The Importance of Worker Reputation Information in Microtask-Based Crowd Work Systems.

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Abstract- **This paper presents we first formalize the optimal task assignment problem when workers' reputation estimates are available, as the maximization of a monotone (submodular) function subject to Matroid constraints. Then, being the optimal problem NP-hard, we propose a simple but efficient greedy heuristic task allocation algorithm. We also propose a simple "maximum a-posteriori" decision rule and a decision algorithm based on message passing. Finally, we test and compare different solutions, showing that system performance can greatly benefit from information about workers' reputation. In this our main findings are that: i) even largely inaccurate estimates of workers' reputation can be effectively exploited in the task assignment to greatly improve system performance; ii) the performance of the maximum a-posteriori decision rule quickly degrades as worker reputation estimates become inaccurate; iii) when workers' reputation estimates are significantly inaccurate, the best performance can be obtained by combining our proposed task assignment algorithm with the message-passing decision algorithm.**

Index terms- **a-priori, micro task, a-posteriori, message passing.**

I. INTRODUCTION

Crowd work is a term often adopted to identify networked systems that can be used for the solution of a wide range of complex problems by integrating a large number of human and/or computer efforts . Alternative terms, each one carrying its own specific nuance ,to identify similar types of systems are :collective intelligence ,human computation ,master-worker computing, volunteer computing, serious games, voting problems, peer production, citizen science. An entire host of general-purpose or specialized online platforms, such as information-sharing platforms for recommendations co-creation systems, social-purpose communities for urban mobility , micro task-based crowd work systems, etc., can be defined under these terms. In this paper, we specialize to micro task-based crowd work systems. The key characteristic of these systems is that a requester structures his problem in a set of tasks, and then assigns tasks to workers that provide answers, which are then used to determine the correct task solution through a decision rule. A well-known example of such systems is Amazon Mechanical Turk, which allows the employment of large numbers of low-wage workers for tasks requiring human intelligence(Human Intelligence Tasks). Examples of HIT are image classification, annotation, rating and recommendation, speech labeling, proofreading, etc. In the Amazon Mechanical Turk, the workload submitted by the requester is partitioned into several micro tasks, with a simple and strictly specified structure, which are then assigned to workers. Since task execution is typically tedious, and the economic reward for workers is pretty small, workers are not 100% reliable, in the sense that they may provide incorrect answers. Hence, in most practical cases, the same task is assigned in parallel to several workers, and then a majority decision rule is applied to their answers. A natural trade-off between reliability of the decision and cost arises; indeed, by increasing the replication factor of every task, we generally increase the reliability degree of the final decision about the task solution, but we necessarily incur higher costs (or, for a given fixed cost, we obtain a lower task throughput). Although the pool of workers in crowd work systems is normally large, it can be abstracted as a finite set of shared resources, so that the allocation of tasks to workers (or, equivalently, of workers to tasks) is of key relevance to the system performance. Some believe that micro task-based crowd work systems will provide a significant new type of work organization paradigm, and will employ ever increasing numbers of workers in the future, provided that the main challenges in this new type of organizations are correctly solved. identify a dozen such challenges, including i) workflow definition and hierarchy, ii) task assignment, iii) real-time response, iv) quality control and reputation. All these aspects can represent an interesting research subject and some of them have already stimulated a large bulk of literature, as it will be detailed in the next subsection. However, this paper deals mainly with task assignment and with the quantitative assessment of the gain (in terms of increased decision reliability for a given cost) that a coarse knowledge of worker quality can offer. Indirectly, thus, we deal also with worker reputation, although we do not study mechanisms through which reputation is built upon time. Indeed, we consider a one-shot approach in which the requester has to assign a bunch of tasks to a pool of workers that are statically divided into classes according to their probabilities of answering correctly. We highlight that the way this division into classes is built is out of the scope of this paper, although we will analyze the effect of errors in this classification on the decision reliability.

II. EXISTING SYSTEM

These algorithms exploit existing redundancy and correlation in the pattern of answers returned from workers to infer an a-posteriori reliability estimate for every worker. The derived estimates are then used to properly weigh workers' answers. The main drawback of existing workflows for complex work is that the decomposition structure is static and fixed by the requestor. For example, while a requestor might specify a workflow in which workers first partition work into sub-problems before workers then perform a map step, the workflow itself is fixed and cannot vary in response to the work done. Workers editing a function may also wish to reuse existing functionality or break up the work to be implemented into multiple functions. In Crowd Code, workers do not need to choose between these cases.

