AAAI-2011 Tutorial

Sentiment Analysis and Opinion Mining

New book:

Bing Liu. Sentiment Analysis and Opinion Mining

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Introduction

- Opinion mining or sentiment analysis
  - Computational study of opinions, sentiments, subjectivity, evaluations, attitudes, appraisal, affects, views, emotions, etc., expressed in text.
    - Reviews, blogs, discussions, news, comments, feedback, or any other documents
- Terminology:
  - Sentiment analysis is more widely used in industry.
  - Both are widely used in academia
- But they can be used interchangeably.

Why are opinions important?

- "Opinions" are key influencers of our behaviors.
- Our beliefs and perceptions of reality are conditioned on how others see the world.
- Whenever we need to make a decision, we often seek out the opinions of others. In the past,
  - Individuals: seek opinions from friends and family
  - Organizations: use surveys, focus groups, opinion polls, consultants.

Introduction – social media + beyond

- Word-of-mouth on the Web
  - Personal experiences and opinions about anything in reviews, forums, blogs, Twitter, micro-blogs, etc
  - Comments about articles, issues, topics, reviews, etc.
  - Postings at social networking sites, e.g., facebook.
- Global scale: No longer – one's circle of friends
- Organization internal data
  - Customer feedback from emails, call centers, etc.
- News and reports
  - Opinions in news articles and commentaries

Introduction – applications

- Businesses and organizations
  - Benchmark products and services; market intelligence.
    - Businesses spend a huge amount of money to find consumer opinions using consultants, surveys and focus groups, etc
- Individuals
  - Make decisions to buy products or to use services
  - Find public opinions about political candidates and issues
- Ads placements: Place ads in the social media content
  - Place an ad if one praises a product.
  - Place an ad from a competitor if one criticizes a product.
- Opinion retrieval: provide general search for opinions.

A fascinating problem!

- Intellectually challenging & many applications.
  - A popular research topic in NLP, text mining, and Web mining in recent years (Shanahan, Qu, and Wiebe, 2006 (edited book); Surveys - Pang and Lee 2008; Liu, 2006 and 2011; 2010)
  - It has spread from computer science to management science (Hu, Pavlou, Zhang, 2006; Archak, Ghose, Ipeirotis, 2007; Liu Y, et al 2007; Park, Lee, Han, 2007; Dellarocas, Zhang, Awad, 2007; Chen & Xie 2007).
  - 40-60 companies in USA alone
- It touches every aspect of NLP and yet is confined.
  - Little research in NLP/Linguistics in the past.
- Potentially a major technology from NLP.
  - But it is hard.

A large research area

- Many names and tasks with somewhat different objectives and models
  - Sentiment analysis
  - Opinion mining
  - Sentiment mining
  - Subjectivity analysis
  - Affect analysis
  - Emotion detection
  - Opinion spam detection
  - *Etc.*

About this tutorial

- Like a traditional tutorial, I will introduce the research in the field.
  - Key topics, main ideas and approaches
  - Since there are a large number of papers, it is not possible to introduce them all, but a comprehensive reference list will be provided.
- Unlike many traditional tutorials, this tutorial is also based on my experience in working with clients in a startup, and in my consulting
  - I focus more on practically important tasks (IMHO)

Roadmap

- **Opinion Mining Problem**
- Document sentiment classification
- Sentence subjectivity & sentiment classification
- Aspect-based sentiment analysis
- Aspect-based opinion summarization
- Opinion lexicon generation
- Mining comparative opinions
- Some other problems
- Opinion spam detection
- Utility or helpfulness of reviews
- Summary

Structure the unstructured (Hu and Liu 2004)

- Structure the unstructured: Natural language text is often regarded as unstructured data.
- The problem definition should provide a structure to the unstructured problem.
  - Key tasks: Identify key tasks and their inter-relationships.
  - Common framework: Provide a common framework to unify different research directions.
  - Understanding: help us understand the problem better.

Problem statement

- It consists of two aspects of abstraction

(1) Opinion definition. What is an opinion?

- Can we provide a structured definition?
  - If we cannot structure a problem, we probably do not understand the problem.

(2) Opinion summarization. why?

- Opinions are subjective. An opinion from a single person (unless a VIP) is often not sufficient for action.
- We need opinions from many people, and thus opinion summarization.

Abstraction (1): what is an opinion?

- **Id: Abc123 on 5-1-2008** "*I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old Blackberry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, …*"
- One can look at this review/blog at the
  - document level, i.e., is this review + or -?
  - sentence level, i.e., is each sentence + or -?
  - entity and feature/aspect level

Entity and aspect/feature level

- **Id: Abc123 on 5-1-2008** "*I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old Blackberry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, …*"
- What do we see?
  - Opinion targets: entities and their features/aspects
  - Sentiments: positive and negative
  - Opinion holders: persons who hold the opinions
  - Time: when opinions are expressed

Two main types of opinions
(Jindal and Liu 2006; Liu, 2010)

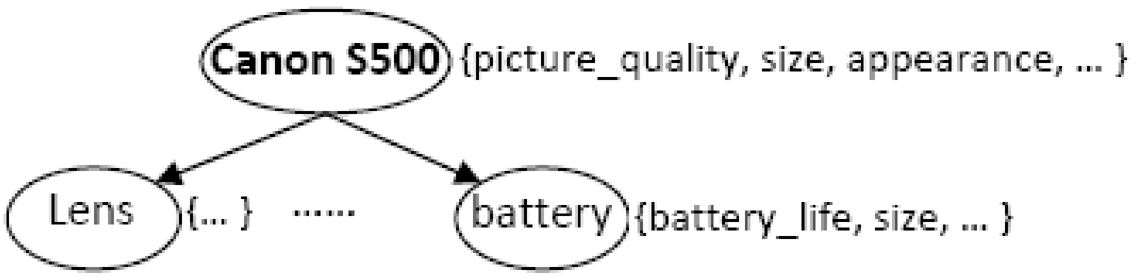
- Regular opinions: Sentiment/opinion expressions on some target entities
  - Direct opinions:
    - "The touch screen is really cool."
  - Indirect opinions:
    - "After taking the drug, my pain has gone."
- Comparative opinions: Comparisons of more than one entity.
  - E.g., "iPhone is better than Blackberry."
- We focus on regular opinions first, and just call them opinions.

A (regular) opinion

- Opinion (a restricted definition)
  - An opinion (or regular opinion) is simply a positive or negative sentiment, view, attitude, emotion, or appraisal about an entity or an aspect of the entity (Hu and Liu 2004; Liu 2006) from an opinion holder (Bethard et al 2004; Kim and Hovy 2004; Wiebe et al 2005).
- Sentiment orientation of an opinion
  - Positive, negative, or neutral (no opinion)
    - Also called *opinion orientation*, *semantic orientation*, *sentiment polarity*.

Entity and aspect (Hu and Liu, 2004; Liu, 2006)

- **Definition** (**entity**): An *entity e* is a product, person, event, organization, or topic. *e* is represented as
  - a hierarchy of components, sub-components, and so on.
  - Each node represents a component and is associated with a set of attributes of the component.



- An opinion can be expressed on any node or attribute of the node.
- For simplicity, we use the term ***aspects*** (features) to represent both components and attributes.

Opinion definition (Liu, Ch. in NLP handbook, 2010)

- An *opinion* is a quintuple

  $(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$,

  where
  - e_j is a target entity.
  - a_{jk} is an aspect/feature of the entity e_j.
  - so_{ijkl} is the sentiment value of the opinion from the opinion holder h_i on feature a_{jk} of entity e_j at time t_l. so_{ijkl} is +ve, -ve, or neu, or more granular ratings.
  - h_i is an opinion holder.
  - t_l is the time when the opinion is expressed.

Some remarks about the definition

- Although introduced using a product review, the definition is generic
  - Applicable to other domains,
  - E.g., politics, social events, services, topics, etc.
- (e_j, a_{jk}) is also called the opinion target
  - Opinion without knowing the target **is of limited use.**
- The five components in $(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$ must correspond to one another. Very hard to achieve
- The five components are essential. Without any of them, it can be problematic in general.

