Quality Enhancement by Weighted Rank Aggregation of Crowd Opinion

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Abstract
Expertise of annotators has a major role in crowdsourcing based opinion aggregation models. In such frameworks, accuracy and biasness of annotators are occasionally taken as important features and based on them priority of the annotators are assigned. But instead of relying on a single feature, multiple features can be considered and separate rankings can be produced to judge the annotators properly. Finally, the aggregation of those rankings with perfect weightage can be done with an aim to produce better ground truth prediction. Here, we propose a novel weighted rank aggregation method and its efficacy with respect to other existing approaches is shown on artificial dataset. The effectiveness of weighted rank aggregation to enhance quality prediction is also shown by applying it on an Amazon Mechanical Turk (AMT) dataset.

Introduction
Ranking of various objects is useful in numerous real-life problems (Dwork et al. 2001; DeConde et al. 2006). There are several problems that consider conflicting settings that require to find out better solution from multiple alternatives. In these models, the quality of a solution plays a vital role in predicting the final judgment. Basically different quality metric criteria can be taken to judge the quality of a solution. The reason is that based on a single quality metric the competence level of a solution can not be estimated properly. Therefore, aggregation of those rankings is very much needed to produce final ranking.

Problem Formulation
We consider a set of rankings $R = \{R_1, R_2, \ldots, R_m\}$ and a set of weights $\{w_1, w_2, \ldots, w_m\}$ for each of the ranking. Suppose $c$ is a distance function to compute the closeness between any two rankings. Now, the objective is to find out the ranking that have minimum distance $\delta^*$ from each of the individual ranking $R_i$ in the ranking list $R$. This problem can be mathematically expressed as follows

$$\delta^* = \arg \min \sum \delta(R_i, \delta).$$

The distance $\delta$ can be any measure, i.e., Kendall’s tau distance or Spearman’s footrule distance. Here, $w_i$ denotes the weight of the corresponding ranking $R_i$.

Proposed Model
Suppose, $R_1 = \{1,2,4,3,5\}$ and $R_2 = \{2,1,3,4,5\}$ are two different orderings of 5 objects. If such multiple ranking exist then it is challenging to produce a consensus decision. We now introduce a few basic terms that might be useful for a better understanding of the proposed model.

Gain Score: The Gain score obtained by an object is due to its precedence of position with respect to another object in a particular ranking. So, if there are $m$ objects, then the gain score obtained by the $i^{th}$ object in the list is due to its precedence over ($m-1$) objects. In general, the gain score $G_S_k$ for any object with position $k$ is expressed by $\frac{(m-k)(m-k-1)}{2}$.

Penalty score: The penalty score incurred by any object is due to its position lagging behind in a particular ranking. The penalty score $P_S_k$ received by an object with position $k$ is $\frac{k(k+1)}{2}$.
**Overall score:** The position based overall score $SC_k$ for an object with $k^{th}$ position is calculated by subtracting penalty score $PS_k$ from gain score $GS_k$ and it is expressed as $m^2-2m+k-m$.

Now, we illustrate the overall procedure to find out an aggregated ranking from a list of input rankings.

- **Step 1:** Initially, a similarity matrix between different rankings is computed using the weighted Spearman’s footrule similarity measure.

- **Step 2:** From the similarity matrix, the two most similar rankings are chosen and they are merged in order to get more accurate ranking. The merging of two rankings is done by using the corresponding weight of these rankings. This merging technique takes into account the goodness of the parent rankings.

Now if the weight of ranking $R_1$ is $w(R_1)$ and weight of ranking $R_2$ is $w(R_2)$, then according to the formula, the merge score $MS^k$ of the object $k$ is calculated as follows.

$$MS^k = \frac{w(R_1) * a + w(R_2) * b}{w(R_1) + w(R_2)}, \quad (2)$$

where $a, b$ are the scores of the same object based on the positions in two different rankings. In this way, the merged scores of all the objects are computed. Finally, the ranking can be obtained after sorting all the merged scores. If multiple rankings contain similar values then all the possible merging is computed and suitable ranking with minimum distance to all input ranking is chosen.

- **Step 3:** In this process, the weight of the new ranking is also computed. To compute the weight of new ranking, past experience (goodness of the parent rankings) as well as the present fitness (based on the closeness of new ranking with all the input rankings) are considered.

- **Step 4:** The steps 1-3 are repeated until a single aggregated ranking is reached.

**Experimental Results**

We have artificially generated several datasets with different dimensions by adding Gaussian noise to each input rank list in a step-wise manner. Inclusion of noise means position of a few bits are altered from the original ranking. When the noise is maximum, most of the bits are altered. For the dataset, the algorithm is applied for 50 iterations and in each iteration the Gaussian noise is incremented slowly by varying the standard deviation. Now, in each iteration (i.e., for any particular step), the rank aggregation algorithm is applied on the input ranking list and the weighted similarity values (Spearman’s footrule distance) between the resultant aggregated ranking and the input rankings are computed (see Fig. 1). Finally, to compute the area under the curve (AUC) trapezoidal function is applied. The AUC values for different rank aggregation algorithms and for the proposed approach are given in Table 1.

![Figure 1: Comparative values of Spearman’s footrule similarity measure between the aggregated ranking and all of the input rankings with the increment of noise.](image)

| Algorithm      | Instance 1 | Instance 2 | Instance 3 |
|----------------|------------|------------|------------|
| MC4            | 0.2360     | 0.3394     | 1.0359     |
| Robust RA      | 0.2401     | 0.3227     | 1.0124     |
| Mean           | 0.2342     | 0.3378     | 1.0273     |
| Geometric      | 0.2356     | 0.3385     | 1.0344     |
| Stuart         | 0.2345     | 0.3364     | 1.0314     |
| Simple Voting  | 0.2463     | 0.3398     | 1.0325     |
| Borda          | 0.2344     | 0.3379     | 1.0296     |
| Proposed       | 0.2367     | 0.3416     | 1.0406     |

Table 1: The AUC values obtained for the proposed approach and other existing approaches for different instances of a dataset with dimension $20 \times 30$. Here, the standard deviation is varied by 0.004 (Instance 1), 0.01 (Instance 2) and 0.02 (Instance 3) in each step. The best scores over a column (i.e., for a particular instance) are shown in bold.

| Algorithm      | RTE Dataset |
|----------------|--------------|
| Majority Voting| 89.88%       |
| MACE (Hovy et al. 2013) | 93.00%       |
| Raykar (Raykar and Yu 2011) | 93.00%       |
| GLAD (Whitehill et al. 2009) | 78.7%       |
| DS (Dawid and Skene 1979) | 82.7%       |
| Proposed       | 93.3%        |

Table 2: Accuracy values obtained for different opinion aggregation approaches by applying on the RTE dataset. The best accuracy scores over a column are shown in bold.

In this paper, we show the utility of weighted rank aggregation in the field of crowd based judgment analysis problem. To investigate how good the proposed method is, with respect to other methods, the applications has been done on a real-life AMT dataset. The model can be made more robust if the crowd workers’ self-reported confidence scores are taken as input while collecting the annotation scores.

**Conclusion**

In this paper, we show the utility of weighted rank aggregation in the field of crowd based judgment analysis.
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