Implicit Feature Extraction for Sentiment Analysis in Consumer Reviews

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Introduction

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- Aspects denote specific characteristics of the product or service being reviewed
- Aspect-level sentiment analysis allows for a fine-grained overview of a product or service, which is more useful than one overall score
- This research is limited to finding aspects (no actual sentiment analysis) in consumer reviews

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Examples

- *“I can’t see a thing when it’s sunny.”*
- *“The phone lasts all day.”*

Introduction - Human processing of implict aspects

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- Mapping from the words in the sentence to the invisible implicit aspect(s)
- This mapping is shared across all users of the language
- Hence, usually only well-known aspects or broad categories are implied

Examples

- Price, size, weight, service, etc.

Proposed Method

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- Count the number of co-occurrences between the implicit aspects and the words in the sentence
- For an unlabeled sentence, the implicit feature that co-occurs most often with the words in the sentence is chosen...
- ...if it exceeds a certain threshold

Training Algorithm - Counting

Initialize set of word lemmas with frequencies O
Initialize set of implicit features F
Initialize co-occurrence matrix C
for sentence $s \in$ training data do
    for word $w \in s$ do
        $O(w) = O(w) + 1$
    end for
    for implicit feature $f \in s$ do
        add f to F
        for word $w \in s$ do
            $C(w, f) = C(w, f) + 1$
        end for
    end for
end for

Training Algorithm - Threshold optimization

threshold$=0$
$bestF_1 = 0$
for $t = 0$ to 1 step 0.001 do
    Process training data
    Compute F_1
    if $F_1 > bestF_1$ then $threshold = t$
    end if
end for

Processing Algorithm

for sentence $s \in$ test data do
currentBestImplicitFeature $=$ *empty*
scoreOfCurrentBestImplicitFeature $= 0$
for implicit feature $f \in F$ do
$score = 0$
for word $w \in s$ do
if $O(w) > 0$ then
$score = score + C(w, f)/O(w)$
end if
end for
$score = score/$ length(s)
if $score > scoreOfCurrentBestImplicitFeature$ then
$currentBestImplicitFeature = f$
$scoreOfCurrentBestImplicitFeature = score$
end if
end for
if $scoreOfCurrentBestImplicitFeature > threshold$ then
Assign $currentBestImplicitFeature$ to s
end if
end for

Formula Notation

$$score_i = \frac{1}{v} \sum_{j=1}^{v} \frac{c_{i,j}}{o_j}, \tag{1}$$

where

- i is the ith aspect in the list of possible aspects for which the *score* is computed
- v is the number of words in the sentence
- j represents the jth word in the sentence
- $c_{i,j}$ is the co-occurrence frequency of aspect i and lemma j in the data set
- o_j is the frequency of lemma j in the data set

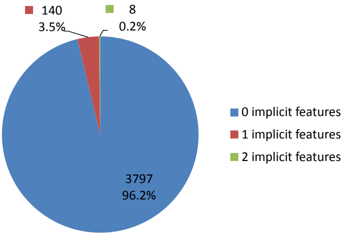
Known Limitations

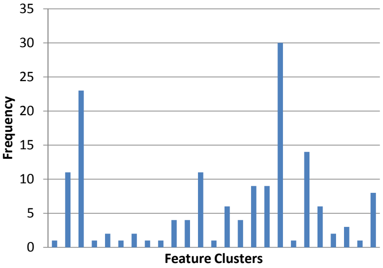
- Only one implicit aspect is chosen per sentence
- Sufficient amount of labelled training data is required

Data Analysis

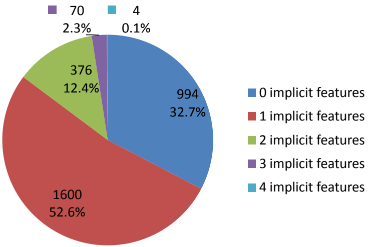
- Two data sets: product reviews and restaurant reviews
- Both contain about 3000 sentences