Some remarks (contd)

- Of course, one can add any number of other components to the tuple for more analysis. E.g.,
  - Gender, age, Web site, post-id, etc.
- The original definition of an entity is a hierarchy of parts, sub-parts, and so on.
  - The simplification can result in information loss.
    - E.g., “The seat of this car is rally ugly.”
    - “seat” is a part of the car and “appearance” (implied by ugly) is an aspect of “seat” (not the car).
  - But it is usually sufficient for practical applications.
    - It is too hard without the simplification.

“Confusing” terminologies

- Entity is also called object.
- Aspect is also called feature, attribute, facet, etc
- Opinion holder is also called opinion source
- Some researchers also use topic to mean entity and/or aspect.
  - Separating entity and aspect is preferable
- In specific applications, some specialized terms are also commonly used, e.g.,
  - Product features, political issues

Reader's standing point

- See this sentence
  - "I am so happy that Google price shot up today."
- Although the sentence gives an explicit sentiment, different readers may feel very differently.
  - If a reader sold his Google shares yesterday, he will not be that happy.
  - If a reader bought a lot of Google shares yesterday, he will be very happy.
- Current research either implicitly assumes a standing point, or ignores the issue.

Our example blog in quintuples

- **Id: Abc123 on 5-1-2008** *"I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old Blackberry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, …"*
- In quintuples

  (iPhone, GENERAL, +, Abc123, 5-1-2008)

  (iPhone, touch_screen, +, Abc123, 5-1-2008)

  ....

  - We will discuss comparative opinions later.

Structure the unstructured

- Goal: Given an opinionated document,
  - Discover all quintuples $(e_j, f_{jk}, so_{ijkl}, h_i, t_l)$,
  - Or, solve some simpler forms of the problem
    - E.g., sentiment classification at the document or sentence level.
- With the quintuples,
  - Unstructured Text → Structured Data
    - Traditional data and visualization tools can be used to slice, dice and visualize the results.
    - Enable qualitative and quantitative analysis.

Two closely related concepts

- Subjectivity and emotion.
- **Sentence subjectivity**: An *objective sentence* presents some factual information, while a *subjective sentence* expresses some personal feelings, views, emotions, or beliefs.
- **Emotion**: Emotions are people's subjective feelings and thoughts.

Subjectivity

- Subjective expressions come in many forms, e.g., opinions, allegations, desires, beliefs, suspicions, speculations (Wiebe 2000; Wiebe et al 2004; Riloff et al 2006).
  - A subjective sentence may contain a positive or negative opinion
- Most opinionated sentences are subjective, but objective sentences can imply opinions too (Liu, 2010)
  - “The machine stopped working in the second day”
  - “We brought the mattress yesterday, and a body impression has formed.”
  - “After taking the drug, there is no more pain”

Emotion

- No agreed set of basic emotions of people among researchers.
- Based on (Parrott, 2001), people have six main emotions,
  - love, joy, surprise, anger, sadness, and fear.
- Strengths of opinions/sentiments are related to certain emotions, e.g., joy, anger.
  - However, the concepts of emotions and opinions are not equivalent.

Rational and emotional evaluations

- Rational evaluation: Many evaluation/opinion sentences express no emotion
  - e.g., “The voice of this phone is clear”
- Emotional evaluation
  - e.g., “I love this phone”
  - “The voice of this phone is crystal clear” (?)
- Some emotion sentences express no (positive or negative) opinion/sentiment
  - e.g., “I am so surprised to see you”.

Sentiment, subjectivity, and emotion

- Although they are clearly related, these concepts are not the same
  - Sentiment $\neq$ subjective $\neq$ emotion
- Sentiment is not a subset of subjectivity (without implied sentiments by facts, it should be)
  - sentiment $\not\subset$ subjectivity
- The following should hold
  - emotion $\subset$ subjectivity
  - sentiment $\not\subset$ emotion, …

Abstraction (2): opinion summary

- With a lot of opinions, a summary is necessary.
  - A multi-document summarization task
- For factual texts, summarization is to select the most important facts and present them in a sensible order while avoiding repetition
  - 1 fact = any number of the same fact
- But for opinion documents, it is different because opinions have a quantitative side & have targets
  - 1 opinion ≠ a number of opinions
  - Aspect-based summary is more suitable
    - Quintuples form the basis for opinion summarization

Aspect-based opinion summary[1]
(Hu & Liu, 2004)

"“I bought an iPhone a few days ago. It is such a nice phone. The touch screen is really cool. The voice quality is clear too. It is much better than my old Blackberry, which was a terrible phone and so difficult to type with its tiny keys. However, my mother was mad with me as I did not tell her before I bought the phone. She also thought the phone was too expensive, …”

1. Originally called ***feature-based opinion mining and summarization***

Feature Based Summary of iPhone:

Feature1: **Touch screen**

Positive: 212

- *The touch screen was really cool.*
- *The touch screen was so easy to use and can do amazing things.*

…

Negative: 6

- The screen is easily scratched.
- I have a lot of difficulty in removing finger marks from the touch screen.

…

Feature2: **voice quality**

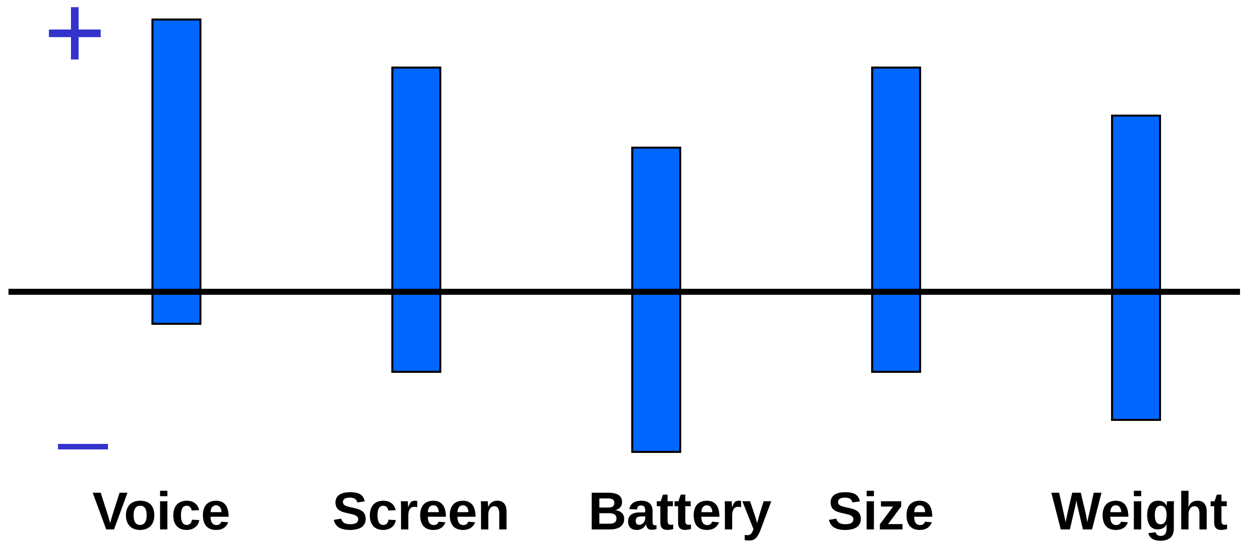
…

Note: We omit opinion holders

Opinion Observer (Liu et al. 2005)

