# An Approach to Controlled Crowd-sourced Activities

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***Abstract* - This paper is concerned with defining contributors' selection for crowd-sourced task execution. Based on reputation measures that we introduce, a general mathematical model of controlled crowd-sourcing is presented. The model offers easy to manage, flexible selection of predefined trustworthy contributors based on their prior performance in similar activities. A simple choice of model parameters within specified range to suit user's intended quality of the crowd involvement is introduced. The abstraction of the problem that we present can be tailored for applications in different domains and crowd-sourced activities. Further extensions of presented concepts conclude the paper.**

***Keywords - crowd-sourcing; reputation; credibility***

## I. INTRODUCTION

Many activities normally performed by employees of a company or social organization need some form of assistance from the outside. Since the concept of cooperating parties has became commonly acceptable and effective way to achieve business goals, the term of outsourcing as the contracting out of a business process or function to a third-party became a strategy in many domains of business.

It is important to note that the concept of outsourcing is also used to exemplify the practice of delegating fragments of the overall activity on ad hoc bases to the third party without any obligation of persistence of such association. Outsourcing is not limited to a single country; it includes both foreign and domestic contracting, and recently often includes relocation of a business function to another country, but in all such cases the main player is aware of the subcontracting party, its competences and associated costs. In outsourcing situation, the relationship is covered by the formal agreements. The economical considerations are often the driving force for such business strategy but not always.

The concept of crowd-sourcing is one but significant step further [15]. It is the process of obtaining required services, ideas, or content by soliciting contributions from a large group of unidentified people, and especially from an online community, rather than from conventional employees or suppliers. It combines the efforts of many self-identified volunteers or part-time personnel, where each contributor of their own initiative adds a portion to the final result. Let us note that often many contributors perform the same task not knowing about each other. So, the final selection of acceptable results is additional function of the owner of such out contracted process. A most natural way to distinguish crowd-sourcing from outsourcing is fact that the completion of individual task comes from an undefined public rather than being made to order by a specific, named and bounded by initial agreements group. Understanding of associated issues, especially in relation to evaluation of the quality of the work completed is essential for the real applications leading to genuine business benefits [3][7][9][16].

The paper is structured as follows. In Section II only relevant related work is presented, followed by discussion on general objects evaluations in Section III in order to build a perspective on the evaluation process as discussed in Section IV. The main contribution of this work is described in Section V where the formalization of the crowd-sourcing quality involvement is introduced. Finally, in the last Section VI we indicate directions of future research work in this area.

## II. RELATED WORK

The most frequently used example of a crowd-sourced work is Wikipedia. Another, but different in nature examples, can be associated with the Internet content evaluation or extensive testing of publically accessible e-service functionality or a design task.

Let us briefly discuss some related issues that occupy researchers recently. They are web content evaluation in general, its integrity, credibility and trustworthiness.

The Internet became the first source of information for many users regardless of the investigated topic. On the other hand information presented on websites either of companies or private authors, social networks and social portals frequently doesn't have any structured evaluation. Thus the credibility of content of web pages is an important issue for all the users and could serve here as a motivation example of work presented in this paper. However, the features of presented model are not limited to this application.

Perhaps, a precise definition of the credibility may vary from case to case, depending on the purpose of the examination of the content. One could look at this issue as cross check of content with any other related source providing similar information. It is easy to observe that we already strike a problem – measure and identification of information similarity. If it is not identical (a copy) then, it must be syntactically different but semantically may be similar. The issue of integrity of information, in general, is hard to define thus computing semantic similarity of two texts is not a tractable problem. There are numerous examples of cases when information on hand has different form but its content is comparable – for instance, financial data from stock exchanges, recorded temperature in the same geographical

 ISBN: 978-1-61208-395-7 

locations but independently provided by many sources etc. In most cases of Web information we deal with a written text, for a specific audience of readers, to achieve a specific impact, at a specific time, generally, on a large group of receivers. For instance medical information could be in form of a public forum sharing personal experience, or a professional outline presented in a simple exploratory form to provide some health related information written by an expert. The problem of measuring quality of information has been identified in particular by [5][7][16].

