A Study on Quality Management with Relevance Judgment Data from the Wisdom of Crowds

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ABSTRACT

The objective of this project is to study a quality management on crowdsourcing with a large-scale relevance judgment dataset. First, we propose a novel multiple feature weighted majority voting algorithm with seven features of each worker. Next, we try to find outliers by our Z-score based detection algorithm.

Our experiments presents that our proposed weighted majority outperforms the existing single feature weighted majority algorithm. Moreover, Z-score based outlier detection improves the accuracy of consensus with the proposed weighted majority algorithm.

INTRODUCTION

Relevance Judgment Data(Amazon Mechanical Turk)
- The workers’ task: to judge a query / document pairs on a ternary scale: irrelevant, relevant, and strongly relevant
- The number of unique examples: 3,277 examples with gold expert judgments (1,501 non-relevant, 863 relevant, 913 strongly relevant)
- 760 workers annotates 19,232 examples with 3,277 examples. (5.88 labels per example)
- The number of Broken Link Task : 1,183 additional tasks

DataSet

Feature Generation
Feature 1 - Graded accuracy vs. gold (GACG)
Feature 2 - Binary accuracy vs. gold (BACG)
Feature 3 - Graded accuracy vs. majority vote (GACM)
Feature 4 - Binary accuracy vs. majority vote (BACM)
Feature 5 - Graded distance vs. gold (GDSG)
Feature 6 - Graded distance vs. majority vote (GDSM)
Feature 7 - Accuracy vs. broken-links (AHNP)

Weighted Majority Voting

<table>
<thead>
<tr>
<th>Feature 1</th>
<th>Feature 2</th>
<th>Feature 3</th>
<th>Feature 4</th>
<th>Feature 5</th>
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Z-score based Outlier Detection

Z-Score
Given a set of features of workers, we apply Z-scores based outlier detection which is based on the property of the normal distribution that if \( X \sim N(\mu, \sigma^2) \), then \( Z = \frac{X - \mu}{\sigma} \sim N(0,1) \). Z-scores are a very popular method for labeling outliers and are defined as following:

\[
Z_{score}(i) = \frac{x_i - \bar{x}}{s} \quad \text{where} \quad s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}
\]

Z-Score based Outlier Detection Algorithm
1. Compute Z-score of all features of each worker
2. If one of Z-score > threshold THEN filter out the worker’s labels
3. Re-compute the consensus label by using a majority vote with anyone who survives.
4. Re-compute the accuracy of consensus labels over gold.

Evaluation

Objective
- Tuned the Z-score threshold parameter with simple linear sweep from (by 0.1)
- Both tuning and testing use 5-fold cross-validation on the set of 3,277 examples

Configuration
- 5-fold cross validation(Training Set, Testing set)
- Simple Majority(SM), Single Feature Weighted Majority(SWM), Multiple Feature Weighted Majority(MWM)

Accuracy of Consensus Label

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<th>GA+SWM</th>
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CONCLUSIONS

- We present a Z-score based outlier detection algorithm for filtering out low-quality crowd workers.
- We find that filtering in combination with multi-feature weighted majority voting reduces the error of consensus accuracy by 8.94% absolute for graded accuracy and 5.32% for binary accuracy.

REFERENCES

- Papagoula G. Ipeirotis, Foster Provost, Jing Wang, Quality Management on Amazon Mechanical Turk, ACM KDD-HCOMP’10
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