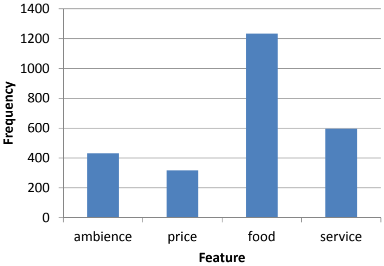
Data Analysis - Product Data





Data Analysis - Restaurant Data





Evalution

Method

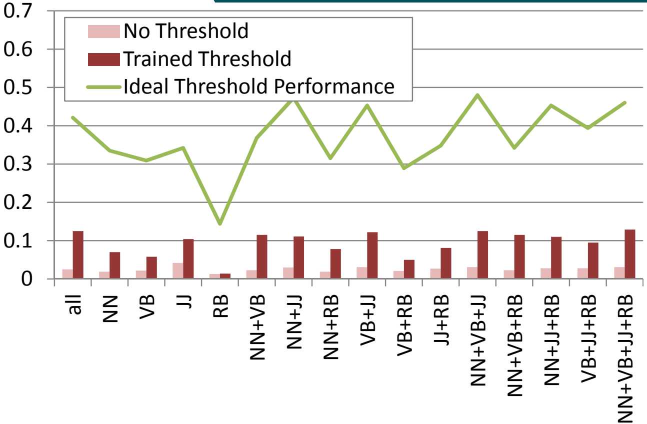
- All evaluations have been performed using 10-fold cross-validation
- Both the counting and the threshold optimization are done using training data only
- Because of previous work, we used different combinations of part-of-speech filters to control what kind of words would be contained in the co-occurrence matrix

Evalution

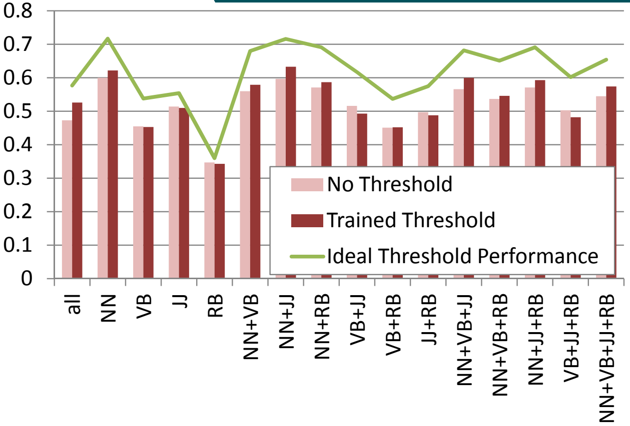
Error types

- Incorrectly state that a sentence contains some implicit aspect: *lower precision*
- Incorrectly state that a sentence does not contain an implicit aspect: *lower recall*
- Correctly state that a sentence contains an implicit aspect, but pick the wrong one: *both precision and recall will be lower*

Results - Product Data

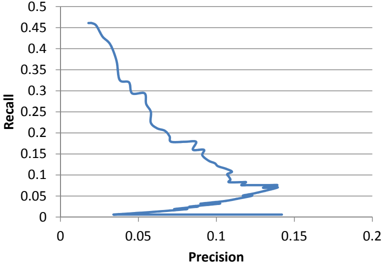


Results - Restaurant Data



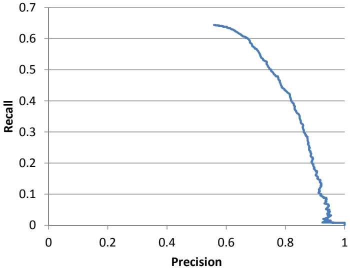
Results - Precision-Recall curves

Product Data



Using NN+VB+JJ+RB filter

Restaurant Data



Using NN+JJ filter

Results - Comparison

product review data set

method	no threshold	trained threshold	difference
Zhang & Zhu	1.2% (`all`)	1.4% (`NN+VB+JJ+RB`)	+0.2 pp.
proposed method	4.2% (`JJ`)	12.9% (`NN+VB+JJ+RB`)	+8.7 pp.
difference	+3 pp.	+11.5 pp.	

restaurant review data set

method	no threshold	trained threshold	difference
Zhang & Zhu	31.5% (`all`)	32.4% (`all`)	+0.9 pp.
proposed method	59.7% (`NN+JJ`)	63.3% (`NN+JJ`)	+3.6 pp.
difference	+28.2 pp.	+31.1 pp.	

Conclusions

- Significantly improved on existing method, although at the cost of being a supervised method
- The algorithm needs a sufficient amount of data to work properly
- The use of a threshold is beneficial, especially for the small data set

Future Work

- Allow for more than one implicit aspect per sentence
- Learn a threshold for each implicit aspect
- Move towards a more concept-level approach
  - "This phone doesn't fit in my pocket"

Questions?

Contact

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