Efficient Scheduling in Crowdsourcing based on Workers' Mood

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***Abstract*—Crowdsourcing workers need to properly schedule when to work and when to rest in order maintain good productivity and ensure the long-term operation of crowdsourcing systems. However, existing algorithmic crowdsourcing works largely overlook this problem and only focus on strategies to optimize the distribution of tasks among workers. In this paper, we propose the Affective Crowdsourcing (*AC*) approach to fill this important gap. It is a distributed dynamic scheduling approach which minimizes crowdsourcing worker effort expenditure while achieving high collective productivity. Our approach leverages the emerging body of evidence about the relationship between people's mood and their productivity to operationalize the 'productive laziness' concept from workforce management research. Extensive experimental studies based on a large-scale dataset released by *Tianchi* demonstrate that AC significantly conserves worker effort, while making the smallest sacrifice in terms of task completion rates as compared to other alternative scheduling approaches. The proposed approach is novel and establishes a framework for crowdsourcing workers to optimize their work and rest schedules.**

***Keywords*-Crowdsourcing; Affective computing; Dynamic work-rest scheduling; Productive laziness;**

I. Introduction

In today's context, crowdsourcing refers to the process of connecting with large groups of people via the Internet to tap into their knowledge, expertise, time, and/or resources [1]. Online crowdsourcing markets take many forms, from Amazon's Mechanical Turk (mTurk) which focuses on micro-tasks, collaborative sensing [2], to 99designs.com which crowdsources sophisticated creative design work. Although a typical crowdsourced task does not offer a high financial reward, crowdsourcing markets have managed to attract a large and diverse pool of workers who participate for fun and to earn extra cash [3].

Improving the productivity of crowdsourcing systems is an important problem facing the crowdsourcing field, as the sustainability of such systems is tied to their overall throughput. Artificial intelligence (AI) techniques are increasingly being applied to help crowdsourcing systems strive for superlinear productive output [4]. Existing approaches focus on imitating human strategies [5], [6], reputation-based techniques [7], [8], [9], [10], [11] or automated task delegation mechanisms to efficiently utilize workers' productivity [12], [13], [14], [15], [16], [17]. Being human, workers may not be able to continuously maintain their highest level of productivity over time. Well rested workers are necessary for replacing active workers when they become fatigued and help sustain long-term operation of the systems [18], [19]. Thus, they need to properly schedule when to work and when to rest in order to optimize their overall productivity and thus help sustain the long-term operation of a given crowdsourcing system. However, to the best of our knowledge, there is no published work which helps crowdsourcing workers intelligently optimize their work and rest schedules in order to boost their long-term productivity.

In recent years, a large number of empirical studies have found strong evidence supporting the hypothesis that happiness makes people more productive [20], [21]. In general, people in a good mood have been found to be more productive than people who are in a neutral mood. Lower mood has also been shown to be systematically related to lower productivity [22]. This same association can be expected to hold in crowdsourcing systems. The emergence of interactive mood diary mobile apps, such as *MoodPanda* (http://www.moodpanda.com/), has provided practical ways to track people's mood frequently over time. With such tools, it becomes possible to leverage crowdsourcing workers' mood information to design computational approaches that optimize their work schedules in order to improve the overall productivity of a given crowdsourcing system (i.e. spending less effort in total while maintaining, or even achieving a higher, collective productivity).

In this paper, we propose the *Affective Crowdsourcing* (AC) approach which leverages this emerging body of evidence about the relationship between people's mood and their productivity. It is a dynamic scheduling approach which jointly minimizes crowdsourcing workers' effort expenditure while maximizing collective task throughput. As it is a fully distributed approach with computational time complexity of $O(1)$, it can be implemented as a personal assistant agent [23], [24], [25] that provides recommendations to a crowdsourcing worker when to work and when to rest. Through extensive numerical experiments based on a large-scale real-world dataset released by Taobao.com's *Tianchi* big data platform, we demonstrate that AC outperforms three baseline scheduling approaches. It manages to significantly conserve worker effort, while making the smallest sacrifice in terms of task completion rates compared to these approaches. The proposed approach establishes a novel framework to enable intelligent agents to help crowdsourcing workers achieve productive laziness [26].