- Summary of reviews of

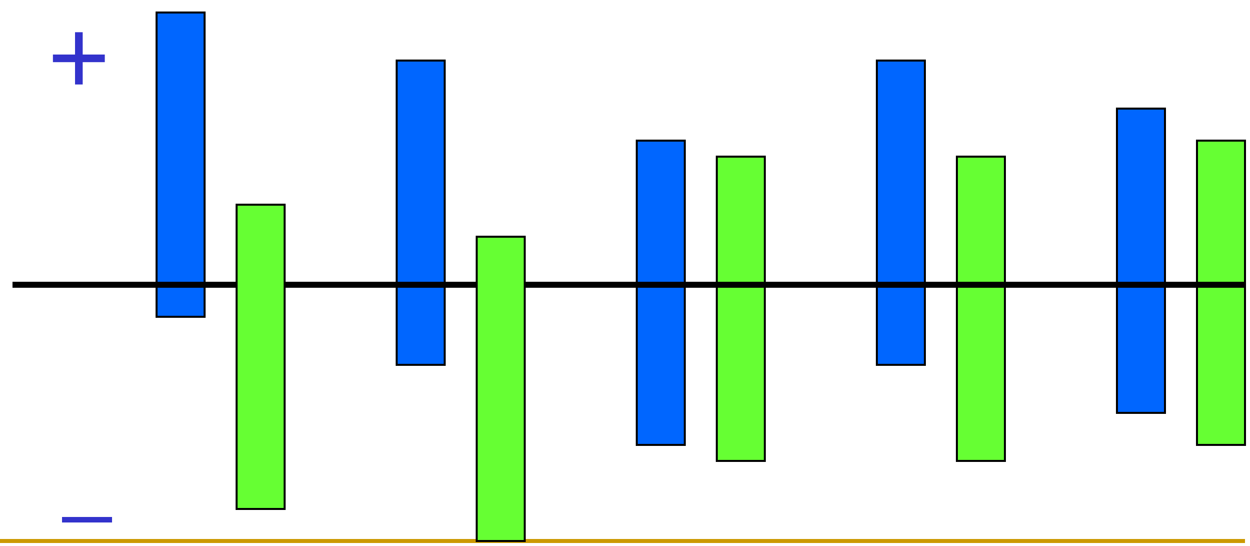
Cell Phone 1



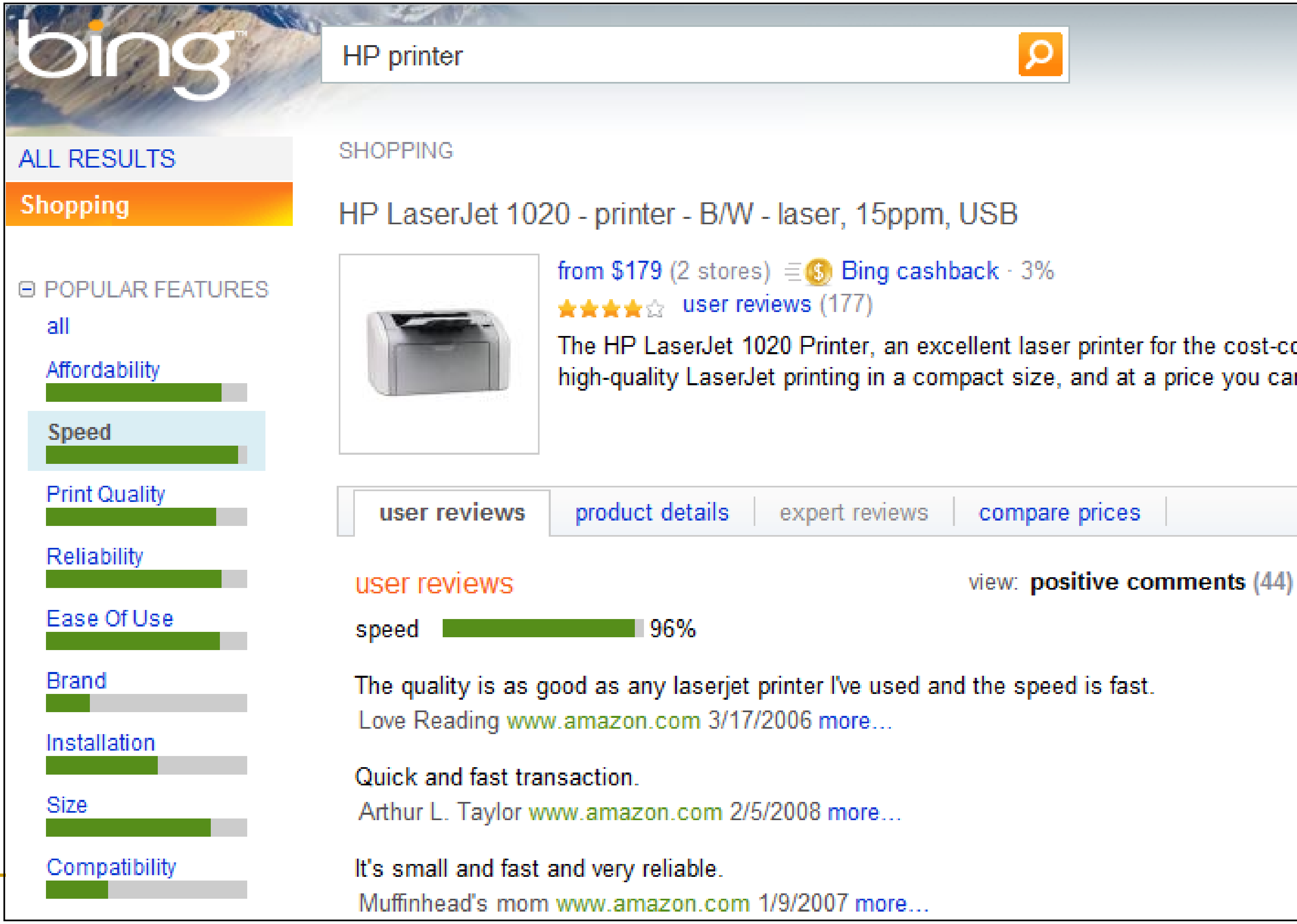
- Comparison of reviews of

Cell Phone 1

Cell Phone 2

