Incorporating Author Preference in Sentiment Rating Prediction of Reviews

Subhabrata Mukherjee, Gaurab Basu and Sachindra Joshi

IBM Research, Human Language Technologies (India)

22nd International World Wide Web Conference
WWW 2013,
Rio De Janeiro, Brazil, May 13 - May 17, 2013 (Poster)
Motivation

- Traditional works in sentiment analysis do not incorporate author preferences during sentiment classification of reviews.

- We show that the inclusion of author preferences in sentiment rating prediction of reviews improves the correlation with ground ratings, over a generic author independent rating prediction model.
Learning Reviewer Preferences

Reviewer 1: “The hotel has a nice+ ambience and comfortable+ rooms. However, the food is not that great-1” (+4)

Reviewer 2: “The hotel has an awesome+ restaurant and food is delicious+. However, the rooms are not too comfortable-”. (+5)

Same features, but different feature ratings and different overall rating

The challenge is to learn individual author preferences and predict the overall rating as a function of facet ratings
Objectives

- Discover Facets and Generic Facet-Specific Ratings from Review
- Find Facet-Specific Author Preferences
- Find overall review rating as a function of generic facet-specific ratings and author-specific facet preferences.
Algorithm 1. Extract Generic Facet Ratings from Review

1. Consider a review with a set of known seed facets
2. Initialize clusters corresponding to each seed facet
3. POS tag sentences, retrieve nouns as potential facets
4. Assign extracted facets to its most relevant cluster using Wu-Palmer WordNet Similarity Measure. Ignore facets with low score.
5. Given a facet, use Dependency Parsing based Feature Specific Sentiment Analysis to identify polarity of a sentence with respect to the facet
6. For each of the clusters, aggregate the polarity of all sentences in the review with respect to the cluster members
7. Assign the aggregated polarity to the seed facet of the cluster and map it to a rating between 1-5.
Dependency Relations for Feature Specific Sentiment Extraction

- **Direct Neighbor Relation**
  - Capture **short range dependencies**
  - Any 2 consecutive words (such that none of them is a StopWord) are directly related
  - Consider a sentence $S$ and 2 consecutive words $w_i, w_{i+1} \in S$
  - *If* $w_i, w_{i+1} \notin \text{Stopwords}$, then they are directly related.

- **Dependency Relation**
  - Capture **long range dependencies**
  - Let $\text{Dependency\_Relation}$ be the list of **significant relations**.
  - Any 2 words $w_i$ and $w_j$ in $S$ are directly related, *if* $\exists D_i \ s.t. \ D_i(w_i, w_j) \in \text{Dependency\_Relation}$
Algorithm 2. Feature Specific Sentiment Extraction

A Graph $G(W, E)$ is constructed such that any $w_i, w_j \in W$ are directly connected by $e_k \in E$, if $\exists R_i$ s.t. $R_i(w_i, w_j) \in R$.

i. Initialize $n$ clusters $C_i \; \forall \; i = 1 \ldots n$

ii. Make each $f_i \in F$ the clusterhead of $C_i$. The target feature $f_t$ is the clusterhead of $C_t$. Initially, each cluster consists only of the clusterhead.

iii. Assign each word $w_j \in S$ to cluster $C_k \; s.t., \; k = \arg\min_{i \in n} dist(w_j, f_i)$, Where $dist(w_j, f_i)$ gives the number of edges, in the shortest path, connecting $w_j$ and $f_i$ in $G$.

iv. Merge any cluster $C_i$ with $C_t$ if $dist(w_j, f_i) < \theta$, Where $\theta$ is some threshold distance.

v. Finally the set of words $w_i \in C_t$ gives the opinion expression regarding the target feature $f_t$. 
Algorithm 3. Extract Author-Specific Facet Preferences from Overall Review Rating

- Consider a review $r$ by an author $a$.

- Overall rating $P_{r,a}$ of the review is given by,
  $$P_{r,a} = \sum_t h_{r,t} \times w_{t,a}$$
  where $w_{t,a}$ is the preference of author $a$ for facet $t$, and $h_{r,t}$ is the rating assigned to the facet $t$ in review $r$.

- Using linear regression to learn the author preferences,
  $$P_{RXA} = H_{RXT} \times W_{TXA}$$
  or $W = (H^T H)^{-1} H^T P$
Baselines

- First baseline is simple linear aggregation of all opinions in the review.

- For the second baseline, the facet weights are learnt over the entire corpus, over all authors.

- Pearson’s Correlation Co-efficient (PCC) is used to find correlation between ratings.
Dataset

- Trip advisor is used to collect 1526 reviews

- We chose restaurant as the topic and a list of 9 authors along with their ratings

- The seed facets chosen are: cost, value, food, service and atmosphere

<table>
<thead>
<tr>
<th>Authors</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reviews/Author</td>
<td>152</td>
<td>102</td>
<td>322</td>
<td>383</td>
<td>169</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Avg. Words/Review</td>
<td>40.4</td>
<td>150</td>
<td>181</td>
<td>52</td>
<td>108</td>
<td>242</td>
<td>113</td>
<td>84</td>
<td>56.4</td>
</tr>
</tbody>
</table>

Dataset Statistics for 9 Authors
## Evaluation

<table>
<thead>
<tr>
<th>Majority Voting over All Facets</th>
<th>Facet Specific, General Author Preference</th>
<th>Facet and Author Specific Preference</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.550</td>
<td>0.573</td>
<td>0.614</td>
</tr>
</tbody>
</table>

### PCC Score Comparison of Different Models

![Graph showing PCC scores for different facets and authors](image)

**Figure 1.** Facet Specific Preferences of Different Authors
Conclusions

- Simple majority voting of opinions in the review achieves the lowest correlation with the ground ratings.

- Performance is improved by considering overall rating to be a function of facet specific ratings:
  - Facet ratings are weighed by the general importance of the facet to the reviewers.

- The best correlation is achieved by considering each author’s preference for a given facet, which is learnt from the reviews of the given author.