

Developing a Flexible Sentiment Classification Technique for Multiple Domains

Nathan Agrin

School of Information
University of California, Berkeley

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Implications

- Find opinions on current events, products or specific interests
- Determine what people like about specific services, or products
- Can allow for more specific retrieval of opinionated content, and better mapping of a global sentiment, localized sentiment, as well as a specific user's opinions on a given subject

Project Goals

- When searching, sentiment can be calculated at runtime or determined prior to a query and used to formulate the results
- Create a classification method with which to determine if text contains a positive or negative sentiment, then store this data in a format for assisting search

Data Set

- **Movie Review Set (Primary)**

Created by Bo Pang and Lillian Lee at Cornell

Contains 2,000 positive & negative movie reviews

- **Product Review Set (Secondary)**

Created by Minqing Hu and Bing Liu

Contains 110 negative and 185 positive product reviews

- **General Inquirer**

Used as seed list and filter for affective words

Identified Problems

- Sentiment content often contains many discrete opinions about different aspects of a larger topic, or quotations of other text
- Sentiment may use made-up words, or sarcasm:

“HmMMM, well, the main actor, Justin Chambers, is basically an **uncharismatic** version of Chris O'Donnell but with less range (think about that!), and Mena Suvari, is just plain off.

- Sentiment is often based on syntactical structure, implying negation:

I feel like I should have had a grand time with "Detroit Rock City."

It's the sort of movie I wish I could've had a lot of fun with, but I didn't.

Approach

- **Statistical Classification**

 - SVM and Complimentary Naive Bayes

 - Tested across domains

- **Rule Based Classification**

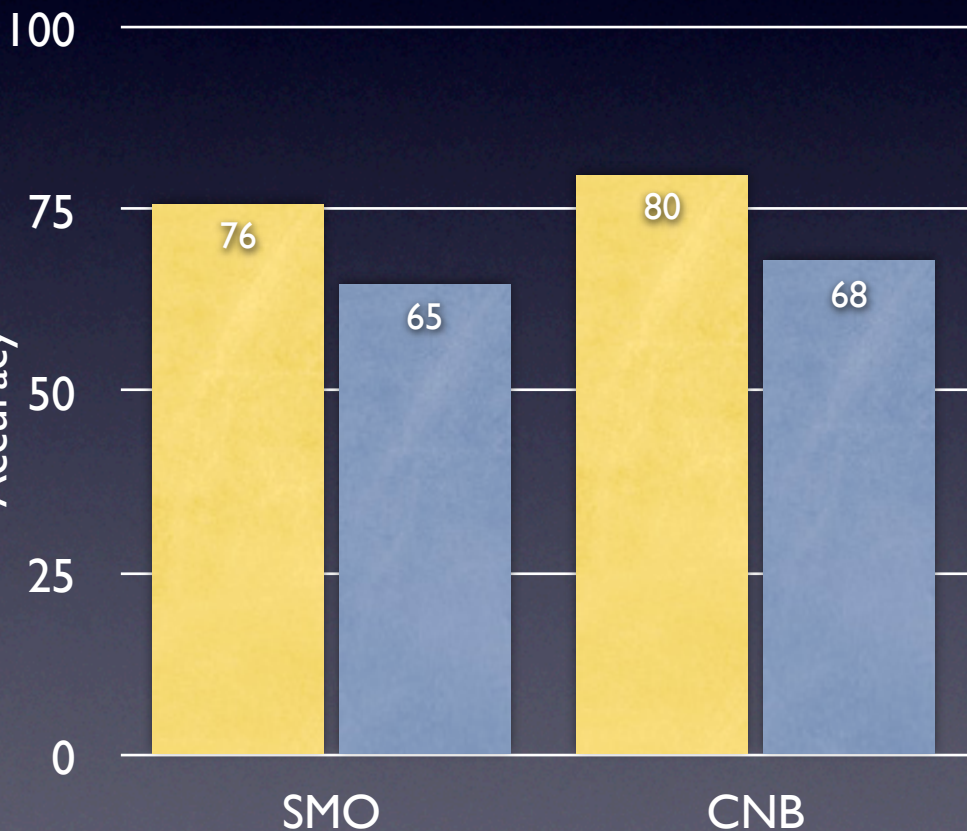
 - Used General Inquirer data as seed list