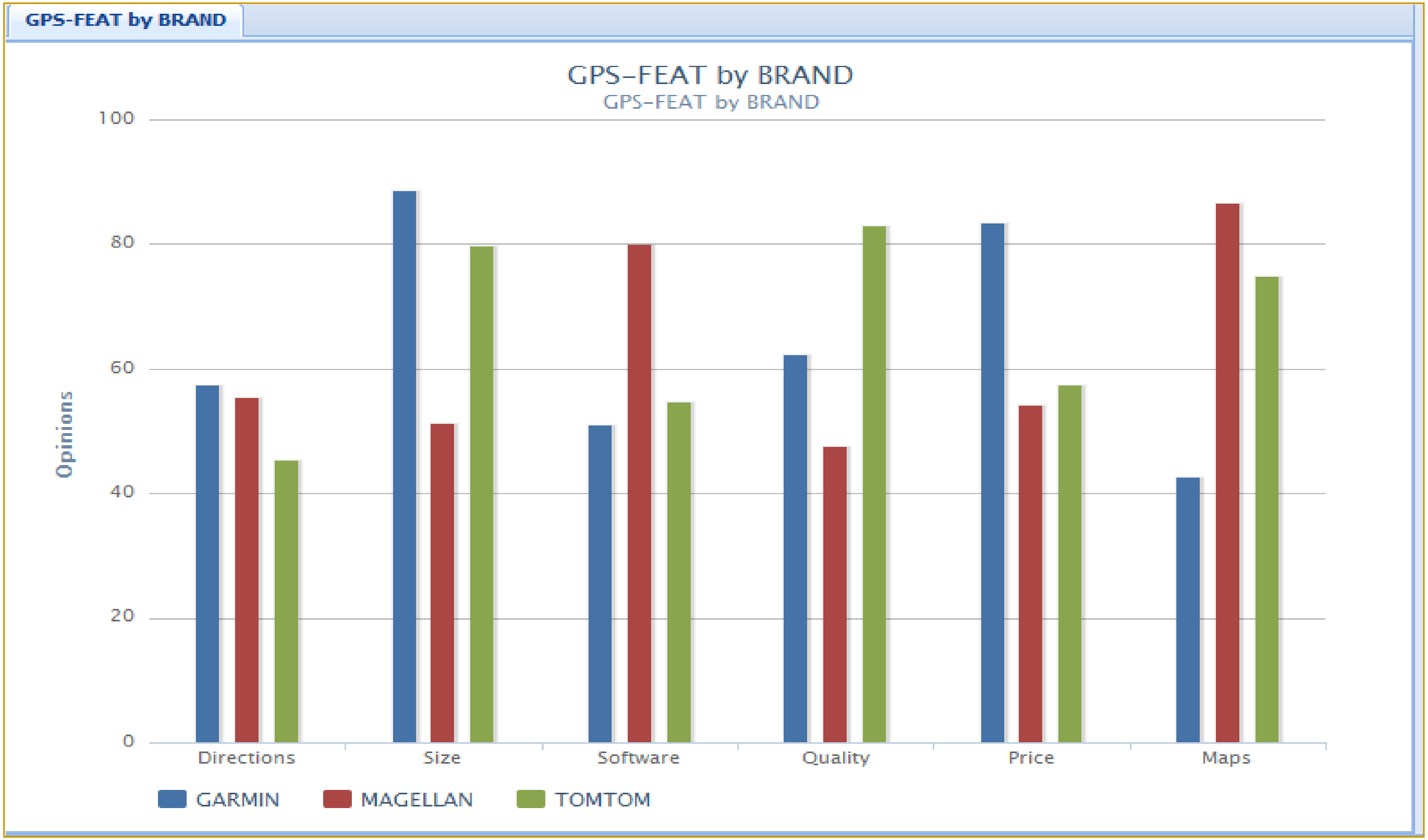


Aspect-based opinion summary



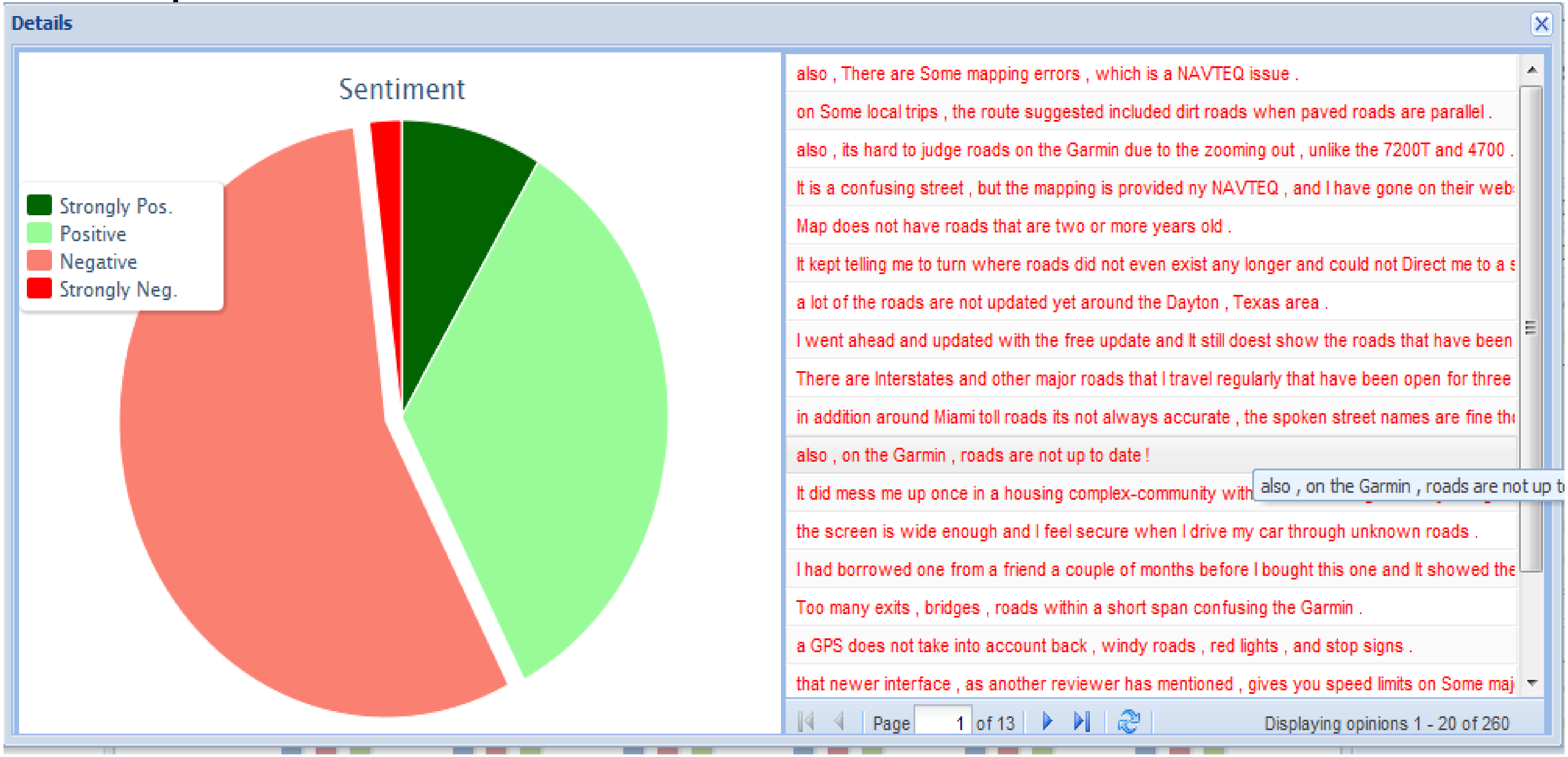
Google Product Search (Blair-Goldensohn et al 2008 ?)

