

Fair and Explainable Dynamic Engagement of Crowd Workers

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Abstract

Years of rural-urban migration has resulted in a significant population in China seeking ad-hoc work in large urban centres. At the same time, many businesses face large fluctuations in demand for manpower and require more efficient ways to satisfy such demands. This paper outlines *AlgoCrowd*, an artificial intelligence (AI)-empowered algorithmic crowdsourcing platform. Equipped with an efficient explainable task-worker matching optimization approach designed to focus on fair treatment of workers while maximizing collective utility, the platform provides explainable task recommendations to workers' personal work management mobile apps which are becoming popular, with the aim to address the above societal challenge.

1 Introduction

As a result of rural-urban migration in China [Yang, 2013], there exist a large number of people working on an ad-hoc basis in large Chinese cities. This group of people are considered to be vulnerable [Chen *et al.*, 2016]. Many of them look for ad-hoc work through untrustworthy agents, thus exposing them to high risk of exploitation and swindle [Xie and Zhou, 2014]. On the other hand, many brick-and-mortar businesses such as franchised department stores experience large fluctuations in terms of demand for manpower under different situations (e.g. peak periods of customer influx, periods of inventory restocking). Is there a solution that can address the aforementioned societal challenge while empowering this market sector to satisfy manpower needs more efficiently?

In this paper, we outline *AlgoCrowd* - an artificial intelligence (AI)-empowered algorithmic crowdsourcing [Doan *et al.*, 2011] platform, which aims to address the aforementioned challenge. It is designed to provide optimized task-worker matching recommendations to workers' personal work management mobile apps which are starting to become popular in China (e.g. the Zhiyouren app <http://www.zyrwork.com/>) to support dynamic engagement of the large pool of ad-hoc workers. The AI Engine of this platform is a data-driven real-time multi-agent organization [Yu *et al.*, 2007; 2011; Li *et al.*, 2009; 2015; Lin *et al.*, 2015] approach extended from [Pan *et al.*, 2016;

Yu *et al.*, 2013; 2015; 2016; 2017b; 2017a; Zheng *et al.*, 2018]. In order to comply with emerging best practices for building ethical AI [Yu *et al.*, 2018; 2019a; 2019b; AI HLEG, 2019], the algorithm focuses on fair treatment of workers and explainability for human oversight.

2 The AlgoCrowd Platform

2.1 System Architecture

Figure 1 illustrates the AlgoCrowd system architecture. It communicates with a personal work management mobile app through database profiles for tasks and workers. Key information such as task rewards, completion criteria, task types, worker capability levels for different types of tasks, productivity, availability, and sensitivity to price changes can be estimated based on task proposers' input and track records about the workers in the system. Such information is supplied to the AI engine which contains the proposed task-worker matching optimization approach. The resulting task allocation plan produced by the AI engine at any given point in time is fed back to the engaged workers through their personal work management mobile apps. The outcomes of the tasks can be monitored through sensors for well-defined tasks or manual assessment by for less well-defined tasks.

2.2 The AI Engine

In order to treat workers fairly, we aim to ensure that workers of similar capability and productivity earn equitable in-

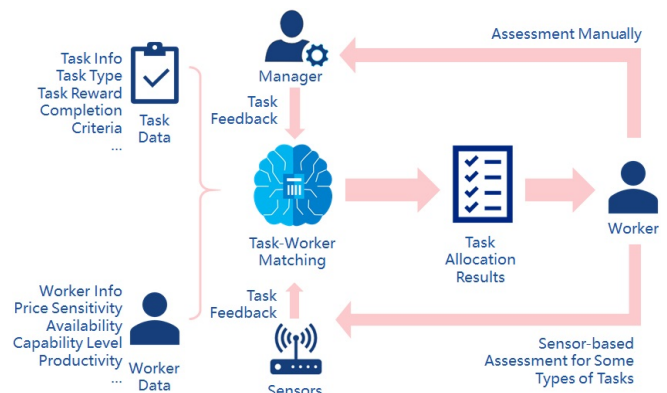


Figure 1: System architecture *AlgoCrowd*.

comes in the long run. Such an objective can be translated into minimizing the regret by any worker when his income is compared to similar peers. The AI engine adopts queueing system concepts to model the dynamics of a worker’s regret $Y_i(t)$ as $Y_i(t + 1) = \max[0, Y_i(t) + \bar{v}(t - 1) - v_i(t)]$, where $v_i(t)$ is the income from a task allocated to worker i in the current round t , and $\bar{v}(t - 1)$ is the average income received by i ’s similar peers during $(t - 1)$.

