An Explorative Approach for Crowdsourcing Tasks Design

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ABSTRACT

Crowdsourcing applications are becoming widespread; they cover very different scenarios, including opinion mining, multimedia data annotation, localised information gathering, marketing campaigns, expert response gathering, and so on. The quality of the outcome of these applications depends on different design parameters and constraints, and it is very hard to judge about their combined effects without doing some experiments; on the other hand, there are no experiences or guidelines that tell how to conduct experiments, and thus these are often conducted in an ad-hoc manner, typically through adjustments of an initial strategy that may converge to a parameter setting which is quite different from the best possible one. In this paper we propose a comparative, explorative approach for designing crowdsourcing tasks. The method consists of defining a representative set of execution strategies, then execute them on a small dataset, then collect quality measures for each candidate strategy, and finally decide the strategy to be used with the complete dataset.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

Keywords

crowdsourcing, social computation, empirical method

1. INTRODUCTION

A new class of software applications, called crowd-based applications, is emerging. These applications use crowds, engaged through a variety of platforms, for performing tasks; the most typical application scenarios include fact checking, opinion mining, localized information gathering, marketing campaigns, expert response gathering, image recognition and commenting, multimedia decoding and tagging, and so on.
The common aspect of these applications is the interaction between the requestor (who poses a task), the system (which organizes the computation by mixing conventional and crowd-based modules), and a potentially wide set of performers (who are in charge of performing crowd tasks and are typically unknown to the requestor). The system may take multiple forms: in addition to crowdsourcing platforms (such as Amazon Turk or CrowdFlower) or question-answering systems (such as Quora or Yahoo!Answers), a recent trend is to use social networks (such as Facebook, Twitter or LinkedIn) as sources of human labor.

Crowd-based computations undergo a new set of design principles and phases, as dealing with crowds introduces many concurring objectives and constraints. A non-exhaustive list of such objectives and constraints includes:

- **Performers selection**, possibly on the basis of their expertise on the task that they should perform;
- **Performers rewarding**, that that includes the monetary aspect (how much to pay for an elementary task) as well as non-monetary ones (such as fun, self-esteem, altruism, visibility and reputation);
- **Performers exclusion**, the set up of explicit mechanisms for determining low-quality performers and either banning them from the computation or simply disregarding their contributions to the result;
- **Convergence criteria**, determining on an object basis when the number of results that have been collected is sufficient to take a final decision about the outcome of cowdsourcing for that object;
- **Global time constraints**, i.e. the time at which the crowd-based computation should be stopped and results should be taken as final;
- **Global cost constraints**, i.e. the maximum amount that should be spent on the overall crowdsourcing task;
- **Object-specific cost constraints**, i.e. the maximum amount that should be spent for producing the result relative to a single object;
- **Performer-specific cost constraints**, i.e. the maximum amount that should be given to each specific performer.

As consequence, a requestor has several design dimensions to consider when building a successful crowdsourcing task; some of these dimensions influence the first and most important decisions, i.e. the choice of the platform to be used

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(crowdsourcing vs social, possibly multi-platform) and of the community of engaged performers on those platforms.

The next choices are instead concerned with the setting of control parameters, whose number is smaller than the design dimensions, as it typically includes the task-specific reward, object-specific convergence criteria, and performer-specific exclusion criteria. Defining the appropriate values for these parameters is hard, as they are not independent and are linked by hidden relations, and may be influenced by the domain of application.

Current approaches address this problem by offering tools where a programmer (e.g. using *Turkit* for Amazon Mechanical Turk) can easily define and configure crowd-based applications, without considering how to do their setting (and at most providing defaults, e.g.[16], [14], [1], [3]); other approaches define a mathematical formulation of the problem in terms of constrained optimization but fail to guarantee a consistency check of the effectiveness of the optimal solution in terms of real-life application execution; moreover, no mathematical model can cover the variety of optimization dimensions and constraints, as each model typically addresses a small set of decisions for a specific crowdsourcing ask (e.g., [20], [2], [12], [22], see the next section); even under such limitations, many mathematical models are hardly tractable, as the underlying problems fall into exponential of NP-hard classes.

In this paper, we propose a domain-independent, explorative design method which uses rapid prototyping *in the small* in order to select the design parameters to be used for big datasets. The method consists of defining a representative set of execution strategies, then execute them on a small, unbiased dataset, then collect quality measures for each candidate strategy, and finally decide the strategy to be used with the complete dataset. In our approach, the designer has to empirically choose execution strategies which are compared, and then empirically decide the best strategy by looking at how the solution satisfies the various objectives and constraints, without a formalization of these empirical choices, as we believe that any mathematical formulation is not of practical use for this problem. However, we suggest to use diversification criteria in determining the initial space of execution strategies, so as to guarantee that the final selection is among alternatives that yield to significant differences along the considered dimensions.

