

Adapting systems for different domains and languages

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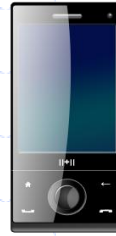
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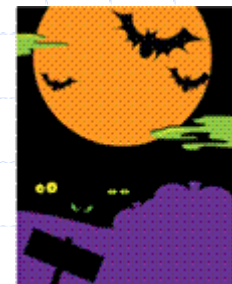
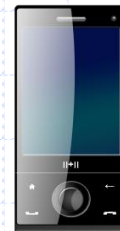
Contents



- ◆ The importance of domain in sentiment analysis
- ◆ Techniques for transferring from one domain to another
- ◆ Domain-independent methods
- ◆ Language issues and methods to translate a sentiment analysis method from one language to another

Are these positive or negative, and what are the sentiment terms?

- ◆ The Maxtor hard disk was very large and could fit all of my data.
- ◆ The cellphone was very large and could not fit in my pocket.
- ◆ The horror movie was very frightening.
- ◆ The car brakes were very frightening.



Two issues



1. Non-sentiment words may express clearly positive or negative opinions in a particular context

- E.g., large (memory, screen), heavy (computer, cellphone), long (travel time, film duration), reliable (brakes), unpredictable (movie plot)

2. Non-sentiment words (and even some sentiment words) vary in typical meaning according to context

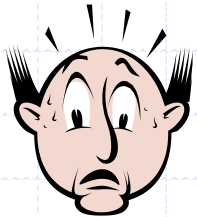
- Typically positive words in horror movie reviews
 - ◆ Frightening, scary, unexpected, entertaining, Depp(?), good, excellent, recommend
- Typically positive words in family car reviews
 - ◆ Reliable, economical, roomy, large, strong, Honda(?), good, cheap



- ◆ What could be typically negative words in these contexts?

Domain dependence

- ◆ The polarity and strength of words may vary by domain
- ◆ This is typically opinion or judgement words rather than direct sentiment words – e.g.,



- “frightening” is typically positive for a horror movie review, but negative for a car review
- “large” is typically positive for hard disk reviews, negative for cellphones

Domain context dependence

◆ The polarity and strength of words may also vary by context within a domain, e.g.,



- “large” is typically positive for a cellphone screen but negative for cellphone size
- “cheap” may be positive for a car overall but negative for the seats (or individual parts)



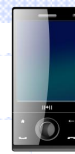
- Any other examples??

Domain dependence – implications for sentiment analysis

- ◆ Generic sentiment algorithms will miss some domain-specific expressions
- ◆ Domain-specific algorithms can therefore be more accurate
- ◆ But domain-specific algorithms need domain-specific training data – often time consuming and difficult to produce

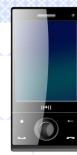
Cross-domain sentiment analysis

- ◆ Domain transfer is the problem of taking a sentiment classifier trained on one domain and adapting it to work on another domain
- ◆ Why not train a new classifier on the new domain?
 - Because of the problem creating training data
 - Especially if *many* new domains need sentiment classifiers

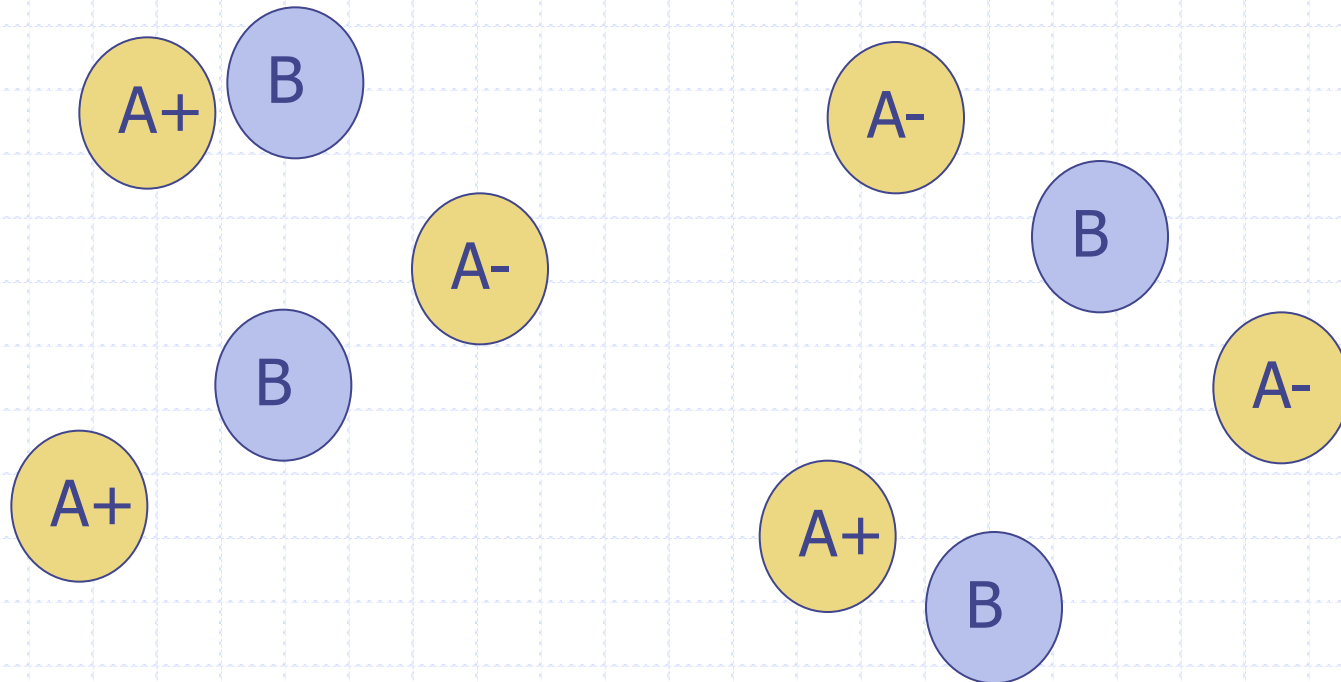


Cross domain A -> B: 5 methods

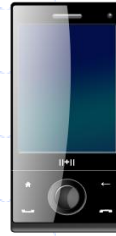
1. Train classifier on A, apply to B (no domain transfer)
2. Use ensembles of classifiers trained on different domain As
3. Train classifier on A, classify texts in B with the classification of texts in A that they are most similar to (e.g., TF-IDF)
4. Train classifier on A, annotate texts in B with the classification of texts in A that they are most similar to (e.g., TF-IDF) & retrain classifier on A & B
5. Train a classifier for B on the data from A but with only features found in B



How should the Bs be classified?



Summary



- ◆ Domain-specific sentiment analysis can be more accurate than general sentiment analysis
 - Especially for product reviews
- ◆ Domain-specific algorithms can be difficult to create due to the need for large gold standard text collections
- ◆ Cross-domain methods make it easier to generate domain-specific algorithms

Bibliography

- ◆ Aue, A., & Gamon, M. (2005). Customizing sentiment classifiers to new domains: A case study. *Proceedings of the International Conference on Recent Advances in Natural Language Processing*, http://research.microsoft.com/pubs/65430/new_domain_sentiment.pdf