Following the Lyapunov optimization technique [Neely, 2010], we derive the distribution of regret among workers at t as the l_2 -norm $L(t) = \frac{1}{2} \sum_{i=1}^N Y_i^2(t)$. Thus, the fluctuation in workers’ incomes over time can be expressed as $\Delta = \frac{1}{T} \sum_{t=0}^{T-1} [L(t + 1) - L(t)]$. By minimizing Δ , the algorithm provides two dimensions of fairness to workers: 1) workers with similar capability and productivity receive equitable incomes from tasks in any given round of task allocation, and 2) the fluctuation in a worker’s regret over time remains small. At the same time, the collective utility of the business engaging the workers, which can be modelled as $v_i(t)q_{i,j}(t)p_i(t)$ where $q_{i,j}(t)$ and $p_i(t)$ are respectively worker i ’s capability level for tasks of type j and his productivity, shall be maximized. Following techniques developed in [Yu *et al.*, 2016; 2017a], we can derive the joint objective function as maximizing $\frac{1}{T} \sum_{t=0}^{T-1} \sum_{i=1}^N v_i(t)[\rho q_{i,j}(t)p_i(t) + Y_i(t)]$, subject to $\sum_{j=1}^M 1_{j \rightarrow i} \in (0, 1)$ and $q_{i,j}(t) \geq \theta_j(t), \forall i, j, t$. Here, $\rho > 0$ is a control variable for a manager to signal the AI engine how to trade off between generating higher revenue and fair treatment of workers; and $\theta_j(t)$ is the minimum capability level required for a worker to be eligible for a type of tasks.

The optimization can be solved efficiently through the index ranking approached developed in [Yu *et al.*, 2016; 2017a]. Workers are ranked in descending order of their $[\rho q_{i,j}(t)p_i(t) + Y_i(t)]$ indices, while tasks are ranked in descending order of their “reward-times-waiting time” values. Then, high-ranking tasks are assigned to high-ranking workers until no more tasks or no more suitable workers can be found. The algorithm has $O(N \log N)$ time complexity if mergesort is adopted, which supports large-scale operations.

The result from this solution algorithm is a tensor of fine granularity mapping workers’ capability, productivity, regret, system managers’ preference, and task rewards and waiting

time into a task allocation plan. Explanations can be generated through argumentation techniques [Fan and Toni, 2015] with emotional connotations generated based on the Affect-Button [Broekens and Brinkman, 2013] shown to the user. Since situations may change with time, the explanations also offer suggestions on better alternatives if the user can wait for more suitable workers to become available in order to balance explicability with explanations [Sreedharan *et al.*, 2017].

2.3 The Prototype System

Figure 2 shows the demonstration system of AlgoCrowd. The system offers two modes of operations. Firstly, a manager can manually initiate the process of loading worker information and new task information from the database system, and initiating the task allocation algorithm of the AI engine. Visualization facilities are provided to illustrate the distribution of workers’ capability (i.e. their reputation values [Shen *et al.*, 2011]) as well as productivity. Once the task allocation operation is complete, results are visualized as a tree-view in the central panel of the system user interface. Users can expand the it to view key statistics related to the optimization algorithm. They can also click on any given task to trigger the explanation function to view the rationale behind that particular recommendation generated by the AI engine.

Secondly, the system provides an “auto-pilot” mode of operation in which it autonomously queries worker and task databases at preset intervals to update the latest information concerning worker and task status for a given business, and performs the task allocation operation. Summary information for each round of task allocation including Jain’s Fairness Index [Jain *et al.*, 1998] and the expected collective utility achieved are plotted automatically for users to view.

3 Discussions and Future Work

The AlgoCrowd platform enables businesses to dynamically engage workers in need of flexible ad-hoc employment. Compared to existing systems, it offers efficient and explainable AI task allocation optimization designed to emphasize on fair treatment of workers, whiling reducing managers’ workload to find suitable works for tasks. It offers a promising solution to a significant societal problem in China as a result of large-scale rural-urban migration, while empowering traditional businesses to efficiently satisfy their manpower needs.

One key aspect for the success of such a system is the accurate prediction of new workers’ performance. Although each business can use their locally stored worker data, the resulting fragmented machine learning models may not be able to provide satisfactory performance. Here, we see opportunities for federated learning [Yang *et al.*, 2019] for building a powerful aggregated model from locally stored worker data while complying with privacy protection regulations.

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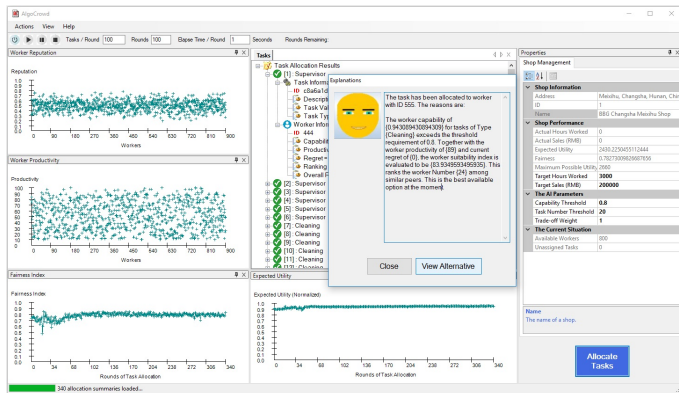


Figure 2: The AlgoCrowd demonstration system.

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