The proposed method is of general applicability, but it is complemented by the availability of a tool, called Crowdsearcher [5][4], that supports the definition of multi-platform crowd-based applications through step-by-step specifications, where the application is initially configured and then automatically generated, and therefore it is possible to create the execution strategies in the small by simply changing the parameters settings in the tool.

This paper is organized as follows: Section 2 describes related work ; Section 3 describes in details the proposed approach; Section 4 shows the experimental scenario and discuss the results and Section 5 concludes.

2. BACKGROUND AND RELATED WORK

Most crowd programming approaches rely on imperative programming models to specify the interaction with crowdsourcing services (e.g., see *Turkit* [16], *RABJ* [14], *Jabberwocky* [1]). *AutoMan* [3] is integrating human computations with Scala, providing a rich variety of options for adaptive quality control, although expressed within a low-level programming style.

Other works are centered on supporting workflows which include humans. *CrowdLang* [19] supports workflow design and execution of tasks involving human and machine activities. *CrowdWeaver* [13] is a system for visually manage complex crowd work. The work [21] presents a declarative approach to crowdsourcing workflows based on XML specifications through BPEL4People.

From the databases world studies has been done for both designing and optimizing crowdsourcing task. *CrowdDB* [9] uses an extension of SQL (called CrowdSQL) for both modelling the data and querying the crowd and it exploits query optimization techniques. *Qurk* [17] is a query system for human computation workflows that exploits a relational data model and SQL, it provides a series of optimizations like: batch predicates, run-time pricing, heuristics for reducing the cost of the join operation, pre-filling the tables with results coming from past HIT and training algorithms.

A lot of studies have been done on mode for optimizing the design of a crowdsourcing task. Usually they focus on the problem of task allocation and results aggregation, and they usually use statistical methods [20]. For instance, [2] proposes a method based on active learning for inferring the correct solution given a set of answers. The authors in [12] show how to use the probabilistic matrix factorization approach in order to aggregate results of a labeling task. In [22] the authors propose a Bayesian model for aggregating the results of a labeling task bu taking into the account the quality of the workers. Notice that all these works focus on a single type of operation (labeling) and address only the problem of aggregating the results of the single evaluations given by each performer.

On the other hand in [24] the authors propose a probabilistic framework for choosing which HIT is better to send to the crowd from a set of candidates based on the informativeness of the HIT (modeled as entropy). Furthermore [11] proposes a model for decomposing a task into simpler sub-task, focusing on the quality of the final results.

Other works use experiments to understand how different task design configurations impact on the final results. Typically they focus on a single dimension like incentives (both monetary [18][23] or not [7]), task types [8] and task decomposition [15].

At the best of our knowledge this is the first time that an empirical method has been integrated in the task design process. The results of the experiments are promptly used to decide the configuration of the task.

3. METHOD

Our approach refers to a simple concept model shown in Figure 1, which describes how each elementary execution of a crowdsourcing step, called *Execution*, is referred to an underlying operation (e.g. classifying, tagging, labeling, liking, commenting) called *Task*, to a specific *Platform* (that can be either a crowdsourcing marketplace or a social network), to a specific *Object* of a given collection, and to a specific *Performer* who executes. This model is a simplified version of the *control mart* presented in [4].

These concepts, in turn, are characterized by a set of properties, whose ranges of values define the design space. Typically, they should be assigned by the application designer in order to configure the crowdsourcing tasks, either by in-

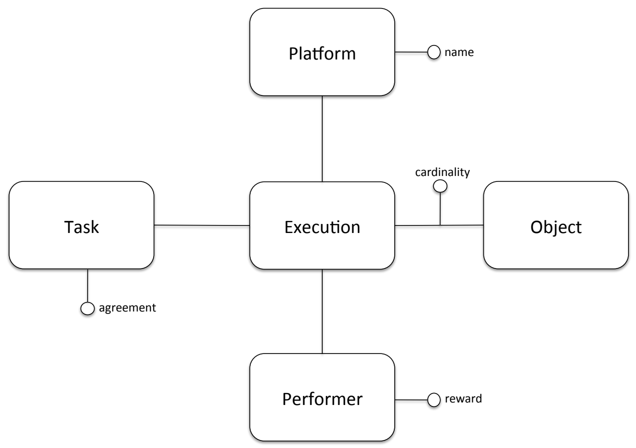


Figure 1: Concept model and parameters used by our approach

teracting with a design tool, or by using scripting languages (which in turn invokes an API where they appear as parameters), or for directly configuring the application. For instance, figure 1 illustrates a setting where we define four properties; the method is agnostic to the specific choices of properties but assumes that they can be referred to the concept model and, of course, that they can be used for configuring the execution task. They are:

- **Platform**: where the task will be executed. This is a very important dimension because each platform targets different crowds which have different skills.
- **Cardinality**, i.e. the number of object shown to the performer: this parameter controls the amount of work that a performer has to face each time. It influences the cost and time required by the task.
- **Reward**, i.e. the cost of a HIT on Amazon Mechanical Turk.
- **Agreement**: i.e., with a majority based decision for each objects, it indicates the amount of agreement needed in order to consider an object as evaluated. A high level of agreement should correspond a better quality of the results while negatively impacting on the time and cost.

