Intelligent Feature Selection for Opinion Classification

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Although text opinion mining involves many important tasks, accurately assigning sentiment polarities (such as positive, negative, or neutral) and intensities (such as high or low) remains a critical challenge. Given the complexities and nuances associated with opinion classification, it is generally considered more difficult than traditional text mining tasks such as topical and sentiment analysis. Consequently, prior sentiment-analysis studies have used more sophisticated feature representations, well beyond bag-of-words and word n-grams. The features used include part-of-speech tag n-grams, syntactic phrase patterns, legomena-based collocations, as well as manually and semiautomatically constructed syntactic and semantic phrase patterns and lexicons. Although these features represent potentially important sentiment discriminators, incorporating them in unison can produce feature spaces spanning tens of thousands of attributes, a situation resulting in the age-old conundrum of disentangling quality from quantity. In addition to the obvious ramifications pertaining to computational feasibility, we must also consider the trade-offs between representational richness and noise, between generalization ability and over-fitting (memorization). Without appropriate feature-selection mechanisms, using large heterogeneous feature spaces is analogous to “throwing the kitchen sink.”

This problem is exacerbated by the lack of feature-selection methods specifically crafted for opinion classification. Most existing feature-selection methods are generic techniques that are uniformly applied to input feature value matrices. Examples include information gain, log likelihood, chi squared, and decision-tree models. When applied to text, these methods are often more artificial than they are intelligent. Text features are multidimensional in terms of their informational composition.

In addition to various occurrence measures (such as presence and frequency), they encompass lexicology and morphology-based characteristics (including semantics and syntax). There is a need for intelligent feature-selection (IFS) methods that can exploit the syntactic properties of text features while simultaneously leveraging relevant sentiment-related semantic information.

An excellent example of a feature-selection approach tailored to sentiment analysis that utilizes the syntactic relations between text attributes is feature subsumption hierarchies (FSH). Given a set of word n-grams and syntactic n-gram patterns, FSH uses the idea of performance-based feature subsumption to remove redundant or irrelevant higher order n-grams. For instance, only the word bigrams and trigrams that provide additional information (measured using some heuristic) over the unigrams they encompass are retained. For example, the bigram “I like” may be subsumed by the unigram “like,” but “basket case” may be retained because it contains important sentiment information not provided by “basket” or “case” alone.

Inspired by FSH, this article presents an IFS approach that incorporates syntactic and semantic information. The proposed approach helps illustrate how rich, heterogeneous feature sets, coupled with appropriate feature-selection mechanisms, can improve opinion-classification performance.

References


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An IFS Approach

Figure 1 depicts the design layout for the proposed IFS approach, which uses semantic and syntactic information to refine large input feature spaces. In the example presented here, various categories of n-gram features were used. Although others could also have been incorporated, those utilized include character n-grams, word n-grams, parts-of-speech (POS) tag n-grams, word plus POS tag n-grams, legomena n-grams, information extraction patterns (IEP), and semantic patterns. For each category, I use unigrams, bigrams, and trigrams.

Semantic Information

The features’ initial weights are an amalgamation of their occurrence distribution across classes in the training data as well as their degree of subjectivity, which is derived from SentiWordNet, a publicly available lexical resource. Figure 2 presents the initial weighting formulation for word n-grams. Given a word n-gram feature \(a_x\) that consists of \(d\) tokens, the initial weight \(w(a_x)\) is the sum of \(wt(a_x)\) and \(ws(a_x)\), where \(ws(a_x)\) is computed by determining the average polarity value across the individual tokens encompassed within the n-gram.

For each token \(a_{xi}\), the polarity value is the average of the sum of its positive and negative scores for each word-sense pair \(s(a_{xi}, j)\) in SentiWordNet, where \(j\) is one of the \(k\) senses of \(a_{xi}\). The computation of \(ws(a_x)\) for other n-gram feature categories differs slightly. For instance in the case of parts-of-speech (POS) tag plus word n-grams, the word polarity values are only computed for word-sense pairs in SentiWordNet where the sense has the same POS as that of the tag associated with the word.

Syntactic Information

The IFS approach uses a feature relation network (FRN) that utilizes two important syntactic n-gram relations: subsumption and parallel relations.
In the syntactic information box in Figure 1, subsumption relations are denoted with arrows, while parallel relations are depicted using solid lines. These two relations enable intelligent comparison between features to facilitate enhanced removal of redundant and/or irrelevant attributes. Each remaining feature with a weight greater than 0 is first checked for potential subsumptions, then analyzed for parallel relations.