II. Related Work

A number of existing approaches focus on managing workers' productivity. In general, they either provide incentives to motivate workers to work harder, or induce good mood among workers to enhance their productivity.

In [27], the authors conducted empirical studies in order to understand how paid crowdsourcing workers perform compared to volunteers. They observed that per-task payment schemes induce workers to work faster but with reduced quality of work, while wage-based payment schemes cause workers to work more slowly but produce better quality results. This work laid the empirical foundation for computational incentive mechanisms for crowdsourcing which dynamically trade off precision, recall, speed, and total attention on tasks.

In [28], the authors proposed BudgetFix, an approach which determines the number of interdependent micro-tasks in a crowdsourcing system and computes the price for each task considering budget constraints. In [29], the authors studied the relationship between crowdsourcing workers' mood and their creative output capacities. They then proposed two approaches for enhancing worker performance in creative tasks: affective priming and affective pre-screening. Their results confirmed that workers who are in a good mood exhibit enhanced creativity.

Currently, there is no published literature which looks into how to dynamically adapt workers' schedules in response to changes in their mood in order to maintain a high level of productivity. To the best of our knowledge, the proposed AC approach is the first work to fill this important gap in the crowdsourcing literature.

III. The AC Approach

In this section, we first formulate an optimization objective function which jointly considers worker effort expenditure minimization and collective task throughput. We then provide an efficient solution to this optimization problem which issues personalized recommendations to workers on when to work and when to rest.

A. Preliminaries

We model the dynamics of the task backlog queue for each worker as:

$$q_i(t+1) = \max[0, q_i(t) + \lambda_i(t) - \mu_i(t)] \tag{1}$$

where $q_i(t)$ is the size of worker i's task backlog queue during time slot t; $\lambda_i(t)$ is the new workload assigned to i during time slot t; and $\mu_i(t)$ is the workload completed by i during time slot t. $\mu_i(t)$ can be expressed as a function of i's mood and effort expenditure as:

$$\mu_i(t) = \mu(e_i(t), m_i(t)) \tag{2}$$

where $e_i(t) \in [0,1]$ is the normalized effort expenditure by worker i during time slot t; and $m_i(t) \in [0,1]$ is i's mood during time slot t, where 1 denotes the most positive mood. The *Lyapunov function* [30] which measures the overall concentration of demand on workers in a crowdsourcing system during time slot t is given by

$$L(t) = \frac{1}{2}\sum_{i=1}^{N} q_i^2(t) \tag{3}$$

where N is the total number of workers.

Using the time-averaged *Lyapunov drift* $\Delta(\mathbf{q}(t))$ as a measure of the variations in workers' workload (i.e., a form of surprise to each individual worker), we formulate the $\{$*effort expenditure* + *workload*$\}$ objective function as:

$$\sigma\mathbb{E}\{\mathbf{e}(t)|\mathbf{q}(t), \mathbf{m}(t)\} + \Delta(\mathbf{q}(t)) \tag{4}$$

which is to be minimized. $\sigma > 0$ is the general emphasis placed on conserving worker effort expenditure in a crowdsourcing system. $\mathbf{e}(t)$, $\mathbf{q}(t)$ and $\mathbf{m}(t)$ are vectors containing the effort expenditure values, the backlog queue lengths, and the mood values for all workers in a given crowdsourcing system during time slot t, respectively.

Based on Eq. (1) and Eq. (3), the time-averaged Lyapunov drift can be expressed as:

$$\begin{aligned}\Delta(\mathbf{q}(t)) &= \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\left(\frac{1}{2}q_i^2(t+1) - \frac{1}{2}q_i^2(t)\right)\\ &= \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\Bigg(q_i(t)[\lambda_i(t) - \mu(e_i(t), m_i(t))]\\ &\quad - \mu(e_i(t), m_i(t))\lambda_i(t) + \frac{1}{2}[\mu_i^2(t) + \lambda_i^2(t)]\Bigg).\end{aligned} \tag{5}$$

In practical crowdsourcing systems, neither $\lambda_i(t)$ nor $\mu_i(t)$ can be infinite. Assuming there exist constants $\lambda_{\max} \geqslant \lambda_i(t)$ and $\mu_{\max} \geqslant \mu_i(t)$ for all i and t, we have:

$$\Delta(\mathbf{q}(t)) \leqslant \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}\{B + q_i(t)[\lambda_i(t) - \mu(e_i(t), m_i(t))]\} \tag{6}$$

where $B = \frac{1}{2}[\mu_{\max}^2 + \lambda_{\max}^2]$.