Numerous analyses have been dedicated to study the web credibility assessment process. This process may involve several problems that have been extensively studied in economic theory - for instance the problem of information asymmetry, which may refer to a hidden quality [19] and so called "market-of-lemons" effect, or to a hidden type [3] and the occurrence of moral hazard. The problem of assessing the credibility of Web content may involve both cases of hidden information, i.e., hidden quality for static pages or hidden type for dynamic pages. Tanaka and Yamamoto [16] have identified six measurable factors related to the five main recognized features (i.e., accuracy, authority, objectivity, currency, and coverage of topic) for judging the credibility of web information, namely referential importance, social reputation, content typicality, topic coverage, freshness, and update frequency. Fogg et al. [5] utilized prominence-interpretation theory in order to explain the process of credibility assessment. There have also been other approaches to automatic credibility assessment. These methods aggregated the values of different features. For instance Metzger [7] used information about credentials, advertisements, web page design, type of website, date of update, sentiment analysis, pre-defined search engine page ranking, information commonality, source independence, prestige, experience with the source and authority of information origin. On the other hand, Wierzbicki et al. [1][18] attempted to create a simple game-theoretic model that would capture the salient characteristics of web content credibility evaluation.

Continuing with example of the content evaluation we should bring up the term of trustworthiness. Trustworthiness of the Web content occupied many researches recently. Rapid publication of new Web content affects many aspects of everyday lives of millions of people regardless of geolocation or political beliefs [8]. Moreover, Web content becomes the basis for the operation of digital economy [6], [9] and very often an essential source of information while making decisions concerning shopping, employment, education, health (both self-diagnosis of disease and treatment selection), financial data, investments, etc. [2][20]. On the other hand, Dellarocas [4] and Thompson [17] notice that web content is increasingly often manipulated for the benefit of the authors or content providers.

In the case of crowd-sourcing where involvement of a large group of unidentified testers/evaluators offers independent opinions, the quality of such assessments may depend heavily on many factors such as the background of the participants, education level, willingness to collaborate with good intensions and many more. Thus deploying the crowd-sourcing to such process requires special preparation of the final result compilation. The analysis of collected data may suggest ignoring some submissions and to favor the others.

This brings us to the term of a controlled crowd-sourcing; meaning a well justified selection of the contributed works from a larger collection of submitted results carried out for a specific crowd-sourced activity.

The problem of selecting only credible contribution from reputable but unknown partners will be more and more important in future for large scale business processes. The concept of business workflows partially executed by public input must be properly supported with new workflow facility foreign to the current structured workflow management systems. The assignment of task to partners/workers, the methods and correctness of the process design, data flow, and time constraints for traditional workflows is extensively studied for number of years [10]-[14] by Orlowska et al. The new functionality of workflow services to accommodate crowd-sourced activities with ‘reasonable‘quality of individual tasks execution is a new direction requiring further research.

The purpose of this paper is to build a simple mathematical model of controlled crowd-sourcing when dealing with evaluation of a given set of physical objects. The objects could be selected websites, books, electronic services intended for public use, e-learning platforms, and pieces of software or any publically accessible entity. The consideration of credible contributions is dependent on several parameters that all individually can be controlled within a predefined range of values to suite user’s defined crowd involvement.

The paper is constructed as follows, firstly we point out how multiple single indicators assigned to individual objects are used to rank (order) the set of such items. Then, we construct a linear model of selection only assignments that satisfy defined ‘quality’ conditions. The presented model is general and may well form a foundation for a construction of an evaluation environment appropriate for use in different application domains, independently from the purpose of the crowd sourced involvement into processes.

The conclusion and suggestions of further extensions of these concepts close this presentation.