This list can be extended in order to satisfy specific user needs, for instance adding a spam detection strategy, whose modeling would lead to adding a **Spam** flag on the performer, set to 0 or 1 to indicate its inclusion or exclusion.

Each candidate execution is thus represented by a vector $S = \{s_1, s_2, \ldots, s_n\}$ in an $n-$dimensional space, where n is the number of considered parameters; for instance, an execution on Amazon Mechanical Turk showing 3 objects per HIT, requiring a 2 workers over 3 to agree on the evaluation and paying each worker 0.01$ is represented as:

$$S = ["AMT", 3, 2/3, 0.01] \tag{1}$$

Once the design space is well defined, the designer should then choose some of the possible strategies (represented as a collection of vectors.) It is not possible to consider all possible combinations due to the cost and the required time for conducting all the small-scale experiments. It is important to choose few strategies by including interesting points in the solution space and by using as criteria parameter diversification, at the same time by avoiding to include any two solutions when one of them *dominates* the other. This notion is not easily formalizable, but it takes into account the correlation between parameters. For instance, it makes little sense to include two solutions such as one has a higher cost and a lower object cardinality than another one (i.e., a simpler task which is better paid).

The execution of strategies, both in the small and in the large, can be evaluated by using a set of quality measures that are computed at the end of the process by inspecting how each object has been managed by the crowd (e.g., its classification, tagging, liking and commenting). We use the following quality measures:

- **Cohen's kappa coefficient**, a statistical measure of inter-annotator agreement for categorical annotation tasks [6]. When several performers evaluate the same objects, kappa measures the agreement among them.
- **Precision of responses**, that can be computed only when the ground truth is available; it corresponds to the percent of correct responses over the total and can be aggregated at the level of object, performer, platform, or whole task.
- **Execution time**, the elapsed time needed to complete the whole task.
- **Monetary cost**, the total amount of money spent for rewarding the crowd in order to complete the whole task.

This is only a small set of possible performance measures, and can be extended with more complex (as the ones shown in [10]) or application specific metrics.

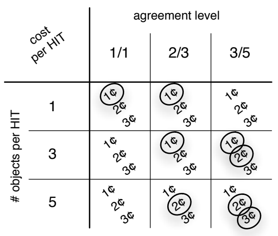
Finally, our approach requires the splitting of the dataset of the objects into two subsets *small* and *large*, with $|small| << |large|$, such that the selection of S is not biased.
Then, all the strategies $\{S_1, S_2, \ldots, S_m\}$ are run on the *small* set (*in the small* phase) and the quality measures are collected; by analysing them, the strategy S_{best} which is associated with the *best quality measures* is selected.

Eventually S_{best} is run on the remaining objects of the *large* dataset and its results are composed with the ones obtained with the *small* set.

4. EXPERIMENT

We designed an image labeling crowdsourcing task in which we ask the crowd to classify pictures related to actors, telling if it represents the actor himself in a portrait, if it is a scene taken from a movie, or if it is not relevant (exclusive options); We used Amazon Mechanical Turk (AMT) as execution platform.
Using our approach, we identified the following design dimensions: number of images shown in each user task, agreement level for each picture classification, and cost of each AMT hit. Then we selected 8 different strategies (as shown in Figure 2) and we ran them on both the small and large dataset.

The experiment had the purpose of assessing the two main assumptions of our method:



(a)

Confi-gura-tions	Images per HIT	Required agree-ment	Reward per HIT
1	1	-	$0.01
2	1	2 over 3	$0.01
3	3	2 over 3	$0.01
4	3	3 over 5	$0.01
5	3	3 over 5	$0.02
6	5	2 over 3	$0.02
7	5	3 over 5	$0.02
8	5	3 over 5	$0.03

(b)

Figure 2: (a) Multi-dimensional matrix of parameters which are compared in the running example, and selection of representative combinations (encircled); and (b) Quality measures of the selected combinations after their execution over a subset of the objects.

1 The outcome of the experiment *in the small* is correlated with the result of the experiment *in the large*;

2 The cost of performing all experiments *in the small* followed by one experiment *in the large* is affordable and the extra-effort is well compensated by the possibility of chosing the experiment with the best quality measures in the small.