By substituting Eq. (6) into Eq. (4), we get:

$$\begin{aligned}&\sigma\mathbb{E}\{\mathbf{e}(t)|\mathbf{q}(t), \mathbf{m}(t)\}\\ &\quad + \Delta(\mathbf{q}(t)) \leqslant \frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}(\sigma_i e_i(t) +\\ &\quad q_i(t)\lambda_i(t) - q_i(t)\mu(e_i(t), m_i(t)) + B)\end{aligned} \tag{7}$$

where $\sigma = \frac{1}{N}\sum_{i=1}^{N}\sigma_i$, and $\sigma_i > 0$ denotes the emphasis worker i places on conserving effort expenditure. We assume that this preference does not change frequently over time, and thus treat it as a constant value with respect to each worker. The proposed approach is only concerned with minimizing effort and maximizing throughput, so we can omit the terms that do not involve $e_i(t)$ in our optimization task. As such, the objective function can be expressed as:

Minimize:

$$\frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N}[\sigma_i e_i(t) - q_i(t)\mu(e_i(t), m_i(t))] \tag{8}$$

Subject to:

$$0 \leqslant e_i(t) \leqslant 1, \forall i, t \tag{9}$$

$$0 \leqslant \mu(e_i(t), m_i(t)) \leqslant \mu_i^{\max}, \forall i, t \tag{10}$$

where $\mu_i^{\max}$ is worker i's maximum task processing capacity based on historical performance data. By minimizing Eq. (8), we simultaneously minimize the time-averaged total worker effort expenditure while maximizing the time-averaged collective task throughput.

B. Generating Work-Rest Recommendations

With the above objective function formulated, there is one last step missing before a solution can be derived: establishing how mood influences productivity. In previous studies, mood has been found to be linearly related to productivity for tasks related to impersonal decision-making [31]. As completing crowdsourcing tasks mostly involves making impersonal decisions, we follow this finding and assume that workers' productivity is linearly related to their mood, up to their maximum possible productivity. Under this assumption, $\mu(e_i(t), m_i(t))$ is expressed as follows:

$$\mu(e_i(t), m_i(t)) = \lfloor m_i(t)e_i(t)\mu_i^{\max}\rfloor. \tag{11}$$

In this case, Eq. (8) can be re-expressed as:

$$\frac{1}{T}\sum_{t=0}^{T-1}\sum_{i=1}^{N} e_i(t)[\sigma_i - q_i(t)m_i(t)\mu_i^{\max}]. \tag{12}$$

We denote $[\sigma_i - q_i(t)m_i(t)\mu_i^{\max}]$ as $\Phi_i(t)$ for simplicity.

To minimize Eq. (12), at each time slot t, each worker i's AC agent computes the values of $\Phi_i(t)$. If $\Phi_i(t) < 0$, the AC agent sets $e_i(t) = \min\left[\frac{q_i(t)}{m_i(t)\mu_i^{\max}}, 1\right]$ which takes into account the actual number of tasks in worker i's pending task queue. It sets $e_i(t) = 0$ and $\mu_i(t) = 0$ if worker i who has no more pending tasks or does not satisfy $\Phi_i(t) < 0$. In general, an AC agent assigns less rest to a worker who expresses less desire to rest, is in a good mood, has more tasks pending, and/or has high task processing capacities. Once the AC agent determines that worker i should not rest for time slot t, it recommends an effort output level such that the larger the worker's current task backlog, the lower his current mood is, and the lower his maximum productivity is, the more effort he should expend. Algorithm 1 computes the exact number of tasks a worker should work on at any given time slot t. Since it is a distributed approach, the computational time complexity of AC is $O(1)$.