## III. OBJECTS EVALUATION IN GENERAL

The needs to evaluate objects from a collection frequently emerge in many domains of applications. Typically, we identify collection of attributes (characteristics) that require to be evaluated independently. Normally, the set of values used to express the results of the evaluation process for each property is specified. Often, it is a finite set with rather small cardinality. Such evaluation cross multiple attributes with the overall purpose of ranking the objects (in contrast to many rankings on the basis of individual properties) is a simple version of a classical multi criterion optimization problem.

Most ranking systems such as for example; ranking of universities, innovation summary index for ranking countries use exactly multi-criterion approach to rank the considered objects.

For the purpose of further considerations, let us recall a few well known facts about ranking/ordering objects in a multi dimensional space defined as a Cartesian product of the domains of considered attributes.

Let us assume that objects are evaluated with respect to several attributes, each having its scale of values to be used by evaluators to express their impression.

To be able to make the ranking list, for instance to communicate the order from the best to the worst object, we must use some expression, a function from multi dimensional space to the set of real values, a 'shrinking" function.

Very often the expression used is a weighted sum of the values assigned to the individual criteria. It is worth to mention here, that regardless of the effort dedicated to the construction of the "shrinking" function, any two points being far (in the sense of Euclidian metric) from each other in multidimensional space, they may become close in the linear order resulting from the shrinking process. The simplest way to demonstrate the above statement is the application of the sum of values as the shrinking function. For example, in two dimensional space - two attributes both with domains {1,…,9} are evaluated for each object; distanced points (1,9) and (9,1) after application of the summation they all get value 10.

There is here also another aspect requiring aggregations of the raw data. Already summarized values submitted by different tester for the same object requires further "shrinking" process. This aggregation function needs to be designed to finally get a single indicator for each object based on many submissions to allow the final ranking process. Such an aggregation may take into account different weights for more experienced testers or higher weights for more credible examiners, etc. However, the masking process illustrated above will also take place here.

Concluding this brief discussion we can sum up it as follows. It is well understood that each classification or comparison procedure of objects requires two important phases. Firstly, an abstraction of the objects by selecting a number of their attributes (characteristics) and ranges of evaluation values assigned to each attribute must be provided. Secondly, functions capable to express our intuitive comparison need should be constructed to shrink the whole multidimensional task to a single, one dimensional comparison problem. Such a mapping will be called an aggregation.

## IV. EVALUATION PROCESS

Let us formulate the problem a bit more precisely but still informally.

Further, we assume that the following set of data and objects are accessible;

1) Set of comparable objects - the evaluated collection,

2) Predefined scope of the evaluation in the form of defined objects' attributes. For instance in the context of websites content evaluations it could be indicated features such as reliability, correctness of the content expressed in an objective sense wherever it is possible, clarity, esthetics, usability or similar,

3) Experts' evaluation for each given examination scope or attribute called an expert value assigned to each attribute for each object.

To effectively crowd-source an evaluation process, we shall have a mechanism to identify reliable testers in a given domain for specific evaluation scope and compile the final evaluation result only on the bases of aggregations across such multiple values. It is important to note that the calculated values may substantially differ from the expert value.

The weakness of such expert's replacement approach is rather obvious. There are no two identical evaluation cases and there are no super experts. As we mentioned in the introduction remarks, it is difficult to think of a similarity function construction between the objects such as, for example websites content or a design task. In other words, based on some prior data from evaluation experience, we select testers only from formerly credible group assuming that the current evaluation task may be a bit different. Thus, in some cases, the direct comparison of recent evaluations' results with given super values may indicate substantial difference even for perfect evaluators in the past. Thus, the fundamental question is how to sensibly identify credible results to the problem based only on the prior testers' experience.

This observation indicates the difficult nature of this of problems but not a total inability to formulate it more precisely. The problem is real one, thus a level of imprecision is unavoidable, and so we must be ready to accept some estimation of perfect results in practice.

