A TOPSIS-based Multi-objective Model for Constrained Crowd Judgment Analysis

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Abstract

In crowdsourcing, although there is a plenty of benefits in terms of cost and time to solve a complex task, there remain many challenges to reach into a consensus judgment from multiple crowd opinions. In this paper, we pay attention to a recently introduced crowd judgment model, termed as "Constrained Crowd Judgment Analysis" model. Unlike the traditional crowdsourced opinions (i.e., binary/multiple opinions), the option set in constrained judgment are undefined and there exist multiple components for a particular question. Moreover, there exist some constraints that should be preserved while deriving the final judgment, hence the problem becomes more difficult. Additionally, it is very difficult to rank the crowd workers as there is no ground truth present in this constrained judgment setting. In this paper, we introduce a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) based multi-objective model for reaching consensus judgment from multiple crowd opinions as well as providing a better ranking among the crowd worker. The preliminary experimental study over a crowdsourced dataset demonstrates the effectiveness of the proposed model.

Introduction

Harnessing the intelligence of crowd (Brabham 2013; Howe 2006; Hovy et al. 2013) in an appropriate manner can have numerous advantages instead of hiring the experts with high remunerations for solving complex tasks. However, as there is a high possibility of underperforming workers in the crowd market, a proper identification of quality workers is very necessary. Hitherto a wide range of research (Hovy et al. 2013; Whitehill et al. 2009) has been accomplished dealing with the crowdsourced opinions to find a consensus from multiple opinions. Nevertheless, in majority cases, the opinions collected from crowd are of binary (e.g., 'Yes', 'No') or multiple (e.g., 'Yes', 'No', and 'Skip') types (Hovy et al. 2013; Sheshadri and Lease. 2013). However, there are many real-life problems (e.g., smart city planning) where there is no defined option sets rather only the range of options are available. Additionally, unlike the traditional question, here one single question may contain multiple components and there should be a certain relationship between any two components. Hence, traditional judgment analysis algorithms cannot be feasible to derive the final judgment due to the unavailability of defined option sets. Moreover, due to the multiple components, component-wise majority voting may not satisfy the constraint, hence performing ranking is also difficult.

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Motivation

The problem of finding the aggregated judgment from multiple constrained crowd opinions is motivated by the recently proposed model (Chatterjee, Mukhopadhyay, and Bhattacharyya 2017). To illustrate the constrained judgment in smart city planning, suppose an organization plans to develop k ATM counters (let $k = 3$) in a city and therefore finding the appropriate locations based on the demand of the people as well as the depending upon the demographic information is very much necessary. In this scenario, multiple components means the locations of multiple ATM counters. Interestingly, the options are not available here, rather only the ranges of locations (i.e., X and Y coordinates) are available. Now in this problem, the probable locations for three ATM counters are solicited from crowd according to their perspectives, therefore, a single question comprises of three components i.e., each for one ATM counter. Here, the constraint is to place any two ATM counters with a distance apart. So, the goal is to find the aggregated judgment from the multiple crowd responses that can be a quality opinion as well as the constraint should be satisfied. A recent multi-objective method (Chatterjee and Lim 2020) dealt with the problem without binning the option sets as binning caused information loss in (Chatterjee, Mukhopadhyay, and Bhattacharyya 2017). However, deciding the final solutions and ranking of crowd to incentivize them was not performed there. Moreover, a proper ranking of crowd workers based on the obtained solutions is challenging while no ground truth is available. In this work, we solve these issues by proposing a TOPSIS-based (Acuña-Soto, Liern, and Pérez-Gladish 2018) multi-objective model. Note that in the traditional TOPSIS model, the positive ideal solution for benefit criteria is taken as 1, whereas, it is considered as 0 for the cost criteria. However, in real-life, specially for conflicting cases, consideration of that optimal values for both the criteria simultaneously is questionable. So, a proper method is needed to find the better ranking among the crowd workers.

Problem Formulation

Inspired by the work (Chatterjee, Mukhopadhyay, and Bhattacharyya 2017), suppose a set of questions $Q = \{q_1, q_2, \ldots, q_t\}$ and a set of crowd workers $A = \{a_1, a_2, \ldots, a_n\}$. The set of opinion vectors is $O = \{\{(o_{1j}^{11}, o_{1j}^{12}, \ldots, o_{1j}^{1m}), (o_{1j}^{21}, o_{1j}^{22}, \ldots, o_{1j}^{2m}), \ldots, (o_{1j}^{k1}, o_{1j}^{k2}, \ldots, o_{1j}^{km})\}, \{(o_{2j}^{11}, o_{2j}^{12}, \ldots, o_{2j}^{1m}), (o_{2j}^{21}, o_{2j}^{22}, \ldots, o_{2j}^{2m}), \ldots, (o_{2j}^{k1}, o_{2j}^{k2}, \ldots, o_{2j}^{km})\}, \ldots, \{(o_{nj}^{11}, o_{nj}^{12}, \ldots, o_{nj}^{1m}), (o_{nj}^{21}, o_{nj}^{22}, \ldots, o_{nj}^{2m}), \ldots, (o_{nj}^{k1}, o_{nj}^{k2}, \ldots, o_{nj}^{km})\}\}$, for any particular question j, where o_{nj}^{km} denotes the opinion provided by the n^{th} worker for the k^{th} dimension of the m^{th} component of the question. Between any pair of components, a relation is needed to be maintained. The snapshot of constrained crowd opinion is elaborated in Fig.1 of (Chatterjee, Mukhopadhyay, and Bhattacharyya 2017).