Algorithm 1 Affective Crowdsourcing (AC)

Require: $q_i(t)$, σ_i, $\mu_i^{\max}$, $m_i(t)$ for worker i at time t.
if $\Phi_i(t) < 0$ **then**
  $e_i(t) = \min\left[\frac{q_i(t)}{m_i(t)\mu_i^{\max}}, 1\right]$;
  $\mu_i(t) = \lfloor m_i(t)e_i(t)\mu_i^{\max}\rfloor$;
else
  $e_i(t) = 0$;
  $\mu_i(t) = 0$;
end if
return $\mu_i(t)$;

IV. Experimental Evaluation

To evaluate the performance of AC under realistic settings, it is compared with three baseline approaches via extensive numerical experiments. To do so, we synthesize a population of crowdsourcing worker agents[1] whose performance characteristics are based on the *Tianchi* dataset released by Taobao.com. This real-world dataset allows us to construct realistic scenarios. The simulations facilitate studying the behavior of AC under different situations.

A. Experimental Settings

The Tianchi dataset contains information regarding the productivity (as measured by the number of tasks that can be completed per time slot) and reliability (as measured by a reputation value in the range of $[0, 1]$) of 5,547 agents. The majority of the worker agents are able to process 10 tasks per time slot while a relatively small percentage of them are able to process up to 100 tasks per time slot. The distribution of reliability roughly follows a Normal Distribution centred around 0.4 to 0.5.

Based on this dataset, we generate four identical populations of 5,547 worker agents for AC and the other three approaches, namely:

1) The *Max Effort* (ME) approach: a worker agent i exerts $e_i(t) = 1$ effort at every time slot (i.e. it never rests);
2) The *Mood Threshold* (MT) approach: a worker agent i exerts $e_i(t) = 1$ effort only when $m_i(t) \geqslant 0.5$. Otherwise, the worker agent rests for the given time slot (i.e., $e_i(t) = 0$);
3) The *Mood and Workload Threshold* (MW) approach: a worker agent i exerts $e_i(t) = 1$ effort only when $q_i(t)\mu(1, m_i(t)) \geqslant \mu_i^{\max}\mu(1, 0.5)$. Otherwise, the worker agent rests for the given time slot (i.e.,

[1]http://dx.doi.org/10.7303/syn7373599

$e_i(t) = 0$). Under this approach, workers who are in a good mood and/or who have high workload expend more effort.

For all approaches, the DRAFT algorithm [15] is used to allocate tasks to workers: at each time slot, DRAFT will take i's current reputation and workload as inputs to determine how many tasks to assign to i (i.e. DRAFT determines $\lambda_i(t)$). The core principle of DRAFT is that the higher i's reputation is and the lower i's current workload is, the more tasks should be assigned to i. DRAFT can also be replaced by other similar approaches in practice.

In our experiments, σ is varied from 5 to 100 in increments of 5. As the workload is measured relative to the collective productivity of the worker agents, we compute the maximum throughput θ of a given crowdsourcing system as $\theta = \sum_{i=1}^{N} r_i \mu_i^{\max}$, where r_i is worker agent i's reputation, and $N = 5,547$ in our experiments. The load factor (LF) placed on the crowdsourcing system is the ratio between the number of tasks to be allocated among the worker agents during time slot t, $W_{req}(t)$, and the maximum throughput value θ of the system (i.e. $LF = \frac{W_{req}(t)}{\theta}$). We vary the LF value between 5% to 100% in 5% increments.

The $m_i(t)$ value for each worker i during time slot t is randomly generated in the range of $[0, 1]$ following a uniform distribution. Such an assumption eliminates the possibility for any of the four approaches to attempt to predict a worker agent's future mood, thereby making the experimental comparisons more focused on the scheduling strategy itself, which is the core of this paper. In our experiments, we assume that the outcome for each task is binary (i.e., a task is successfully completed if the worker agent produces the correct result before the stipulated deadline; otherwise, it is considered unsuccessful). Under each LF setting, the simulation is run for $T = 1,000$ time slots. Task deadlines are randomized following a uniform distribution. On average, a task must be completed within 5 time slots after it is first assigned to a worker agent.

