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A Model for Aggregating Contributions of Synergistic Crowdsourcing Workflows

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Abstract

One of the most important crowdsourcing topics is to study the effective quality control methods so as to reduce the cost and to guarantee the quality of task processing. As an effective approach, iterative improvement workflow is known to choose the best result from multiple workflows. However, for complex crowdsourcing tasks that consists of a certain number of subtasks under some specific constraints, but cannot be split into subtasks to be crowdsourced, the approach merely considers the best workflow without integrating the contributions of all workflows, which potentially results in extra costs for more iterations. In this paper, we propose an assembly model to integrate the best output of subtasks from different workflows. Moreover, we devise an efficient iterative method based on POMDP to improve the quality of assembled output. Empirical studies confirms the superiority of our proposed model.

Introduction

In crowdsourcing, the iterative improvement workflow is an effective approach to gain higher quality output. To improve the iterative workflows, researchers mainly propose three models illustrated in Figure 1. The shaded circles denote outputs of different workflows in the current iteration, and empty circles denote inputs for next iteration. The free choice model freely uses every previous output for further processing (Yu and Nickerson 2011), which incurs too many costs. The single choice model chooses current the best output as the basis for next iteration of improvement. there is a special case (Dai et al. 2013) in which there is only one single workflow running and the input of next iteration is determined by choosing the best one between the outputs of previous iteration and current iteration. Although the single choice model is easy to implement, it neglects most workers' contributions and thus potentially requires more iterations of processing. To address the disadvantages of the single choice model, the switch model (Dai et al. 2013) is proposed to dynamically switch among alternative workflows, which is essentially a dynamic single choice model and does not provide an effective way to aggregate the contributions of different workers either.

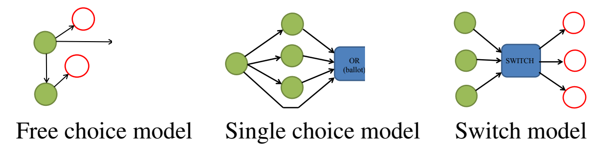

Figure 1: Three workflow models.

In this paper, we aim to solve a common class of crowdsourcing tasks named context-sensitive task (CST), each of which consists of a certain number of subtasks under some specific constraints, but cannot be split into micro-tasks to be crowdsourced. When the same CST is published in different ways, each of which is processed with a workflow. Since all the existing three models are not suitable, we design an assembly model to aggregate the contributions of each workflow and use the aggregated result for next iteration of improvement against the single choice model. Then, we transform the problem of optimizing the quality of CST as a Partially-Observable Markov Decision Problem (POMDP)(Dai et al. 2013) to solve. The experiment result shows that our approach outperforms the single choice model.

Our Model

Our model aims to solve a common class of crowdsourcing tasks which is denoted CST, which have two features: (1) A CST task T is composed of M subtasks, the processing of each of which is correlated within certain contexts; (2) Therefore, each subtask can not be used as a HIT to be crowdsourced. This paper presents our iterative control model based on POMDP for obtaining a high-quality result with low costs. The schematic of the proposed architecture is shown in Figure 2 for CST, which shows the general process of our model.

Task scheduler Task scheduler is responsible for receiving a CST task and scheduling it for crowdsourcing. The task scheduler distributes the same context-sensitive task to multiple workers in different ways, each of which has only one worker to finish. Similar to other model, every worker submits output to our model.

Output assembly gathers results of CST from all workers attended crowdsourcing and reassemble result of subtasks

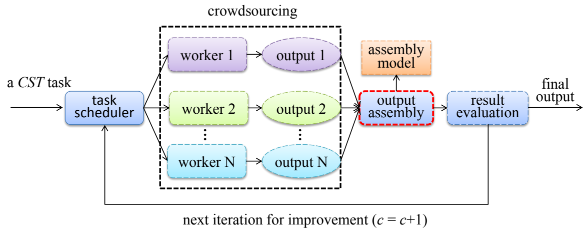

Figure 2: Iterative improvement workflow with the assembly model.

