A Quantum-inspired Genetic Algorithm for Weighted Constrained Crowd Judgement Analysis

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Abstract

Over the years, it has been demonstrated that crowdsourcing can easily and effectively solve complicated real-world problems like smart city planning, resource allocation, etc. Constrained crowd judgement analysis, which compiles several constrained opinions from different people, is a relatively unexplored section of the crowdsourcing problem. In this kind of situation, each person's opinion is essentially made up of one or more components, and there is a relationship between the components. A majority voting or other opinion aggregation approaches are not appropriate for this type of problem since they do not ensure that the constraint requirement will be satisfied. There are many issues in everyday activities that may involve more than one constraint. Additionally, the crowd workers impart some weight to their opinions. As a result, this kind of issue can be introduced a new variant of constrained judgement analysis, i.e., weighted constrained judgement analysis. However, the inherent challenges are to find appropriate judgement in presence of spammers. We propose a Quantum-inspired method to find the aggregated judgement satisfying all the constraints. The experimental results over a real-life dataset demonstrate the effectiveness of the proposed method.

Motivation and Background

Crowdsourcing is a popular technique for coming up with an efficient solution to solving difficult real-world problems (Raykar and Yu 2011; Jung and Lease. 2012; Dawid and Skene 1979; Howe 2006; Whitehill et al. 2009). In general, the crowd are asked to select binary options ('Yes' or 'No') or multi-options ('Yes', 'No', 'I cannot tell') to a series of questions. Here, majority voting-based solutions are not always reliable as it considers all the crowd workers as equal expert. Hence, various other aggregation approaches (Howe 2006), (Demartini, Difallah, and Mauroax 2012) are developed in order to identify the proper crowd worker effectively. Although there are several ways already in existence, there are limited studies that deal with the constrained opinions of the crowd using both numerical and textual judgement. Numerous real-world applications, such as facility placement and city planning, solicit the constrained opinions of the people to improve planning (Chatterjee and Lim 2020; Allahbakhsh et al. 2019).

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Constrained judgement is a newly introduced category of judgment analysis problem where the opinions of crowd workers are subject to certain limitations (Chatterjee and Lim 2020; Chatterjee and Bhattacharyya 2017). In most constraint judgement analysis problems, the opinions of a single question have multiple components and there exists a relationship between the components. This acts as a constraint and satisfying the constraint is essential. Moreover, in this type of problem, the crowd can provide their priority over a particular component over the others. Hence, aggregation of these types of weighted constrained opinions is very challenging. The reason is that while crowd workers provide their opinions individually then he/she satisfies the constraint and provides the weight for different components from his/her perspective. However, while aggregating all the opinions, the constrained satisfaction criteria cannot be guaranteed. Hence, finding proper aggregation for weighted constrained opinions is also difficult. In addition to their numerical opinions, the crowd also provides a textual justification of their reasoning. To exemplify, suppose, one University administration body, for instance, plans to hand out some masks as soon as the university finally opens following the COVID crisis. However, it is a very challenging and time-consuming task to gather and comprehend the actual locations (suppose k locations) with diverse time domains from the viewpoint of teachers, students, and staff.

Therefore, it is quite helpful to delegate this kind of issue by outsourcing it to the instructor, pupils, and staff as a whole and seeking their weighted opinions about the proper locations. To achieve the greatest amount of coverage, the two nearby distribution centers must be kept apart. Again, as there are spots where the crowd worker can keep some preferences, the combined total weight of the m locations supplied by the crowd must be 1. Furthermore, while collecting their opinions from the crowd, it is very important to provide the opinions of the crowd in different time duration and there should be some defined gap (e.g., one hour/two hours). Hence, aggregating these types of crowd opinions raises a new type of judgement analysis problem and an efficient strategy is needed to resolve this problem.

Problem Formulation

There are a set of questions $Q = \{q_1, q_2, \ldots, q_j\}$ and a set of annotators $A = \{a_1, a_2, \ldots, a_n\}$. Opinion of individual crowd worker is considered as a triplet like $\{(\{x_1, y_1\}, w_1, p_1), (\{x_2, y_2\}, w_2, p_2), (\{x_3, y_3\}, w_3, p_3)\}$ where the first item $\{x_1, y_1\}$ is the 2D coordinate of the 1st location, while $\{x_2, y_2\}$ is the same for the 2nd position and so on. The corresponding weights and text information (i.e., logic to support his statement) based on their availability are w_i and p_i respectively where $i \in 1, 2, 3$. Responses have been collected satisfying two constraints as follows:

- The sum of all the weights for d numbers of coordinates should be equal to 1.
- Also for each of the annotator's opinion, $dist\{(x_k, y_k), (x_m, y_m)\} \geq threshold$ for $k, m \in d$ and $k \neq m$ where $dist(f_1, f_2) =$ Euclidean distance between two points.