The performances of the four approaches are compared using the following metrics:

1) The time-averaged worker effort expenditure (the smaller the better): $e = \frac{1}{TN}\sum_{t=0}^{T-1}\sum_{i=1}^{N} e_i(t)$.
2) The time-averaged task completion rate (the larger the better): $c = \frac{1}{T}\sum_{t=0}^{T-1}\frac{\sum_{i=1}^{N}\mu_i(t)}{N_{\text{Total}}}$, where N_{Total} is the total number of tasks to be completed by the crowdsourcing system per time slot.

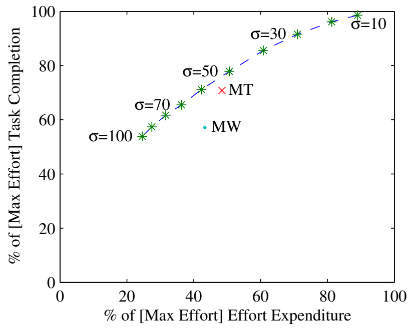
B. Experimental Results

As ME achieves the highest task completion rate (at the expense of full worker effort expenditure, i.e. workers never rest), we use it as a gauge for the performance of the other 3 approaches under different LF and σ settings.

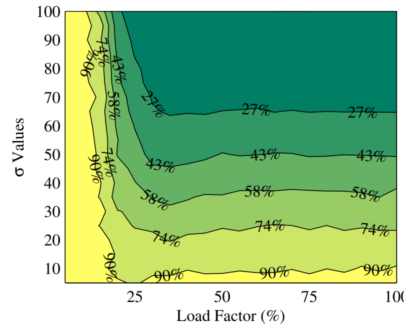
Firstly, we analyze the performance of AC under different experimental settings. Figure 1(a) shows the performance profile (i.e. task completion rates against the worker effort expenditure) of AC under different σ settings as well as those of MT and MW. Both variables are displayed as a percentage of that achieved by ME and are averaged across all LF settings used in our experiment. As σ increases, the trade-off between the average task completion rate and the average worker effort expenditure rate roughly follows a logarithmic function. In other words, a large reduction in the average worker effort expenditure results in a relatively small reduction in the average task completion rate. It can be observed from Figure 1(b) that under low LF conditions, AC does not conserve much worker effort. This is because in such conditions, DRAFT assigns most tasks to a small number of highly reliable workers; those workers then need to work close to capacity in order to complete the assigned tasks. As LF increases, tasks are spread out among more workers. AC can then schedule workers with lower mood to rest more and workers with higher mood to work more, thereby conserving more worker effort overall. Under low σ settings, less emphasis is placed on conserving worker effort expenditure. This signals AC to allocate less time for rest on average. As LF and σ increase, AC is able to achieve more conservation in worker effort expenditure. A similar trend can be observed in terms of the average task completion rate (Figure 1(c)). As LF and σ increase, AC trades the reduced average task completion rate for less worker effort expenditure. The results can be used as a guide for crowdsourcing system administrators to determine appropriate values for the control variable σ. It can be observed that the points representing the performance profiles of both MT and MW are below the curve representing the performance profile of AC. This indicates that with the same worker effort expenditure as under AC, both MT and MW achieve lower task completion rates. Overall, AC makes the best trade-off between work and rest among the comparison approaches by dynamically taking advantage of favourable working conditions (spending, on average, 25% of the effort and completing over 55% of the tasks in the worst case in Figure 1(a)).

Secondly, we compare the performance of AC against other approaches. Based on the above analysis, we know that the performance of AC can be controlled through the variable σ. We select $\sigma = 20$, which provides a reasonable trade-off for a crowdsourcing system, given that the primary objective of such systems is to complete as many tasks as possible. Figure 1(d) shows the relative performance of the 4 approaches in terms of worker agents' effort expenditure as a percentage of the worker agents' effort expenditure under the ME approach. MW achieves the best performance, with MT and AC trailing behind. On average, AC conserves 19.8% of worker effort, whereas MT and MW conserve 51.6% and 56.7% of worker effort, respectively.