## V. A FORMAL MODEL DEFINITION

For the simplicity of the presentation, but without losing generality, we assume that objects are evaluated with respect to only one attribute and evaluated by many examiners. This assumption reduces required aggregation process to a single one, only across the testers' submitted values for each object. An extension to cover the evaluation with respect to several attributes is conceptually simple and as such is deliberately omitted in this paper. Further, we assume that each object is evaluated by a different group of testers due to the voluntarial character of crowd-sourcing activities. Thus some objects may attract more opinions then others. At this stage, we assume that the experiment is done over a fixed period of time so there is no need to accommodate dynamic change of number of tests and involved testers.

 ISBN: 978-1-61208-395-7 

We introduce formal notation in Table 1 below where: $W = \{w_i,\ i \in \{1, 2,\dots, I\}$ is a finite set of comparable objects, $E = \{e_k,\ k \in \{1, 2,\dots, K\}$ is a set of examiners with different competences, $s_i$ is an expert value for each $i \in \{1, 2,\dots, I\}$ (a single value due to the assumption above), $f_{k,i}$ is the evaluation f by the k-th examiner for the i-th object.

TABLE I. NOTATIONS INTRODUCTION

| Objects | Expert value | *Tester $e_1$* | *Tester $e_2$* | … | *Tester $e_k$* |
|---|---|---|---|---|---|
| $w_1$ | $s_1$ | $f_{1,1}$ | - | | $f_{k,1}$ |
| $w_2$ | $s_2$ | $f_{1,2}$ | $f_{2,2}$ | | - |
| … | … | … | … | | … |
| $w_j$ | $s_j$ | $f_{1,j}$ | $f_{2,j}$ | | $f_{k,j}$ |

In general, by the evaluation of an object by a tester we mean an assignment of a value from the predefined subset of natural numbers f: $(W, E) \rightarrow \{0, 1, \dots, v\}$.

An extension of such notation for multiple attributes requires several evaluations f1, f2, etc for a given object by a tester. As we assumed earlier, we consider a single attribute evaluation only, hence there is only one function f in this formalization.

Further, for each tester k we assign two values $[d_k, z_k]$, where $d_k, z_k \in \{0,1,\dots, B_{k,}\}$ $d_k$ is the count of so-called good evaluations submitted by the k-th evaluator, and correspondingly, $z_k$ is the count of bad evaluations of this examiner and $B_k$ is the total number of submitted tests by the k-th examiner $d_k + z_k = B_{k..}$

For the clarity of the presentation, we suggest the simplest approach to separate the good from bad evaluations below.

Formally, we define good and bad evaluations as follows;

An evaluation of an object $w_i$ by a tester k is good if $|s_i - f_{k,i}| \leq c$, is bad otherwise, meaning

$|s_i - f_{k,i}| > c$ for each $k \in \{1, 2,\dots, K\}$ where c is a constant value indicating acceptable distance to the expert evaluation.

It is obvious that one could consider immediate generalization of this approach by introducing many levels of the goodness of evaluation, however for the sake of simplicity we consider further only one cutting point c.

We illustrate graphically the concepts introduced. Let us consider the first quarter of the (D,Z) space where Z and D are sets of natural numbers. For a given period of time and given constant c, we depict collected data of k testers by assigning a single point $[d_k, z_k]$ for each k. Hence, submitting additional test by a tester k (for an object) moves its' point either to the right or to the top, depending whether the evaluation is regarded as a good or bad one. Clearly, if all evaluators would submit the same number of tests t , meaning that they all evaluated t objects but not necessarily the same set of objects as indicated by entries in the table above, then all those points would be positioned on a straight line $z = - d + t$.

It is easy to see that all points positioned on any straight line from the family $z = a\,d$, where $a$ is a positive number, identify all testers with the same proportion of good to bad evaluations but with different total count of the completed tests. It is depicted on Figure 1 below.

One may interpret those points as an image of history for submitted evaluations for all testers without indication which objects these individuals examined.

Our first goal is to group testers of similar credibility into classes. We provide a simple but flexible definition of such partitioning by introducing two constant values $g_1$, $g_2$. As before, one could consider more comprehensive model by introducing additional values for a finer partition of this space. However, for the purpose of this presentation, only two values will give required flexibility and natural partition of set of all testers into tree classes.