Some examples from OpinionEQ

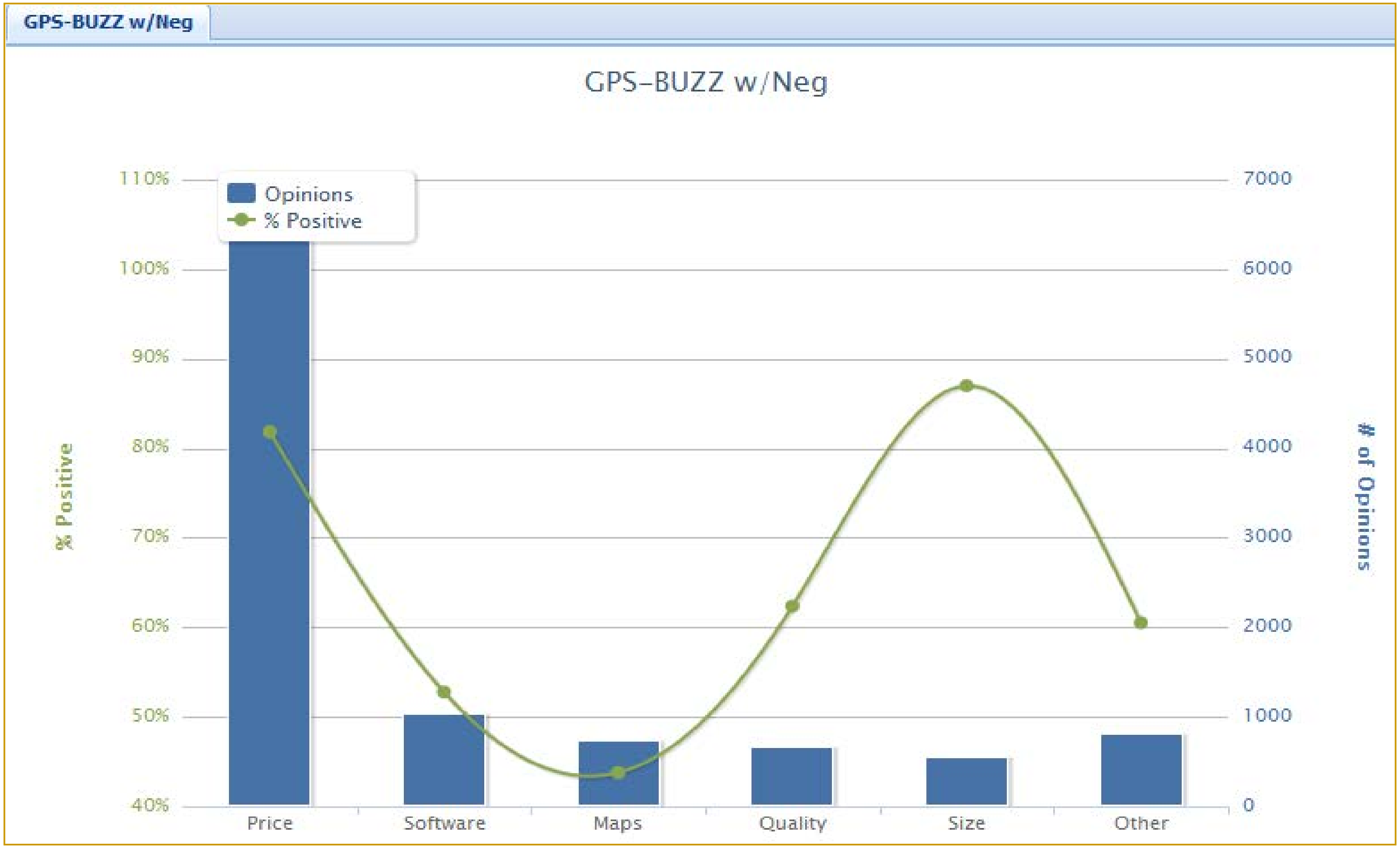


Detail opinion sentences

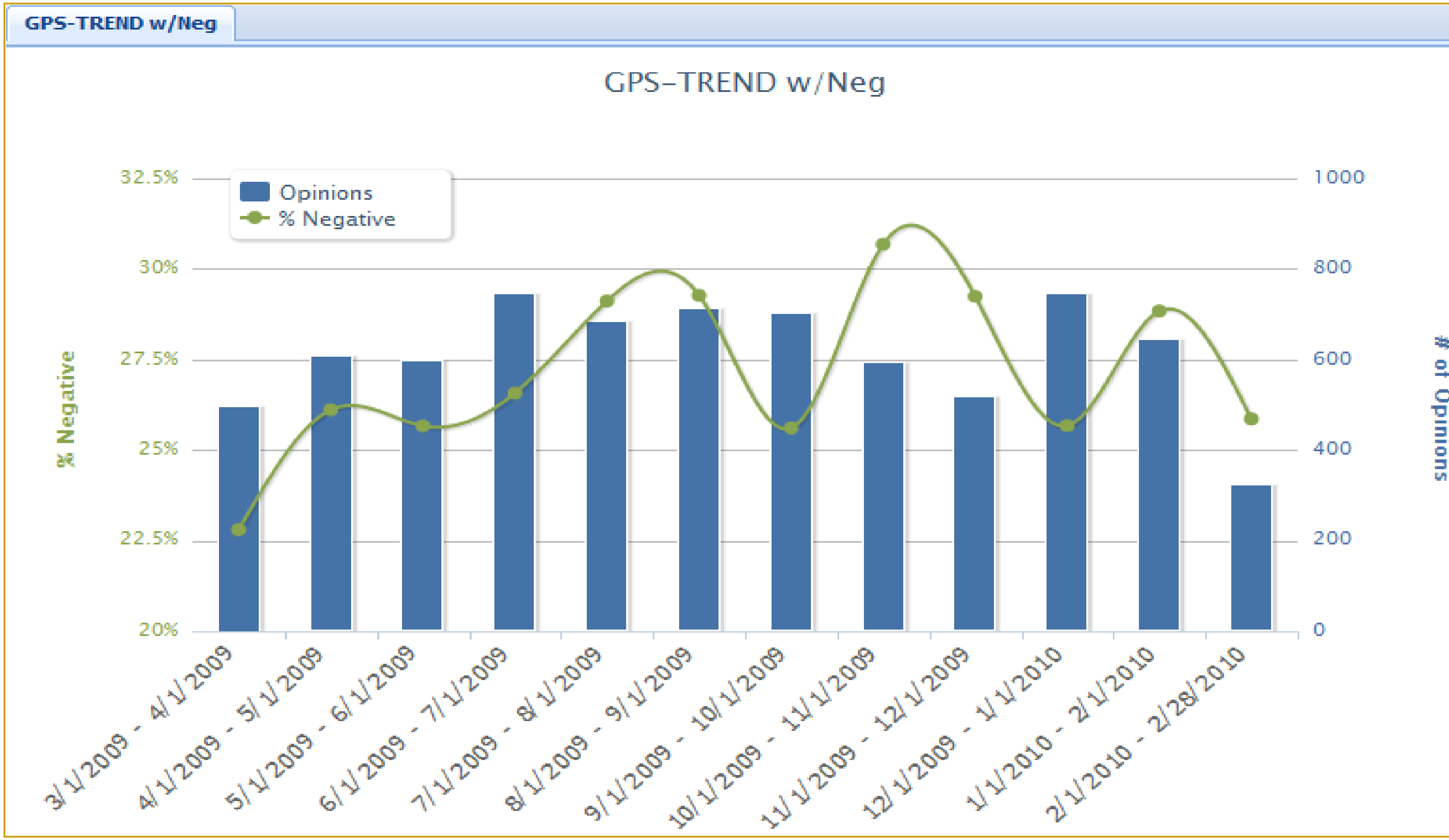
- Click on any bar (previous slide) to see the opinion sentences. Here are negative opinion sentences on the maps feature of Garmin.



% of +ve opinion and # of opinions

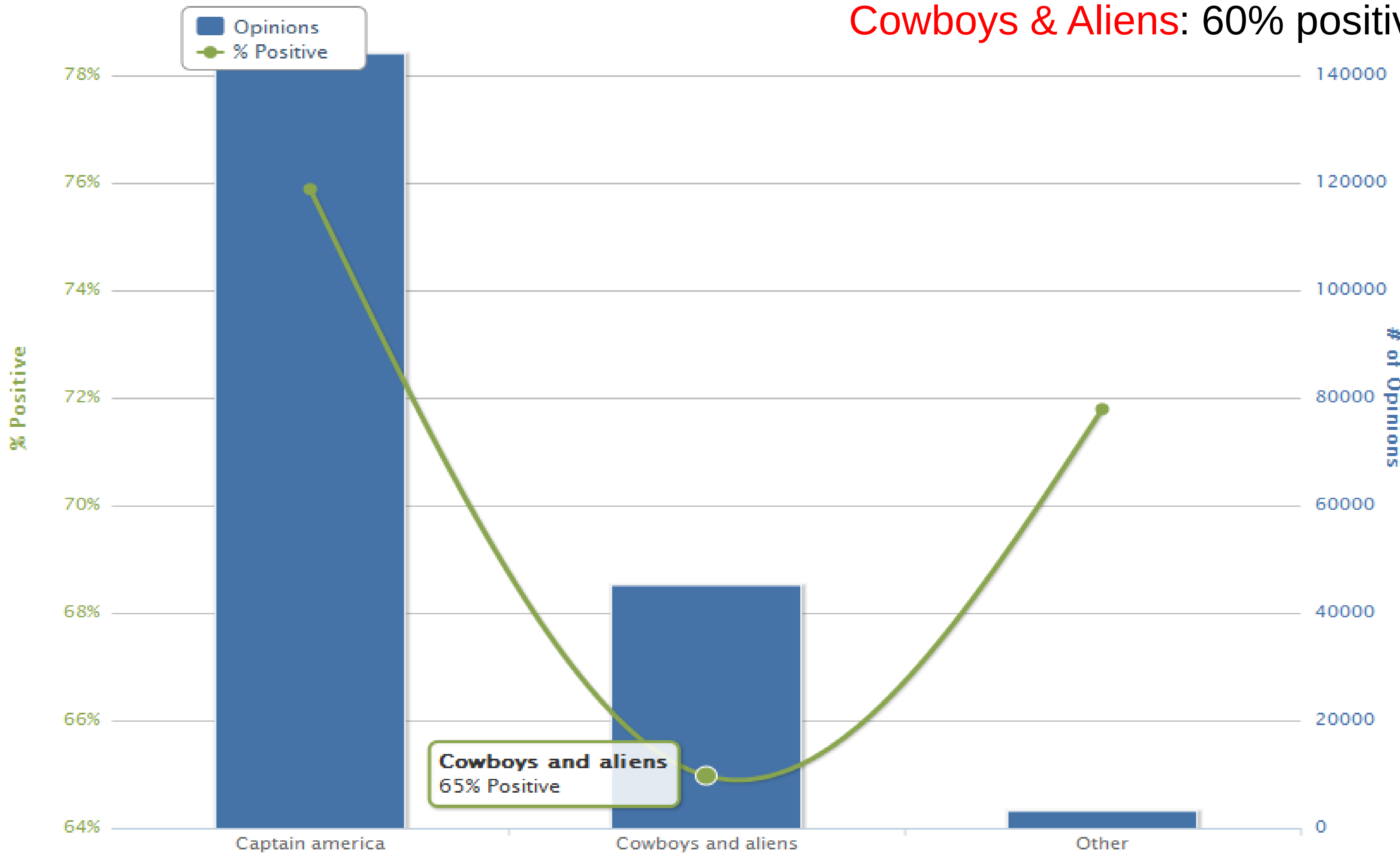


Aggregate opinion trend



Live tracking of two movies (Twitter)

User ratings from Rotten Tomatoes: Captain America: 81% positive
Cowboys & Aliens: 60% positive



July 8, 2011 to Present

Not just ONE problem

- (e_j, a_{jk}, so_{ijkl}, h_i, t_l),
  - e_j - a target entity: Named Entity Extraction (more)
  - a_{jk} – an aspect of e_j: Information Extraction
  - so_{ijkl} is sentiment: Sentiment Identification
  - h_i is an opinion holder: Information/Data Extraction
  - t_l is the time: Information/Data Extraction
  - 5 pieces of information must match
- Coreference resolution
- Synonym match (voice = sound quality)
- …

Opinion mining is hard!