Hence, our objective is in two folds. First, the aggregated judgment from the multiple crowd opinions are derived by optimizing two conflicting criteria (i.e., the first objective as the coverage area enclosed by the k locations and the second objective as the deviation of the solution from the mean solution) and then the TOPSIS model is employed to find a better ranking of the crowd workers. As the better coverage means a wide range of people can be facilitated by the k facilities (i.e., ATM counters), so the coverage should be maximized. Similarly, to prevent too outlier solution, the deviation of the solution from the original crowd is minimized.

Proposed Model

Here, primarily some random solutions are generated guided by the original crowd and these solutions are combined with the crowd solutions as the initial population. Again, as there is no perfect correspondence (i.e., one crowd worker's first ATM location can be same as the other worker's third ATM location) between the components, so the label correspondence (Chatterjee, Mukhopadhyay, and Bhattacharyya 2017) is performed. After the label correspondence, the proposed multi-objective approach (MOA) is applied and finally modified TOPSIS is employed for a better ranking.

Multi-objective Approach

After relabeling of all the crowd solutions, the solutions are improved employing the NSGA-II-based (Deb et al. 2002) multi-objective approach (MOA). In our proposed model, the chromosome encodes the solution in the search space and each gene of the chromosome denotes the real values (i.e., X or Y coordinate value of each location). So if there are three ATM counters, the chromosome encoding it consists of the length of $3 \times 2 = 6$ due to the $2D$ coordinate values and each cell value denotes the X or Y coordinate value of each location. After that, different genetic operators like selection, crossover and mutation operators are applied. In this process, the solutions are improved by optimizing the two conflicting criteria until a certain number of iterations is reached and these improved solutions are then utilized in order to find the better ranking in the modified TOPSIS model.

Modified TOPSIS Method

After obtaining the improved solutions in terms of both the objectives, these solutions are filtered based on the original crowd solutions. In this problem, no weight information over the two objective functions is available from the decision maker, but the priority of the coverage is higher than the deviation to them. The reason is that any solution having zero coverage with the minimum deviation cannot be treated as the promising one. After obtaining the solutions from MOA, one reference solution from the original crowd having the highest value in terms of the coverage is selected. Thereafter, all the solutions having greater or equal values in terms of the coverage and lesser or equal value in terms of the deviation of the reference solution are chosen. Then, the average values of the filtered solutions in terms of both the objectives are considered to be used as the positive ideal solution. After that, the steps of traditional TOPSIS method is performed in order to obtain the better ranking.

Preliminary Results and Discussions

In order to perform the experiments, we utilized the dataset prepared in (Chatterjee and Lim 2020). Here, a grid map of Ulsan National Institute of Science and Technology (UNIST) is demonstrated with the question that "UNIST authority wishes to install three ATM counters and what will be best possible three locations according to their perspective?". The constraint here is the distance between any two ATM counters should be within 20 units. There are 20 crowd responses and out of them 2 workers violated the constraint.

Table 1: Performance measure for the top-4 solutions (based on the first objective) after applying the proposed algorithm. Here, population size = 100 and generation number = 50.

Solutions	Objective 1	Objective 2
Solution 1	1.9502	0.0569
Solution 2	1.8234	0.0546
Solution 3	1.7754	0.0537
Solution 4	1.6846	0.0519

The experimental results obtained from the crowd responses after applying the multi-objective approach is demonstrated in Table 1. It can be seen that when all the original crowd solutions are compared with others, the best solution in terms of the first objective has the value 1.2 and the second objective value has 0.0499. Similarly, the second best solution has value 1.13 for the first objective and 0.0551 for the second objective. There is another solution which has the first objective value as 0.3375 and the second objective value as 0.0393, but it cannot be considered as good due to the low value in the first objective. However, we obtain many better solutions in both the objectives when compared to all the original crowd solutions after applying the method (demonstrated in Table 1). For example, Solutions 2, 3, and 4 of Table 1) perform better than the second best crowd solution. Thereafter, one reference solution is chosen from crowd depending on the highest value in terms of the first objective. Finally, the solutions obtained by MOA are filtered based on the reference solution (as described in the last section) and the average values in respective of both the objectives are calculated to find the proper positive ideal solution of TOPSIS for better compromise in both the objectives with an aim to obtain a better ranking of crowd.

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