A subsumption relation occurs between two n-gram feature categories where one category is a more general, lower-order form of the other. A subsumes B (A → B) if B is a higher order n-gram category with n-grams that contain the lower-order n-grams found in A. For example, word unigrams subsume word bigrams and trigrams, while word bigrams subsume word trigrams. Hence, given A → B, we keep features from category B if their weight exceeds that of their general lower-order counterparts found in A by some threshold t. For instance, the bigrams “I love” and “love chocolate” would only be retained if their weight exceeded that of the unigram “love” by t—that is, if they provided additional information over the more general unigram. Otherwise, they would be assigned a final weight of 0.

A parallel relation occurs when two heterogeneous same-order n-gram feature groups may have some features with similar occurrences. For example, word unigrams can be associated with many POS tags, and vice versa. However, certain word and POS tags’ occurrences might be highly correlated. Given two n-gram feature groups with potentially correlated attributes, A is considered to be parallel to B (A → B). If two features from categories A and B, respectively, have a correlation coefficient greater than some threshold p, one of the attributes is removed to avoid redundancy—that is, it is assigned a final weight of 0.

### Evaluation

The IFS approach was evaluated on three online product review testbeds, each consisting of 2,000 reviews: digital camera reviews from Epinions, automobile reviews from Edmunds, and movie reviews from Rotten Tomatoes. All three test beds had two classes that were balanced in terms of the number of reviews per class (1,000 each).

Table 1 depicts the area under the curve (AUC) values for different feature-selection methods across test beds.

<table>
<thead>
<tr>
<th>Feature selection</th>
<th>Digital cameras</th>
<th>Automobiles</th>
<th>Movies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Best accuracy (%)</td>
<td>AUC</td>
<td>Best accuracy (%)</td>
</tr>
<tr>
<td>IFS</td>
<td>89.2</td>
<td>1581</td>
<td>90.7</td>
</tr>
<tr>
<td>Semantic IFS</td>
<td>87.8</td>
<td>1566</td>
<td>89.7</td>
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<tr>
<td>Syntactic IFS</td>
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<td>1559</td>
<td>89.2</td>
</tr>
<tr>
<td>Information gain</td>
<td>86.7</td>
<td>1549</td>
<td>87.8</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>86.1</td>
<td>1540</td>
<td>88.2</td>
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<tr>
<td>Word n-gram</td>
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<td>1519</td>
<td>86.0</td>
</tr>
</tbody>
</table>

Table 1. Best accuracy and area under the curve (AUC) values for different feature-selection methods across test beds.
Using semantic and syntactic information, IFS resulted in feature sets with the best accuracy and AUC values on all three test beds. IFS outperformed information gain and log likelihood by 2 to 4 percent in terms of best accuracy and 30 to 55 points in terms of AUC, while the word n-gram feature set was surpassed by 4 to 5 percent in terms of best accuracy. These comparison feature-selection methods were outperformed by the word n-gram feature set on the movie review test bed, demonstrating how larger feature sets can be detrimental when appropriate feature-selection methods are not availed. Moreover, both the semantic and syntactic information contributed to the IFS approach’s overall effectiveness, as evidenced by the performance degradation that resulted when either form of information was omitted.

**Future Research**

This approach was intended to illustrate how IFS can be combined with larger feature sets for enhanced opinion-classification performance. There are many ways in which IFS for opinion classification can be extended in future research. Numerous additional feature categories could be used, resulting in even more robust feature sets. The syntactic and semantic information modules could be expanded on, for instance, by incorporating additional lexical resources and real-world knowledge bases.

Traditionally, sentiment-analysis research has relied on two types of feature occurrence measures (frequency and presence), while researchers have yet to methodically explore additional distributional and positional measurements. Recently, distributional measures such as compactness and first appearance have been successfully applied to topic-based text categorization. These measures could be used to supplement existing occurrence measures. Hence, we could use IFS mechanisms to reduce opinion-classification feature spaces in a 2D manner: across feature categories (such as specific text features) and various occurrence measures associated with those features.

Future feature-selection efforts could explore the unique challenges associated with performing opinion classification at the document-level versus sentence-, phrase-, and word-level classification. Furthermore, there are other sentiment-analysis tasks that could benefit from improved feature selection, such as opinion holder identification and sentiment target.
detection. Given the plethora of potential future directions, one thing is for certain: IFS could help alleviate the quagmire associated with learning features for opinion classification, thereby allowing the kitchen sink to remain where it belongs.

References

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