- "*This past Saturday, I bought a Nokia phone and my girlfriend bought a Motorola phone with Bluetooth. We called each other when we got home. The voice on my phone was not so clear, worse than my previous Samsung phone. The battery life was short too. My girlfriend was quite happy with her phone. I wanted a phone with good sound quality. So my purchase was a real disappointment. I returned the phone yesterday.*"

Easier and harder problems

- Tweets from Twitter are the easiest
  - short and thus usually straight to the point
- Reviews are next
  - entities are given (almost) and there is little noise
- Discussions, comments, and blogs are hard.
  - Multiple entities, comparisons, noisy, sarcasm, etc
- Determining sentiments seems to be easier.
- Extracting entities and aspects is harder.
- Combining them is even harder.

Opinion mining in the real world

- Source the data, e.g., reviews, blogs, etc

  (1) Crawl all data, store and search them, or

  (2) Crawl only the target data
- Extract the right entities & aspects
  - Group entity and aspect expressions,
    - Moto = Motorola, photo = picture, etc …
- Aspect-based opinion mining (sentiment analysis)
  - Discover all quintuples

    (Store the quintuples in a database)
- Aspect based opinion summary

Roadmap

- Opinion Mining Problem
- **Document sentiment classification**
- Sentence subjectivity & sentiment classification
- Aspect-based sentiment analysis
- Aspect-based opinion summarization
- Opinion lexicon generation
- Mining comparative opinions
- Some other problems
- Opinion spam detection
- Utility or helpfulness of reviews
- Summary

Sentiment classification

- Classify a whole opinion document (e.g., a review) based on the overall sentiment of the opinion holder (Pang et al 2002; Turney 2002)
  - Classes: Positive, negative (possibly neutral)
  - Neutral or no opinion is hard. Most papers ignore it.
- An example review:
  - *"I bought an iPhone a few days ago. It is such a nice phone, although a little large. The touch screen is cool. The voice quality is clear too. I simply love it!"*
  - Classification: positive or negative?
- Perhaps the most widely studied problem.

A text classification task

- It is basically a text classification problem
- But different from topic-based text classification.
  - In topic-based text classification (e.g., computer, sport, science), topic words are important.
  - But in sentiment classification, opinion/sentiment words are more important, e.g., great, excellent, horrible, bad, worst, etc.
- Opinion/sentiment words
  - Words and phrases that express desired or undesired states or qualities.

Assumption and goal

- Assumption: The doc is written by a single person and express opinion/sentiment on a single entity.
- Goal: discover (_, _, *so*, _, _),

  where e, a, h, and t are ignored
- Reviews usually satisfy the assumption.
  - Almost all papers use reviews
  - Positive: 4 or 5 stars, negative: 1 or 2 stars
- Many forum postings and blogs do not
  - They can mention and compare multiple entities
  - Many such postings express no sentiments

Some Amazon reviews

248 of 263 people found the following review helpful:

This is one to get if you want 5MP, April 14, 2004

By **Gadgester "No Time, No Money"** (Mother Earth) - See all my reviews

TOP 100 REVIEWER

Amazon Verified Purchase (What's this?)

This review is from: Canon PowerShot S500 5MP Digital Elph with 3x Optical Zoom (Electronics)

The new Canon PowerShot S500 is a 5MP upgrade to the immensely popular S400 model, which was a 4MP digital camera. The S500 produces excellent images, is easy to use, and is compact enough to carry in a pocket. 3X optical zoom is standard on these cameras. Besides shooting still photos, you can record low-res video clips as well as audio clips, but don't expect high quality on either.

For a hundred bux less, you can get the 4MP S410 model which is otherwise identical to the S500. Should you go for this or the S410? I think for most consumers 4MP is plenty enough, with room for cropping and enlargements. 5MP is only necessary if you really crop a lot *and* plan to blow up the cropped images. The S410 strikes a great balance between pixel count and price -- it's a better value.

Help other customers find the most helpful reviews

Was this review helpful to you? Yes No

Report abuse | Permalink

Comment

41 of 41 people found the following review helpful:

E18 Error / problem with the lens, September 29, 2004

By **Johnathan Parker** (Springdale, AR USA) - See all my reviews

REAL NAME

This review is from: Canon PowerShot S500 5MP Digital Elph with 3x Optical Zoom (Electronics)

This is my second Canon digital elph camera. Both were great cameras. Recently upgraded to the S500. About 6 months later I get the dreaded E18 error. I searched the Internet and found numerous people having problems. When I determined the problem to be the lens not fully extending I decided to give it a tug. It clicked and the camera came on,

Unsupervised classification
(Turney, 2002)

- Data: reviews from epinions.com on automobiles, banks, movies, and travel destinations.
- The approach: Three steps
- Step 1:
  - Part-of-speech (POS) tagging
  - Extracting two consecutive words (two-word phrases) from reviews if their tags conform to some given patterns, e.g., (1) JJ, (2) NN.

Patterns of POS tags

	First word	Second word	Third word (Not Extracted)
1.	JJ	NN or NNS	anything
2.	RB, RBR, or RBS	JJ	not NN nor NNS
3.	JJ	JJ	not NN nor NNS
4.	NN or NNS	JJ	not NN nor NNS
5.	RB, RBR, or RBS	VB, VBD, VBN, or VBG	anything

- Step 2: Estimate the sentiment orientation (SO) of the extracted phrases
  - Use Pointwise mutual information

$$PMI(word_1, word_2) = \log_2\left(\frac{P(word_1 \wedge word_2)}{P(word_1)P(word_2)}\right)$$

  - Semantic orientation (SO):

SO(phrase) = PMI(phrase, “excellent”)
- PMI(phrase, “poor”)

  - Using AltaVista near operator to do search to find the number of hits to compute PMI and SO.

- Step 3: Compute the average SO of all phrases
  - classify the review as positive if average SO is positive, negative otherwise.
- Final classification accuracy:
  - automobiles - 84%
  - banks - 80%
  - movies - 65.83
  - travel destinations - 70.53%

Supervised learning (Pang et al, 2002)

- Directly apply supervised learning techniques to classify reviews into positive and negative.
  - Like a text classification problem
- Three classification techniques were tried:
  - Naïve Bayes
  - Maximum entropy
  - Support vector machines
- Pre-processing:
  - Features: negation tag, unigram (single words), bigram, POS tag, position.

Supervised learning

- Training and test data
  - Movie reviews with star ratings
    - 4-5 stars as positive
    - 1-2 stars as negative
- Neutral is ignored.
- SVM gives the best classification accuracy based on balance training data
  - 83%
  - Features: unigrams (bag of individual words)

Features for supervised learning

- The problem has been studied by numerous researchers subsequently
  - Probably the most extensive studied problem
    - Including domain adaption and cross-lingual, etc.
- Key: feature engineering. A large set of features have been tried by researchers. E.g.,
  - Terms frequency and different IR weighting schemes
  - Part of speech (POS) tags
  - Opinion words and phrases
  - Negations
  - Syntactic dependency

A large number of related papers

- Bickerstaffe and Zukerman (2010) used a hierarchical multi-classifier considering inter-class similarity
- Burfoot, Bird and Baldwin (2011) sentiment-classified congressional floor debates
- Cui et al. (2006) evaluated some sentiment classification algorithms
- Das and Chen (2001) extracted market sentiment from stock message boards
- Dasgupta and Ng (2009) used semi-supervised learning
- Dave, Lawrence & Pennock (2003) designed a custom function for classification
- Gamon (2004) classified customer feedback data

A large number of related papers

- Goldberg and Zhu (2006) used semi-supervised learning.
- Kim, Li and Lee (2009) and Paltoglou and Thelwall (2010) studied different IR term weighting schemes
- Li, Lee, et al (2010) made use of different polarity shifting.
- Li, Huang, Zhou and Lee (2010) used personal (I, we) and impersonal (they, it, this product) sentences to help
- Maas et al (2011) used word vectors which are latent aspects of the words.
- Mullen and Collier (2004) used PMI, syntactic relations and other attributes with SVM.
- Nakagawa, Inui and Kurohashi (2010) used dependency relations and CRF.

