Incorporating Author Preference in Sentiment Rating Prediction of Reviews

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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* $w_i, w_{i+1} \notin Stopwords$, then they are directly related.

- Dependency Relation
  - Capture **long range dependencies**
- Let *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.* $D_i(w_i, w_j) \in Dependency\_Relation$

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 $\exists R_l$ s.t. $R_l(w_i, w_j) \in R$.

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., $k = argmin_{i \in n} dist(w_j, f_i)$, *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 θ 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, $P_{\mathrm{r,a}} = \Sigma_t\, h_{r,t} \times w_{t,a}$, 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, $\mathrm{P}_{\mathrm{R\,X\,A}} = \mathrm{H}_{\mathrm{R\,X\,T}}\ \mathrm{X}\ \mathrm{W}_{\mathrm{T\,X\,A}}$
  or $\mathrm{W} = (\mathrm{H}^{\mathrm{T}}\mathrm{H})^{-1}\mathrm{H}^{\mathrm{T}}\mathrm{P}$

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

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

Dataset Statistics for 9 Authors

Evaluation

Majority Voting over All Facets	Facet Specific, General Author Preference	Facet and Author Specific Preference
0.550	0.573	**0.614**

PCC Score Comparison of Different Models

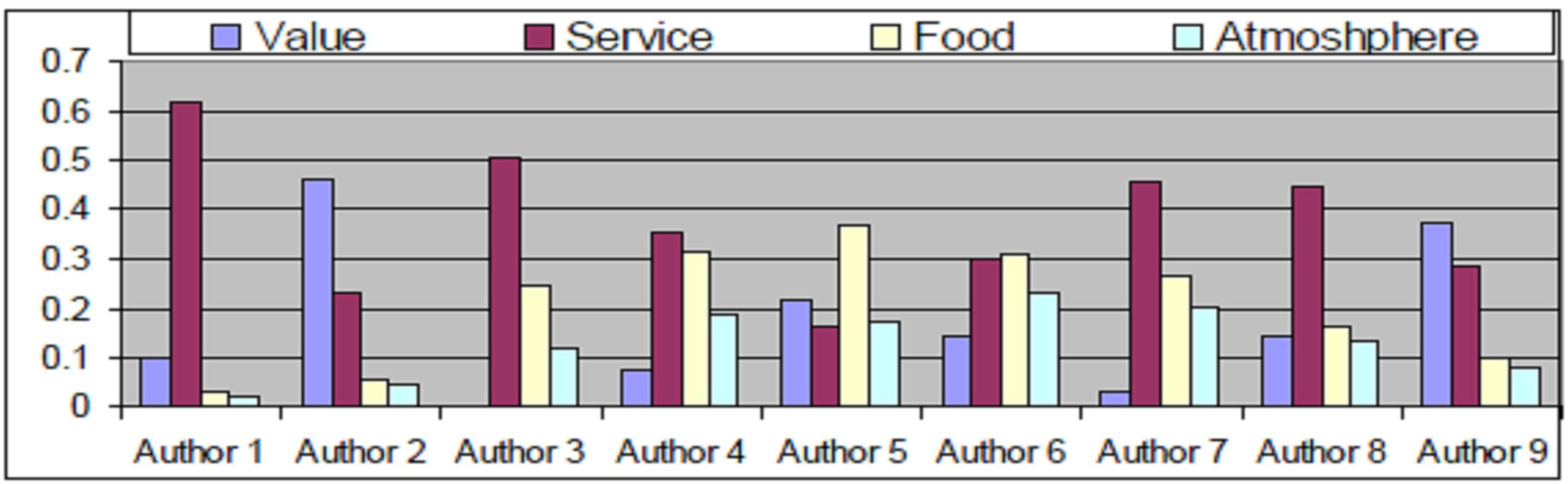

Figure 1. Facet Specific Preferences of Different Authors

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