E.g: Sample response of Annotator 1:{({20,30}, 0.3, 'reason 1'),({30,22}, 0.4, 'reason 2'), ({10,45}, 0.3, 'reason 3')} such that the sum of weights = 0.3+0.4+0.3=1 and coordinate (30,22) with weight 0.4 is preferable over others. Our objective is to find aggregated solutions from the crowd-workers solution such that the final solution satisfies the above-mentioned constraints, as well as the solution, is better than other solutions.

Proposed Method

In order to solve the problem, we provide a Quantum Genetic Algorithm (QGA)-based approach (Xiong et al. 2004) along with the utilization of text information to find a better-compromised solution from the original crowd solutions while optimizing the two objectives as discussed above. The subsequent steps are discussed as follows:

- **Relabeling of the Crowd Solutions**: We have provided a grid map whose coordinates ranges from (X_{min}, Y_{min}) to (X_{max}, Y_{max}) and (x_c, y_c) be any solution collected from a crowd-workers preference such that $X_{min} \leq x_c \leq X_{max}$ and $Y_{min} \leq y_c \leq Y_{max}$. The responses in form of 2-D coordinates are relabelled into a consistent database since the fact that the same set of data may be represented differently due to the unordered property of crowd workers solutions (Chatterjee and Lim 2020).
- **Encoding Scheme of Chromosome:** The crowd workers have submitted their choices of preferences. According to the grid-based map, we can expect a bound of the choices of the crowd workers between (X_{min}, Y_{min}) and (X_{max}, Y_{max}). For d numbers of locations, the chromosome will resemble $\left[[22 \quad 33]_1\, [10 \quad 33]_2 \ldots [28 \quad 14]_d\right]$.
- **Conversion of Integers to Quantum Bits and Vice-Versa:** In our proposed QGA, we need to convert classical chromosomes into quantum chromosomes and vice versa. For the conversion of quantum chromosomes into classical ones and vice versa, we have used the min-max approach as illustrated in (Xiong et al. 2004). Converted classical chromosomes into quantum ones will resemble like $\left[\begin{bmatrix}0.73 & 0.88\\0.27 & 0.12\end{bmatrix}_1 \begin{bmatrix}0.18 & 0.88\\0.82 & 0.12\end{bmatrix}_2 \cdots \begin{bmatrix}1 & 0.26\\0 & 0.74\end{bmatrix}_d\right]$.
- **Objective Function Formulation:** Our proposed QGA follows operations like quantum rotation, mutation, crossover, etc. In addition to that, in every iteration, we have satisfied the constrained while calculating the selection criterion.
  - *Objective I*: The area covered by d-points is denoted with a polygon and measured. The more area covered tends to be a better solution as can serve more people.
  - *Objective II*: Let us suppose we have n number of annotators where $i = 1, 2, \ldots, n$. For each annotator, we have collected 3 preferred choices. For each annotator i, they have $\{(x_{1i}, y_{1i}), (x_{2i}, y_{2i}), \ldots, (x_{di}, y_{di})\}$. Suppose the median of three chosen coordinates for all of the annotators is $\{(X_1, Y_1), (X_2, Y_2), \ldots, (X_d, Y_d)\}$. The deviation of each solution from the median value signifies the goodness based on selection criteria II, i.e., less deviation means better solutions.
- **Computing weights and Processing Text Information:** The weights of newly evolved coordinates are generated with a decision tree-based approach. Additionally, the tf-idf values for each of the newly generated solutions are found with the help of existing text information collected from the crowd workers solutions.

Experimental Design and Analysis

We have designed an interactive website *(http://surveykluniv2.herokuapp.com/)* and it has been deployed to the well-known cloud platform $heroku$ (Middleton and Schneeman 2013). Here, 50 students and staff across various departments of Kalyani University, India have provided their opinions. In most cases, our proposed QGA converges within 100 iterations. In addition, there are associated weight values indicating preferences over an individual's choices and additional tf-idf values for each of the solution sets. The solutions evolved by the proposed method with the tf-idf values (T_f) are shown in Table 1.

	Objective 1	Objective 2	T_f
Solution 1	154	10	7.08
Solution 2	401	29	7.58
Solution 3	352	26	5.35
Solution 4	386	29	7.35
Solution 5	385	29	6.83
Solution 6	287	22	4.10

Table 1: Performance analysis after 100 generations.

The best solution in the original raw crowd workers has a value of 263 for objective 1 and 23 for objective 2. There are very few solutions having good values for both objectives. By applying QGA, as shown in Table 1, we obtain better solutions (i.e., Solution 2, 4, 1) in terms of a ratio of the two objectives. Along with the objectives, the tf-idf values impose importance on particularly those opinions that are more demanded by the crowd. Without additional tf-idf values, it is impractical to interpret the results. Some solutions appearing in the final solution sets may be pretty good in terms of objectives, but not preferable to the crowd workers or some locations may appear that are very far from crowded locations. From Table 1, we can prefer solution 2 or solution 4 over Solution 1 due to high tf-idf value.

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