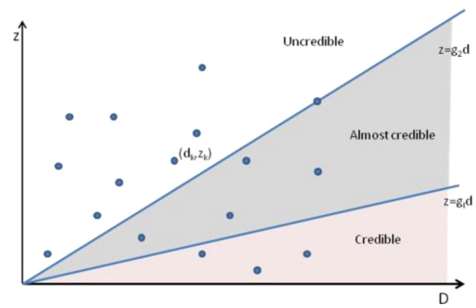


Figure 1. Illustration of introduced classes of examiners

Let us discuss in more details such a division. The two straight lines $z=g_1d$ and $z=g_2d$ divide the first quarter of space (D,Z) into three areas as depicted on Figure 1 above. We might call a tester *credible* if and only if in his history of evaluation process the count of the good evaluations was, for instance, 90%, implying the value of $g_1 = 0{,}1$. Consequently, the count of bad evaluations must be just 10% for this tester. The graphical interpretation of this set is the lowest triangle in Figure 1.

The other class of testers we might call almost credible. In this case, let for instance $g_2=0{,}25$. Naturally, this is the set of points between the two formed lines.

Finally, the third class we consider as not credible (not plausible) for all the points on lines $z=g_2d$ for all $g_2 > 0{,}25$.

It is important to remind us that joining the crowdsourcing evaluation process is on volunteer bases, so we cannot expect that all testers will evaluate the same set of objects and the same number of objects in general. Frequently, some individuals are more active than others so there is a need to reflect this fact in our model.

It is rather clear that if a tester has completed very few examinations then based on such limited activity its allocation to one of the classes might not be well justified. This is why, it is sensible to introduce a new constraint: a minimum number of evaluations m completed before assigning the tester to the appropriate class.

Formally, k-the tester's experience related condition is following $d_k + z_k > m$.

As before, only for the simplicity of the presentation, we consider only one cut-off point - the minimum m, but introduction of several levels of experience $m_1$, $m_2$, ... is natural as shown on Figure 2.

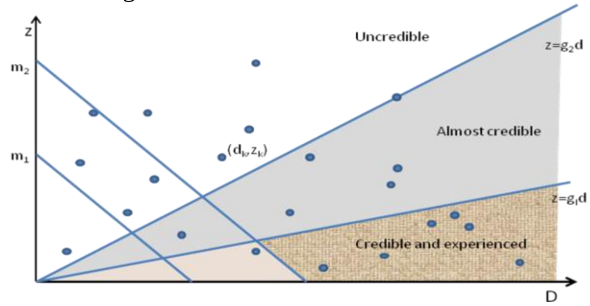


Figure 2. Illustration of introduction of minimum count condition

Introduction of this parameter to the model gives us additional flexibility of selecting only those results of evaluations that come from a group of individuals' satisfying our requirements for their general quality, as it is illustrated in Figure 2 above. Especially, in case of crowd-sourcing, a controlled selection of cooperators is vital for overall sense of sharing such activities. Let us then introduce this condition on our model.

It is easy to see that introduction of parameters in our linear model such as c, $g_1$, $g_2$, m give us opportunity to control the selection of set of points in this space in many ways. We can move those lines freely by changing the values for the parameters to make more or less strict pre-selection of testers.

The sum of all $B_k$ for all k allows us to calculate the number of submitted results for our crowd-sourced task for all objects from W. However, till now, in our model we focused on testers' reputation but there is no reference to the evaluation of individual object by any means. Some objects could be evaluated by many testers, some by only few and some may not be evaluated at all. To assign the final evaluation value by combining opinion of several testers of an object one would expect to have a minimal number of tests completed for this object. Then aggregation procedure smoothes the differences of assigned values (marks) to offer a final and credible result. Theoretically, it is possible that the class of credible and experienced testers is sizeable having many elements thus satisfy model's conditions but as far as object $w_i$ is concerned, is insufficiently rich. This is when none of the testers, or very few from this class, evaluated object $w_i$. In such case there is no raw data for the aggregation function to be applied.