 - Tested term expansion using Wordnet

Statistical Classification

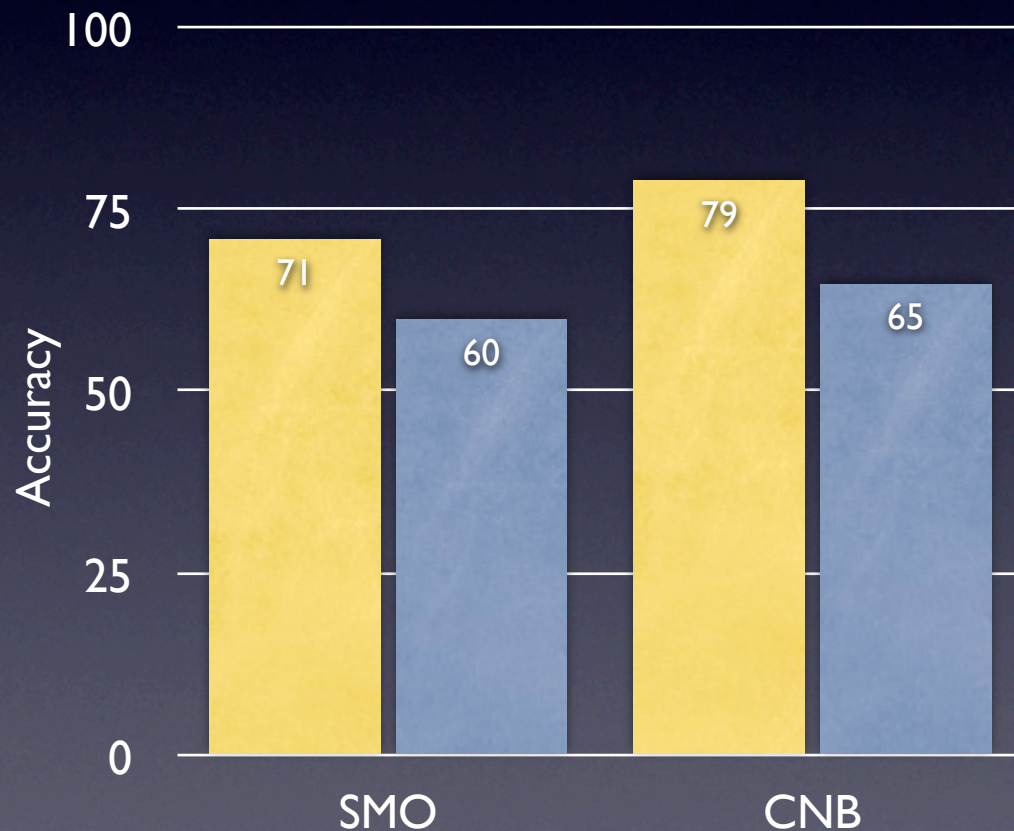
Baseline

Same Domain Cross Domain



Only Affective Words

Same Domain Cross Domain



Rule Based Classifier

Baseline

58	p	n
pos	893	726
neg	107	274

Wordnet

55	p	n
pos	862	695
neg	102	245

Wordnet &
Negation

58	p	n
pos	890	685
neg	81	236

- Documents consistently scored as positive
- 1638 / 2012 : positive / negative words from GI
- Could not determine the cause of accuracy issue...

Rule Based Classifier

- Many documents incorrectly classified as positive had a very small positive rating
- Increasing positive from > 0 to > 5 helped

Wordnet &
Negation

58	p	n
pos	890	685
neg	81	236

Wordnet &
Negation (Positive > 5)

67	p	n
pos	623	290
neg	377	710

Discussion

- Statistical Classifier performed best with little extra data, and across domains
- Rule based classifier may be able to compete with statistical classifier in diverse domains
- Docs tended to contain many positive affective words indicating their POS is misinterpreted, or they appear more frequently, even in negative text
- Use POS tagging and chunking to train a classifier

Questions?