A large number of related papers

- Ng, Dasgupta and Arifin (2006) identified reviews and classified sentiments of reviews
- Pang and Lee (2004) used minimum cuts
- Qiu, Zhang, Hu and Zhao (2009) proposed a lexicon-based and self-supervision approach
- Tong (2001) used a set of domain specific phrases
- Yessenalina, Choi and Cardie (2010) automatically generated annotator rationales to help classification
- Yessenalina, Yue and Cardie (2010) found subjective sentences and then used them for model building
- Zhou, Chen and Wang (2010) used semi-supervised and active learning

Review rating prediction

- Apart from classification of positive or negative sentiments,
  - research has also been done to predict the rating scores (e.g., 1–5 stars) of reviews (Pang and Lee, 2005; Liu and Seneff 2009; Qu, Ifrim and Weikum 2010; Long, Zhang and Zhu, 2010).
  - Training and testing are reviews with star ratings.
- Formulation: The problem is formulated as regression since the rating scores are ordinal.
- Again, feature engineering and model building.

Domain adaptation (transfer learning)

- Sentiment classification is sensitive to the domain of the training data.
  - A classifier trained using reviews from one domain often performs poorly in another domain.
    - words and even language constructs used in different domains for expressing opinions can be quite different.
    - same word in one domain may mean positive but negative in another, e.g., "*this vacuum cleaner really sucks.*"
- Existing research has used labeled data from one domain and unlabeled data from the target domain and general opinion words for learning (Aue and Gamon 2005; Blitzer et al 2007; Yang et al 2006; Pan et al 2010; Wu, Tan and Cheng 2009; Bollegala, Wei and Carroll 2011; He, Lin and Alani 2011).

Cross-lingual sentiment classification

- Useful in the following scenarios:
  - E.g., there are many English sentiment corpora, but for other languages (e.g. Chinese), the annotated sentiment corpora may be limited.
  - Utilizing English corpora for Chinese sentiment classification can relieve the labeling burden.
- Main approach: use available language corpora to train sentiment classifiers for the target language data. Machine translation is typically employed
  - (Banea et al 2008; Wan 2009; Wei and Pal 2010; Kim et al. 2010; Guo et al 2010; Mihalcea & Wiebe 2010; Boyd-Graber and Resnik 2010; Banea et al 2010; Duh, Fujino & Nagata 2011; Lu et al 2011)

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Subjectivity classification

- Document-level sentiment classification is too coarse for most applications.
- We now move to the sentence level.
- Much of the early work on sentence level analysis focuses on identifying subjective sentences.
- Subjectivity classification: classify a sentence into one of the two classes (Wiebe et al 1999)
  - Objective and subjective.
- Most techniques use supervised learning.
  - E.g., a naïve Bayesian classifier (Wiebe et al. 1999).

Sentence sentiment analysis

- Usually consist of two steps
  - Subjectivity classification
    - To identify subjective sentences
  - Sentiment classification of subjective sentences
    - Into two classes, positive and negative
- But bear in mind
  - Many objective sentences can imply sentiments
  - Many subjective sentences do not express positive or negative sentiments/opinions
    - E.g.,"I believe he went home yesterday."

As an intermediate step

- We do not use the quintuple (*e*, *a*, *so*, *h*, *t*) to define the problem here because
  - sentence classification is an intermediate step.
- Knowing that some sentences have positive or negative opinions are not sufficient.
- However, it helps
  - filter out sentences with no opinions (mostly)
  - determine (to some extend) if sentiments about entities and their aspects are positive or negative.
    - But not enough

Assumption

- Assumption: Each sentence is written by a single person and expresses a single positive or negative opinion/sentiment.
- True for simple sentences, e.g.,
  - "I like this car"
- But not true for compound and "complex" sentences, e.g.,
  - "I like the picture quality but battery life sucks."
  - "Apple is doing very well in this lousy economy."

Subjectivity classification using patterns
(Rilloff and Wiebe, 2003)

- A bootstrapping approach.
  - A high precision classifier is first used to automatically identify some subjective and objective sentences.
    - Two high precision (but low recall) classifiers are used,
      - a high precision subjective classifier
      - A high precision objective classifier
      - Based on manually collected lexical items, single words and n-grams, which are good subjective clues.
  - A set of patterns are then learned from these identified subjective and objective sentences.
    - Syntactic templates are provided to restrict the kinds of patterns to be discovered, e.g., <subj> passive-verb.
  - The learned patterns are then used to extract more subject and objective sentences (the process can be repeated).

Subjectivity and sentiment classification
(Yu and Hazivassiloglou, 2003)

- Subjective sentence identification: a few methods were tried, e.g.,
  - Sentence similarity.
  - Naïve Bayesian classification.
- Sentiment classification (positive, negative or neutral) (also called polarity): it uses a similar method to (Turney, 2002), but
  - with more seed words (rather than two) and based on log-likelihood ratio (LLR).
  - For classification of each word, it takes the average of LLR scores of words in the sentence and use cutoffs to decide positive, negative or neutral.

Segmentation and classification

- Since a single sentence may contain multiple opinions and subjective and factual clauses
- A study of automatic clause sentiment classification was presented in (Wilson et al 2004)
  - to classify clauses of every sentence by the *strength* of opinions being expressed in individual clauses, down to four levels
    - *neutral*, *low*, *medium*, and *high*
- Clause-level may not be sufficient
  - "Apple is doing very well in this lousy economy."

Some other related work

- Abdul-Mageed, Diab and Korayem (2011) carried out subjectivity and sentiment analysis of Arabic sentences
- Alm (2011) analyzed subjectivity research motivations, applications, characteristics, etc
- Barbosa and Feng (2010) and Davidov, Tsur and Rappoport (2010) performed Twitter subjectivity and sentiment classification using many features, hashtags, and smileys
- Eguchi and Lavrendo (2006) studied sentiment sentence retrieval
- Gamon et al. (2005) used semi-supervised learning
- Hassan, Qazvinian, Radev (2010) found attitude sentences
- Kim and Hovy (2004) summed up orientations of opinion words in a sentence (or within some word window).
- Hatzivassiloglou & Wiebe (2000) considered gradable adjectives

Some other related work

- Johansson and Moschitti (2011) extracted opinion expressions and sentiments
- Joshi and Penstein-Rose (2009) used dependency triples with “back-off” using POS tags rather than words
- Kim and Hovy (2006a) automatically identified pro and con reasons
- Kim and Hovy (2006b) Identified judgment opinions
- Kim and Hovy (2007) mined predictive opinions in election postings
- Kim, Li and Lee (2010) compared subjectivity analysis tools
- McDonald et al (2007) performed sentence to document sentiment classification
- Mukund and Srihari (2010) performed subjectivity classification with co-training

Some other related work

- Nasukawa and Yi (2003) captured favorability
- Nigam and Hurst (2005) classified subjective and topic sentences
- Tackstrom & McDonald (2011) performed sentence sentiment classification
- Wiebe et al (2004) learned subjective language
- Wiebe and Riloff (2005) used semi-supervised learning with a initial training set identified by some strong patterns
- Wiebe and Mihalcea (2006) studied word sense and subjectivity
- Wilson, Wiebe and Hwa (2006) recognized strong and weak opinion clauses
- Wilson et al. (2004, 2005) found strength of sentiments/opinions in clauses

Roadmap

- Opinion Mining Problem
- Document sentiment classification
- Sentence subjectivity & sentiment classification
- **Aspect-based sentiment analysis**
- Aspect-based opinion summarization
- Opinion lexicon generation
- Mining comparative opinions
- Some other problems
- Opinion spam detection
- Utility or helpfulness of reviews
- Summary

We need to go further

- Sentiment classification at both the document and sentence (or clause) levels are useful, but
  - They do not find what people liked and disliked.
- They do not identify the targets of opinions, i.e.,
  - Entities and their aspects
  - Without knowing targets, opinions are of limited use.
- We need to go to the entity and aspect level.
  - *Aspect-based opinion mining and summarization* (Hu and Liu 2004).
  - We thus need the full opinion definition.