This observation leads to requirement of introduction of subsequent control parameter v – the minimal number of tests for each object before the aggregation function can be applied. Subsequently, aggregation function combining results from at least v contributors satisfying required conditions (selected values c, $g_1$, $g_2$ and m) can be applied.

Let summarize the set of model parameters introduced earlier. They are:

1. Constant value c measuring acceptable difference between the entry and object's expert value,
2. Two constants values $g_1$, $g_2$ defining set of testers classes - credibility conditions,
3. Constant value m measuring minimal number of completed evaluations by a tester - experience condition,
4. Constant value v indicating minimal count of submitted results for the object by testers from selected class prior to the calculation of final result – object occurrence condition.

This summary concludes our discussion on selection of credible examiners, let us then return to the main problem of objects evaluation. It can be completed systematically from now on. For each object, we apply the final aggregation function only on those entries that satisfy parameters defined at the process design phase. Thus the problem has the following formulation; for a given set of objects W, for an undefined and open set of evaluators/testers E, for a given constants c, $g_1$, $g_2$, m and v of the model, for each object $w_i$, compute value of the aggregation function based on all $f_{k,i}$ that satisfying credibility, experience and object occurrence conditions.

In practice, it is possible that concurrent fulfillment of all the conditions may require some time. Only the conjunction of all specified conditions offers some expected level of quality of task execution.

Presented construction of a flexible environment for the visualization of entries coming from the crowd sourced activity appears to be an interesting service. An interface allowing selection of the values for the model parameters and dynamic control of separation lines is envisaged to be a useful tool independent form the application domain and purpose of the application supported. The scalability of such a system needs to be carefully considered. Over period of time, in case of considerable number of new submissions, the data content will grow in size and change of its content where some players may gain reputation but some may loose their already gained status. This observation justify introduction of an additional dimension to the model – temporal aspect. For the purpose of this preliminary presentation, it is sufficient to consider fixed length period of time for each session of the execution. Addition of continuous, dynamic observations requires more complex formalization but this is not a purpose of this article.

## VI. CONCLUSION AND FUTURE WORK

Crowd-sourcing is getting a form of direct collaboration, often on a large scale, between the task provider and public contributors. There is a need to provide easy to manage environment to support controlled crowd-sourcing involvement.

In this paper, a linear model of selecting reputable contributors in the crowd sourced task execution has been presented. Model offers choice of parameters within predefined ranges to allow flexibility in selection of preferred submissions from the large scale crowd sourced assignments.

Automation of introduced control mechanism is a simple implementation task. The concept was tested on synthetic data sets demonstrating potential usability on a large scale. The issue of user interface to such environment should be tested exploring several options. Effective visualization of dynamically changing points' positions maybe a useful tool in practice for a big scale crowd sourcing assignments. Visual observation of the points' density and introduced functionality allowing continuous movement of the introduced lines may in return automatically compute the introduced parameters. Empirical examination of distribution of points in different segments of the dedicated screen, forming a base for future selection of parameters values appears to be an interesting scope for applied study.

The presented model may be extended in many different directions by imposing more conditions on the space defined above. Firstly, a number of levels for all types of presented constraints will bring additional precision of the observed experimentation. Secondly, for the same data segment, for each object several types of aggregation functions can be applied to tailor the best fit. Those extensions depend from the size of the problem, number of players, intended application and the domain of consideration and required expected precision.

A subsequent stage of this work will cover the change of the linear model, where separation of space segments is done by straight lines, for a class of polynomial functions.
An extensive testing and analysis of large real data sets may be a useful source of pointers for well justified extensions.

The ultimate goal of technological support for collaboration of standard business processes with a crowd accomplished activities is one solution for both types of partners.
It is envisaged that the deployment of the controlled crowd sourcing functionality by new generation of workflows technology will form a suite of a novel technological solution for business support and expansion.

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 ISBN: 978-1-61208-395-7 