We determined an experiment of limited size but sufficient to perform such an assessment. We built a dataset consisting of 900 images related to 90 actors, retrieved from Google Images; then we selected 90 images for the phase in the small (i.e. 10 images for 9 actors, including both men and women), so that the comparison of small vs large involves an order of magnitude, which is enough to illustrate the difference between small and large cases. This setting hints to the quality of the method also when the difference between small and large size reaches two or three orders of magnitudes, as in a typical big data scenario.

We then run the experiment eight times, both in the small and in the large, so as to assess the similarity of small and large size experiments; we paid a total of $227 for the sixteen experiments (of course, introducing two or more orders of magnitude of difference between the small and large cases would require a corresponding, proportional increase of the total cost.)

The experiment was implemented using CrowdSearcher[1]; [5][4]; the set up of each experiment in such case is managed by the tool. CrowdSearcher is an important ingredient for our approach, because it allows to quickly define all the variants needed for the experiment and to easily collect and monitor the performance of the single strategy. Thus, setting up a sequence of experiments with Crowdsearcher requires essentially to change parameters within the tool and regenerate another crowd-based run on AMT which creates suitable HITS sets, with suitable intervals between them so as to build independent observations.

Crowdsearcher also collects statistics about each application, which allows us to read some of the quality measures (such as precision and duration of the experiment) directly from the execution controller; other quality measures, such as Cohen's kappa coefficient, must be computed by looking at the output objects.

[1]http://crowdsearcher.search-computing.org/

Table 1 summarizes the results of the experiment, by reporting the four quality measures (kappa, precision, cost and duration).

Regarding the first assumption defined in Section 4, we calculated the Pearson correlation coefficient, configuration-wise, between the experiments in the small and in the large. As one can see, correlation is almost one for the cost, that can be obtained just by considering the scale factor between *small* and *large*; but correlation is quite good also for duration, performer agreement and precision. Note that durations are longer for the *small* experiments than for the *long* ones. This reflects a known behaviour of the crowd, which tends to select tasks with higher number of executions to perform (also due to the bias introduced by crowd platforms, which show the biggest tasks first).

We next compared the strategy by looking for a trade-off between *precision* and *cost*. In particular, based upon the small-scale experiment, we selected Strategy 6, which appears to have enough precision (0.864) associated with a low cost (1.92), yielding a good price/performance ratio.The choice of Strategy 6 completes the decision making.

The designer's choice is anyway driven by cost-benefit analysis, that however is performed *in the small*, e.g. the designer will be able to decide if a difference in precision from .811 of case 3 to .856 of case 5 is justified by an increase in costs from 1.40 to 4.77.

Note that we spent $22.49 for computing all the strategies in the small and $16.86 for executing the strategy number 6, for a total cost of $39.35; these two numbers are comparable, but the difference between the cost of experiments in the small and in the large increases a lot with big input data. When the task is very large, an incremental tuning is also possible, e.g. using datasets of increasing sizes for computing the quality measures of a restricted number of candidates. The case *in the large* of Table 1 can be considered an intermediate-size experiment if one has to process a dataset of millions of photos; in such case, the eight cases in the large would result from a selection starting from a larger number of experiments in the small.

One could note that case 7 is associated with a slightly higher cost of 2.70 compared to case 6 (that was selected by considering quality measures in the small), but it also exhibits a better precision in the large of 0.871 compared to case 6; such better precision is not predicted by the experiment in the small and comes as a surprise. Indeed the method incurs some unexpected differences between tests in the small and in the large due to the intrinsic statistical variability of our study; greater sizes in both small and large cases would yield to less variability.

5. CONCLUSION

In this paper, we have proposed an explorative approach for designing crowdsourcing tasks. The experimental evaluation shows that the method is applicable to this kind of problem (as there is a good correlation between the results of the experiments *in the small* and *in the large*), and that the trade-off between the cost and the added value is affordable.
Future work will focus on formalizing the process for selecting candidate strategies and on the application of the method to a wider set of design dimensions (e.g. varying also the execution platform).

Table 1: **Quality measures and Pearson correlation of experiments *in the small* and *in the large*.**

	Agreement kappa		**Precision**		**Cost ($)**		**Duration (s)**	
Config.	***small***	***large***	***small***	***large***	***small***	***large***	***small***	***large***
1	N/A	N/A	0.733	0.799	1.35	13.68	14885	8832
2	0.692	0.607	0.778	0.855	4.05	43.97	11788	20346
3	0.596	0.612	0.811	0.838	1.40	14.15	52219	30032
4	0.579	0.578	0.822	0.857	2.25	23.10	114186	63963
5	0.442	0.569	0.856	0.858	4.77	46.35	120983	53162
6	0.499	0.540	0.811	0.864	1.92	16.86	110535	65178
7	0.580	0.606	0.800	0.871	2.70	28.05	121945	67676
8	0.533	0.555	0.833	0.838	4.05	41.67	78086	23745
Correlation	**0.707**		**0.619**		**0.999**		**0.915**	

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