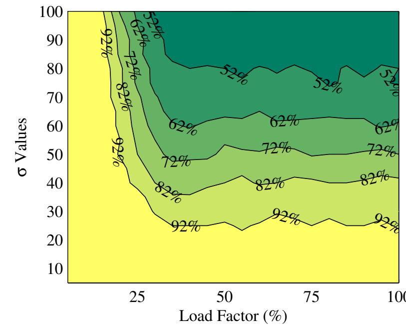
In terms of task completion rate (Figure 1(e)), under low LF conditions, AC matches the performance of ME. MT



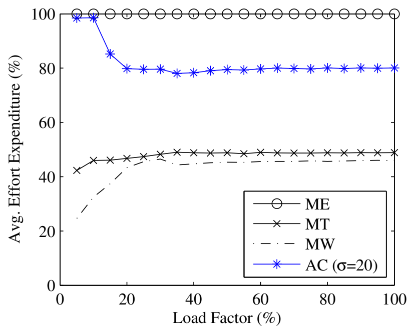
(a) Performance comparison



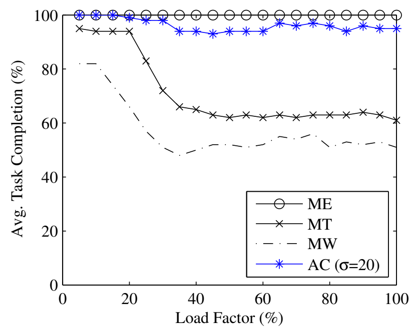
(b) $\frac{e_{\text{AC}}}{e_{\text{ME}}}$



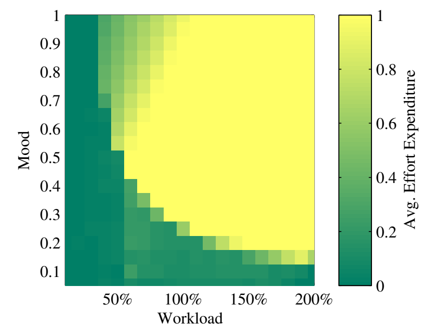
(c) $\frac{c_{\text{AC}}}{c_{\text{ME}}}$



(d) Effort expenditure



(e) Task completion



(f) AC worker agents' effort expenditure landscape (σ = 20, LF = 50%)

Figure 1. Experimental Results.

achieves over 90% of the task completion rate of ME for LF $\leqslant$ 20%. As LF further increases, the performance of MT and MW drops significantly, while AC is able to maintain a high task completion rate. On average, AC achieves 96.2% of the task completion rate of ME, while MT and MW achieve 70.8% and 57.1% of the task completion rate of ME, respectively.

Figure 1(f) shows the average effort exerted by worker agents facing different mood and workload condition under $\sigma = 20$ and a load factor of 50%. The DRAFT task allocation approach used in the experiment ensures that no worker agent's instantaneous workload exceeds 200% of its $\mu_i^{\max}$ value. It can be observed that AC directs worker agents who are in a good mood and having high workloads to exert more effort. When worker agents are in a bad mood, as long as their workloads are not high, AC advises them to exert less effort and rest more. In this way, AC dynamically leverages favourable working conditions to achieve high productivity and conserve worker effort in the long run.

V. Conclusions and Future Work

In this paper, we proposed AC, a dynamic scheduling approach for minimizing crowdsourcing worker effort expenditure while achieving high collective productivity. To the best of our knowledge, it is the first algorithmic crowdsourcing approach that helps workers optimize when to work and when to rest by jointly considering their mood, pending workloads, and task processing capacities. AC does not rely on knowledge of the exact distributions of the workers' capabilities in order to operate. Through extensive numerical experiments based on a real-world dataset released by *Tianchi*, we demonstrated that AC makes the best task completion vs. worker effort conservation trade-offs when compared with three baseline approaches. On average, it achieves the smallest reduction in task completion rate while still significantly conserving worker effort, thereby helping crowdsourcing workers achieve productive laziness.

In subsequent research, we will study the behaviour of AC under non-linear relationships between mood and productivity in a practical crowdsourcing platform [32] so as to enable it to work under a wider range of situations.

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