Predicting Crowd Worker's Stopping Time based on Discounted Satisficing

Mounica Devaguptapu, Venkata Sriram Siddhardh Nadendla

Missouri University of Science and Technology
Rolla, Missouri 65401
{md2rt, nadendla}@mst.edu

Abstract

Decisions made by workers on crowdsourcing platforms can be broadly categorized into three types: (i) picking tasks, (ii) executing tasks, and (iii) the time they decide to stop working (*a.k.a.* stopping time). Assuming that the workers execute the selected tasks with maximum efficiency, our goal is to model and learn how workers choose their task-picks and stopping time. Such an analysis enables crowdsourcing platforms to strategically recommend tasks in a personalized manner to workers in order to improve their overall productivity. In contrary to traditional assumptions in the literature regarding how workers exhibit satisficing behavior on instantaneous utilities, we assume that workers employ a *discounted satisficing* heuristic to compute their stopping time, i.e., the worker stops working if the total accumulated utility goes beyond a dynamic threshold that gets discounted with time. We also propose a novel learning algorithm to estimate our model parameters. Simulation results are presented to demonstrate the error performance.

Motivation

Crowdsourcing is an online mechanism where tasks can be outsourced by any registered agency to a large pool of unknown workers in the form of an open call on Internet. In such a framework, the decisions made by workers can be broadly classified into three types: (i) pick tasks that suit according to their preferences, (ii) make executive decisions in completing the task, and (iii) decide a stopping time beyond which the agent temporarily quits from the crowdsourcing platform. The current literature focuses on analyzing the first type of decisions extensively using various models such as utility maximization and satisficing(Kapelner and Chandler 2010). These studies have led to the design of many recommender systems for crowdsourcing platforms (Schulze, Krug, and Schader 2012; Chilton et al. 2010; Yuen, King, and Leung 2011; Ignatov et al. 2014; Schnitzer 2019). The second type of decisions are analyzed via evaluating the performance quality of the workers (Hata et al. 2017). However, there is very little work on how/when a crowd-worker decides to stop working temporarily in the crowdsourcing platform. Therefore, in this paper, we model agents' decisions about their stopping times using *discounted satisficing* heuristic on a sequential multi-arm bandit framework to model human factors in workers' decisions. For the sake of simplicity and tractability, we focus only on investigating stopping times via ignoring the first two types of decision processes in this work.

Discounted Satisficing Heuristic

Consider a crowdsourcing platform $\mathcal{P}$ where a worker $\mathcal{W}$ is presented with a fixed set of tasks (arms) $C = \{1, 2, \cdots, m\}$ at any time $k \in N$. Let $u_{i,k}$ denote the random utility obtained by the worker $\mathcal{W}$ for choosing the task $i_k \in C$ at time $t \in \mathcal{T}$. In this paper, we ignore the rationality behind choosing the task $i_k \in C$ since our goal is to investigate stopping times employed by the workers. After t time periods, the total utility accumulated at the worker $\mathcal{W}$ is given by $U_t = \displaystyle\sum_{k=1}^{t} u_{i,k}$. Then, we define the worker's rationality as shown below.

Definition 1. An agent is said to follow the *discounted satisficing* heuristic, if there exists two numbers $\lambda \in R_+$ and $\beta \in (0, 1)$ such that the stopping time is given by

$$T = \text{minimize } \left\{ t \in \mathcal{T} \;\middle|\; U_t \geq \beta^{t-1}\lambda \right\} \tag{1}$$

In the above heuristic, the parameter λ denotes the total utility desired by worker $\mathcal{W}$ prior to the commencement of their work-day on platform $\mathcal{P}$. On the other hand, the parameter β captures the discounting behavior of the worker over time due to the increasing levels of weariness.

Learning Model Parameters

Since our goal is to predict the stopping time of any given worker $\mathcal{W}$, we need to estimate model parameters (λ, β) in Definition 1. Assuming that the utilities of different task-picks are perfectly observable, a given stopping time T can be associated with a sequence of inequalities based on the sequence of stopping decisions made by the worker according to Equation (1) until time T.

This system of non-linear inequalities can be linearized by applying logarithms on both sides to obtain a polytope

