are reduced, as shown in Fig. 6. This is because each worker can undertake a limited number of tasks, and thus among the candidate task set, only a fixed number of tasks are finally selected. Among all the methods, cTaskMat takes the second place and has comparable performance as IRGAN, one of the state-of-the-art methods. With respect to task coverage rate of the first round as shown in Fig. 7, our method performs much better than IRGAN. Although RA can achieve high task coverage rate, it still cannot guarantee a good acceptance rate due to its blind assignments.

In order to comprehensively compare all methods, we calculate their F1-score in different n\_card settings and report the results in Fig. 8. When calculating F1-score, we replace recall as task coverage rate and use F1-score as a comprehensive performance indicator. In all n\_card settings, cTaskMat has the best performance on F1-score.

In addition, we evaluate the system performance by varying the task-worker ratio from 2 to 10. We fix the number of workers as 168 and increase the number of total tasks. When the task-worker ratio increases, the total number of tasks that can be assigned by the system also increases proportionally. This impact alone tends to decrease the “coverage” proportionally. For instance, compared with the ratio of 2, the coverage should drop to 1/5 when the ratio is increased to 10. However, because “coverage” is defined as the ratio...
between all the selected tasks by workers over all the tasks that can be assigned in the system, from Fig. 9, we can see that the decreasing of “coverage” is much slower than that speed. This is because when the task-worker ratio is increased, more tasks are available as well. In this case, workers have more chances to select distinct tasks, which will also increase the number of all the selected tasks by workers. Therefore, from this experiment, we find that the task-worker ratio could decrease “coverage” in a moderate level, e.g., when the ratio is up to 10, the “coverage” can be still more than 71% in Fig. 9. On the other hand, since each worker selects tasks from the candidate task list only, the acceptance rate is thus relatively stable across different task-worker ratios.

In summary, these experiment results demonstrate that $cTaskMat$ well balances different metrics and has a more comprehensive performance for real applications.

V. RELATED WORK

The wide popularity of mobile devices (e.g., smartphones and wearables) has brought a novel sensing and computing paradigm named mobile crowdsensing [7], which outsources a large-scale complex job to the crowd having mobile devices to perform location-dependent task at large scale. In recent years, we have witnessed the successes of mobile crowdsensing in a plenty of smart city applications, such as traffic monitoring [16], [46], air quality monitoring [44], urban noise mapping [22], intelligent transit services [3], [18], [41], etc. In order to guarantee the effectiveness and efficiency of mobile crowdsensing applications, other factors of crowdsensing, including incentive mechanism [33], [45], security and privacy protection [12], [13], [19], [26], accuracy of data collected [43], have also been widely explored. Specifically, Meng et al. [19] analyzed the security and privacy problems in urban sensing. Li et al. [13] studied the privacy leakage of location sharing in mobile computing. Zhou et al. proposed a method to recover data from collected data [42]. These works demonstrate and ensure the ability of mobile crowdsensing on addressing large-scale practical problems.

Task assignment, or worker-task matching, is an important problem in the crowdsensing systems and has attracted a lot of research efforts. Difallah et al. [6] proposed a content-based task assignment approach that focuses on dynamically pushing tasks to workers so that to maximize overall task acceptance rate. He et al. [10] considered the optimal task allocation problem in location-dependent crowdsensing. Liu et al. [17] proposed a unified task assignment design for urban sensing, which comprehensively considers the coverage, latency, and accuracy of task assignment to optimize the overall system utility. Karaliopoulos et al. [11] estimated each worker’s probability of accepting a task through the logistic regression technique, and made use of such information to match tasks with workers. Yang et al. [35] studied the personalized task recommendation by considering workers’ sensing reliability in crowdsensing. None of these works, however, comprehensively consider workers’ task preferences and their attitudes on task attributes during the worker-task matching. In contrary, $cTaskMat$ extensively mines such information from historical worker behaviors and exploits their task preferences for better task assignments to balance performance metrics and reduce the system cost.

Incentive mechanism design is another important issue in crowdsensing and will decide the system costs. Zhao et al. [40] considered the problem of budget constrained incentive mechanism design for crowdsensing in both offline and online scenarios. Xu et al. [32] proposed a cost-saving method to lower user burdens. Singer et al. [27] and Singla et al. [28] presented pricing mechanisms for crowdsourcing markets that rely on the bidding model and the posted pricing model. These works need explicit feedback from workers or make some unrealistic assumptions on workers’ preferences. Lin et al. [14] proposed an implicit feedback based recommendation system for crowdsensing. However, their work mainly focuses on the optimization of task acceptance, and omit the concerns on task coverage and system cost. $cTaskMat$ aims to address the misaligned task coverage problem in crowdsensing, and meanwhile optimize other performance metrics.

VI. CONCLUSION

This paper presents $cTaskMat$ for coverage-oriented task assignments in mobile crowdsensing systems. $cTaskMat$ implicitly learns workers’ task preferences and their attitudes on task attributes, and exploits such information to achieve better task assignments. Experimental results using real-world experiment and large dataset-driven evaluation demonstrate that $cTaskMat$ can achieve comprehensive performances on task acceptance and task coverage, while reducing the cost.

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