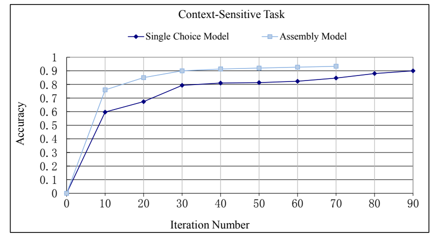

Figure 3: Result accuracy comparison of the two models in different iterations of task running.

of the CST toward aggregating contributions of synergistic crowdsourcing workflows. Given a CST T ($T = \{t_j\}$) with M substasks and N workers to process T, the output matrix is denoted by $O = (o_{ij})$, where o_{ij} is the ouput produced by worker i for subtask j ($0 \leq i \leq N, 0 \leq j \leq M$). We use $O_{.j}$ to denote the output vector of subtask t_j and $O_{i.}$ to denote the output vector of worker i. Based on all subtasks, we can reassemble some outputs of CST denoted by CSTI, and get less than N^M CSTIs. To determine the best result for CST in current iteration, let $p(o_{ij}) = K/N$ measure the accuracy of the subtask result o_{ij}, where K is the number of workers having the same output $o_{ij} \in O_{.j}$ of the t_j. We define relationship $\prec$ (partial order) based on accuracy of the subtask result for all CSTIs denoted by I_T, and learn that $\langle I_T, \prec\rangle$ is partially ordered set. This fact assures all results have a maximal elements set. If there are more than one maximal element in the partial ordered set, we measure workers ability though the *Bernoulli's law of large numbers* to choose the best CSTI, otherwise the maximal is the best result of CST.

Result evaluation determines whether the previous result is improved and whether the obtained assembly result is good enough to submit, which is judged by applying POMDP model with online planning algorithm. In the result evaluation, it is typical auto-control problem to choose the better one from previous best CSTI and current best CSTI as final result to submit or the input of next iteration to run. Let $q_c \in [0, 1]$ and $q_{c+1} \in [0, 1]$ denote the quality of previous best CSTI and current best CSTI, which imply worker has probability $1 - q_{c+1}$ of improving our the best CSTI in the current iteration. Since (q_c, q_{c+1}) is only partially observable, this problem can be formulized as a POMDP and there have been a lot of existing methods to solve it.

In summary, we apply the theory of partial order and the *Bernoulli's law of large numbers* to determine our assembly result in current iteration and employ POMDP to improve the crowdsourcing process iteratively.

Experiment

Experiment Setup

To evaluate the effectiveness and time needed of our proposed model, we give simulation. A CST with M subtasks is simulated with a pool of M objects, each of which represents a subtask. Each object contains ID and difficulty. ID represents the unique identification of a subtask, and the difficulty represents the needed efforts to complete a subtask. Each worker generates a set of objects to simulate the output of CST, which contains the ID of subtask processed by workers and the skill excellence of workers, where the ID follows a Gaussian distribution $N(\mu, {\sigma_i}^2)$, and the skill excellence represents whether the output of the subtask is correct. When the object generated by a worker equals to an object in the pool, then this subtask is processed accurately. we make $R_s = \frac{Z}{M}$ as the rewarding function based on the accuracy, where Z denote the number of objects processed accurately, M denote the number of subtasks.

Compared with Single Choice Model

We invoke the ZMDP package to make decision in our iterative workflow. The progress of the CST consisting of 300 subtasks through the assembly model and the single choice model is simulated. Figure 3 illustrates that the accuracy of the assembly model is higher than the single choice model from 0^{th} iteration to 90^{th}. In addition, the assembly model can get a final output with the accuracy of 0.93333 by 70 iterations and the single choice model get a final output with the accuracy of 0.9 by 90 iterations. Here, under the same conditions, the result shows our model will spend less time to be able to get a better result. These empirical studies confirms the effectiveness of our proposed model.

Conclusions

In this paper, we propose a novel assembly model to aggregate contributions of synergistic crowdsourcing workflows, and leverage POMDP method to control the quality of iterated workflows. The simulations illustrate that our model has higher quality than single choice model to finish in processing CST with the same number of queries to the crowd.

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