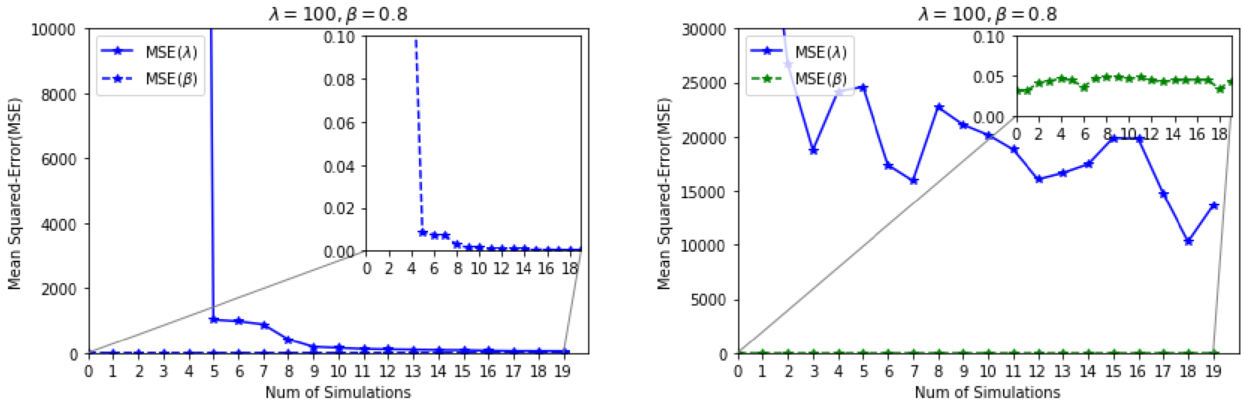

Figure 1: Convergence of mean squared-error in the estimation of $\hat{\lambda}$ and $\hat{\beta}$ over multiple simulation rounds.

described by the following system of linear inequalities:

$$(t-1)\log\beta + \log\lambda > \log U_t,\ \forall\, t = 1, \cdots, T-1,$$

and

$$(T-1)\log\beta + \log\lambda \leq \log U_T. \tag{2}$$

A natural way to compute the parameter estimates $(\hat{\lambda}, \hat{\beta})$ is to consider the centroid of the above polytope as a candidate solution. However, the above polytope is not necessarily compact, making it impossible to employ this method in general. Therefore, we assume the polytope to be compact via imposing limits on β, i.e.

$$0 < \beta_L \leq \beta \leq \beta_U < 1, \tag{3}$$

where β_L, β_U can be justified as prior knowledge about the worker $\mathcal{W}$. This estimate can be further improved via observing worker's decisions over multiple iterations[1].

Let $D = (d_1, d_2, \cdots, d_n)$ denote the worker's decisions over n iterations, where each $d_j = \{u_{i,1},\ u_{i,2}, \cdots,\ u_{i,T_j}\}$ contains the sequence of utilities obtained by worker W until he/she stops at time T_j in the j^{th} iteration, for any $j = 1, \cdots, n$. Since each data tuple d_j produces a compact polytope (denoted as R_j) from Equations (2) and (3), we obtain a reduced polytope $R = R_1 \cap \cdots \cap R_n$ from the intersection of the polytopes obtained from n iterations, which can be efficiently computed using Sutherland-Hodgman Algorithm (Sutherland and Hodgman 1974). In the following section, we show that the centroid of the reduced polytope R approaches to the true values of (λ, β) using simulation experiments. Furthermore, we also show how estimation error in model parameters affects the error in predicting the worker's stopping time.

Results and Discussion

In this section, we will discuss how we have validated the *discounted satisficing* heuristic to model worker's stopping time using (i) simulation experiments, and (ii) real-data.

[1]For example, each iteration could represent a sequence of decisions made by the worker over a single day.

Simulation Results: In our simulation experiment, we assume that 4 tasks (arms) are available at the worker with equal probability, where the k^{th} task produces a uniformly random reward over the support (a_k, b_k). Assuming that the worker's model parameters are $(\lambda = 100, \beta = 0.8)$, and letting $\beta_L = 0.05$ and $\beta_U = 0.99$ in our proposed algorithm, we run several Monte-Carlo simulations of this experiment to compute the average error of the estimated parameters. Since the average error is highly sensitive to outliers, we measure the performance of our algorithm using the median of the estimation error (David and Nagaraja 2006). In the simulation results, we found that the estimation error of our algorithm converges to zero consistently only when $\beta \geq 0.5$. We illustrate this observation in Figure 1 using two examples both with a fixed $\lambda = 100$, where the left subfigure demonstrates the convergence of estimation error to zero when $\beta = 0.8$, while the right subfigure demonstrates the fact that estimation error does not converge to zero when $\beta = 0.4$. This can be attributed to the fact that the dynamic thresholds of the agents with lower β values generally deteriorate at a much faster rate, thereby revealing very little about the model parameters in their choices. In addition, we have also noticed deteriorated performance in the presence of small values of λ, which can also be justified with similar reasons as stated above, in the case of small values of β. In the future, our plan is to study the relationship between the errors in the estimation of model parameters and the error in predicting the worker's stopping time.

Evaluation on Real-Data: Validation on real data is currently in progress. In this regard, we have designed an ANDRIOD application where an agent can play a multi-armed bandit game. Based on preliminary results, we find that our algorithm predicts the workers' stopping time with 26% probability, if the utilities are defined as instantaneous rewards obtained by the workers. However, in practice, people's utility functions are known to constitute preferences across multiple attributes. Therefore, in our future work, our goal is to learn the worker's utility functions along with model parameters to better predict workers' stopping times.

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