III. PROPOSED SYSTEM

Propose a simple but efficient greedy heuristic task allocation algorithm. We also propose a simple "maximum a-posteriori" decision rule and a decision algorithm based on message passing. Finally, we test and compare different solutions, showing that system performance can greatly benefit from information about workers' reputation. when worker's(humans) reputation estimates are significantly inaccurate, the best performance can be obtained by combining our proposed task assignment algorithm with the message-passing decision algorithm. which proposes an adaptive online algorithm to assign an appropriate number of workers to every task, so as to meet a prefixed constraint on the problem solution reliability. we propose a simple "maximum a-posteriori" (MAP) decision rule, which is well known to be optimal when perfect estimates of workers' reputation are available. Moreover, we introduce a message-passing decision algorithm, which is able to encompass a-priori information about workers.

IV. IMPLEMENTATION

Implementation is the stage of the project when the theoretical design is turned out into a working system. Thus it can be considered to be the most critical stage in achieving a successful new system and in giving the user, confidence that the new system will work and be effective.
The implementation stage involves careful planning, investigation of the existing system and it's constraints on implementation, designing of methods to achieve changeover and evaluation of changeover methods.

V. MODULES

In this Project we implemented in four modules

- Worker Reputation Information
- Micro task-based crowd work systems
- Task Assignment problem
- Message-passing

1).Worker Reputation Information:

The worker reputation, we do not study mechanisms through which reputation is built upon time. Indeed, we consider a one-shot approach in which the requester has to assign a bunch of tasks to a pool of workers that are statically divided into classes according to their probabilities of answering correctly. We highlight that the way this division into classes is built is out of the scope of this paper, although we will analyze the effect of errors in this classification on the decision reliability. Whenever worker reputation is not known a-priori, the above decision rule is no more optimal, since it neglects the information that answers to other tasks can provide about worker reputation.

2). Micro task-based crowd work systems:

We specialize to microtask-based crowd work systems. The key characteristic of these systems is that a requester structures his problem in a set of tasks, and then assigns tasks to workers that provide answers, which are then used to determine the correct task solution through a decision rule. A well-known example of such systems is Amazon. Some believe that microtask-based crowd work systems will provide a significant new type of work organization paradigm, and will employ ever increasing numbers of workers in the future, provided that the main challenges in this new type of organizations are correctly solved. We also suppose that each single assignment of a task to a worker has a cost, which is independent of the worker's class. In practical microtask-based crowdsourcing systems, such cost represents the low wages per task the requester pays the worker, in order to obtain answers to his queries.

3).Task Assignment Problem:

First we find the optimal task assignment problem when the worker's reputation estimates are available, as the maximization to monotone function subject to Matroid conditions. Then, being the optimal problem NP-hard, for this we propose a simple but efficient greedy heuristic task allocation algorithm. In this our main findings are that: i) even largely inaccurate estimates of workers' reputation can be effectively exploited in the task assignment to greatly improve system performance; ii) the performance of the maximum a-posteriori decision rule quickly degrades as worker reputation estimates become inaccurate; this paper deals mainly with task assignment and with the quantitative assessment of the gain (in terms of increased decision reliability for a given cost) that a coarse knowledge of worker quality can offer. Indirectly, thus, we deal also with worker reputation, although we do not study mechanisms through which reputation is built upon time.

4). Message Passing:

It is shown that the improved decision rule can be efficiently implemented employing a message-passing technique. In an integrated estimation-allocation approach has been pursued with Bayesian inference and entropy reduction as utility function. Moreover, we introduce a message-passing decision algorithm, which is able to encompass a-priori information about workers' reputation, thus improving upon the one described. Finally, our proposed approach is tested in several scenarios, and compared to previous proposals. We have also described a simple "maximum a-posteriori" decision rule and a well-performing message-passing decision algorithm. We have tested our proposed algorithms, and compared them to different solutions, which can be obtained by extrapolating the proposals for the cases when reputation information is not available.

VI. CONCLUSION

We have presented the first systematic investigation of the impact of information about workers' reputation in the assignment of tasks to workers in crowd work systems, quantifying the potential performance gains in several cases. We have formalized the optimal task assignment problem when workers' reputation estimates are available, as the maximization of a monotone (submodular) function subject to Matroid constraints. Then, being the optimal problem NPhard, we have proposed a simple but efficient greedy heuristic task allocation algorithm. We have also described a simple "maximum a-posteriori" decision rule and a well-performing message-passing decision algorithm. We have tested our proposed algorithms, and compared them to different solutions, which can be obtained by extrapolating the proposals for the cases when reputation information is not available, showing that the crowd work system performance can greatly benefit from even largely inaccurate estimates of workers' reputation.

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