Recall an opinion is a quintuple

- An *opinion* is a quintuple

  $(e_j, a_{jk}, so_{ijkl}, h_i, t_l)$,

  where
  - e_j is a target entity.
  - a_{jk} is an aspect/feature of the entity e_j.
  - so_{ijkl} is the sentiment value of the opinion of the opinion holder h_i on feature a_{jk} of entity e_j at time t_l. so_{ijkl} is +ve, -ve, or neu, or a more granular rating.
  - h_i is an opinion holder.
  - t_l is the time when the opinion is expressed.

Aspect-based sentiment analysis

- Much of the research is based on online reviews
- For reviews, aspect-based sentiment analysis is easier because the entity (i.e., product name) is usually known
  - Reviewers simply express positive and negative opinions on different aspects of the entity.
- For blogs, forum discussions, etc., it is harder:
  - both entity and aspects of entity are unknown,
  - there may also be many comparisons, and
  - there is also a lot of irrelevant information.

Find entities (entity set expansion)

- Although similar, it is somewhat different from the traditional named entity recognition (NER).
- E.g., one wants to study opinions on phones
  - given Motorola and Nokia, find all phone brands and models in a corpus, e.g., Samsung, Moto,
- Formulation**:** Given a set *Q* of seed entities of class *C*, and a set *D* of candidate entities, we wish to determine which of the entities in *D* belong to *C*.
  - A classification problem. It needs a binary decision for each entity in *D* (belonging to *C* or not)
  - But it's often solved as a ranking problem

Some methods (Li, Zhang et al 2010, Zhang and Liu 2011)

- Distributional similarity: This is the traditional method used in NLP. It compares the surrounding text of candidates using cosine or PMI.
  - It performs poorly.
- PU learning: learning from positive and unlabeled examples.
  - S-EM algorithm (Liu et al. 2002)
- Bayesian Sets: We extended the method given in (Ghahramani and Heller, 2006).

Aspect extraction

- Goal: Given an opinion corpus, extract all aspects
- A frequency-based approach (Hu and Liu, 2004): nouns (NN) that are frequently talked about are likely to be true aspects (called frequent aspects) .
- Why the frequency based approach?
  - Different reviewers tell different stories (irrelevant)
  - When product aspects/features are discussed, the words they use converge.
  - They are the main aspects.
- Sequential/association pattern mining finds frequent nouns and noun phrases.

An example review

GREAT Camera., Jun 3, 2004

Reviewer: **jprice174** from Atlanta, Ga.

I did a lot of research last year before I bought this camera... It kinda hurt to leave behind my beloved nikon 35mm SLR, but I was going to Italy, and I needed something smaller, and digital.

The pictures coming out of this camera are amazing. The 'auto' feature takes great pictures most of the time. And with digital, you're not wasting film. …

….

Infrequent aspect extraction

- To improve recall due to loss of infrequent aspects. It uses opinions words to extract them
- Key idea: opinions have targets, i.e., opinion words are used to modify aspects and entities.
  - "The pictures are absolutely amazing."
  - "This is an amazing software."
- The modifying relation was approximated with the nearest noun to the opinion word.
- The idea was generalized to dependency in (Zhuang et al 2006) and double propagation in (Qiu et al 2009;2011).
  - It has been used in many papers and practical systems

Using part-of relationship and the Web (Popescu and Etzioni, 2005)

- Improved (Hu and Liu, 2004) by removing those frequent noun phrases that may not be aspects: better precision (a small drop in recall).
- It identifies part-of relationship
  - Each noun phrase is given a pointwise mutual information score between the phrase and **part discriminators** associated with the product class, e.g., a scanner class.
  - E.g., “of scanner”, “scanner has”, etc, which are used to find parts of scanners by searching on the Web:

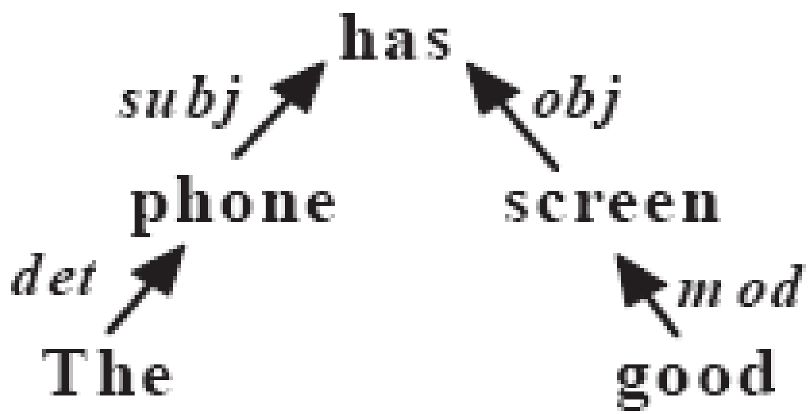
$$PMI(a,d) = \frac{hits(a \wedge d)}{hits(a)hits(d)},$$

Extract aspects using DP (Qiu et al. 2009; 2011)

- A *double propagation* (DP) approach proposed
- Based on the definition earlier, an opinion should have a target, entity or aspect.
- Use dependency of opinions & aspects to extract both aspects & opinion words.
  - Knowing one helps find the other.
  - E.g., "*The rooms are spacious*"
- It extracts both aspects and opinion words.
  - A domain independent method.

The DP method

- DP is a bootstrapping method
  - Input: a set of seed opinion words,
  - no aspect seeds needed
- Based on dependency grammar (Tesniere 1959).
  - "This phone has good screen"



Rules from dependency grammar

	Relations and Constraints	Output	Examples
$R1_1$	$O \rightarrow O\text{-}Dep \rightarrow F$ s.t. $O \in \{O\}$, $O\text{-}Dep \in \{MR\}$, $POS(F) \in \{NN\}$	$f = F$	*The phone has a good "screen".* *good→**mod**→screen*
$R1_2$	$O \rightarrow O\text{-}Dep \rightarrow H \leftarrow F\text{-}Dep \leftarrow F$ s.t. $O \in \{O\}$, $O/F\text{-}Dep \in \{MR\}$, $POS(F) \in \{NN\}$	$f = F$	*"iPod" is the best mp3 player.* *best→**mod**→player←**subj**←iPod*
$R2_1$	$O \rightarrow O\text{-}Dep \rightarrow F$ s.t. $F \in \{F\}$, $O\text{-}Dep \in \{MR\}$, $POS(O) \in \{JJ\}$	$o = O$	same as $R1_1$ with *screen* as the known word and *good* as the extracted word
$R2_2$	$O \rightarrow O\text{-}Dep \rightarrow H \leftarrow F\text{-}Dep \leftarrow F$ s.t. $F \in \{F\}$, $O/F\text{-}Dep \in \{MR\}$, $POS(O) \in \{JJ\}$	$o = O$	same as $R1_2$ with *iPod* is the known word and *best* as the extract word.
$R3_1$	$F_{i(j)} \rightarrow F_{i(j)}\text{-}Dep \rightarrow F_{j(i)}$ s.t. $F_{j(i)} \in \{F\}$, $F_{i(j)}\text{-}Dep \in \{CONJ\}$, $POS(F_{i(j)}) \in \{NN\}$	$f = F_{i(j)}$	*Does the player play dvd with audio and "video"?* *video→**conj**→audio*
$R3_2$	$F_i \rightarrow F_i\text{-}Dep \rightarrow H \leftarrow F_j\text{-}Dep \leftarrow F_j$ s.t. $F_i \in \{F\}$, $F_i\text{-}Dep == F_j\text{-}Dep$, $POS(F_j) \in \{NN\}$	$f = F_j$	*Canon "G3" has a great len.* *len→**obj**→has←**subj**←G3*
$R4_1$	$O_{i(j)} \rightarrow O_{i(j)}\text{-}Dep \rightarrow O_{j(i)}$ s.t. $O_{j(i)} \in \{O\}$, $O_{i(j)}\text{-}Dep \in \{CONJ\}$, $POS(O_{i(j)}) \in \{JJ\}$	$o = O_{i(j)}$	*The camera is amazing and "easy" to use.* *easy→**conj**→amazing*
$R4_2$	$O_i \rightarrow O_i\text{-}Dep \rightarrow H \leftarrow O_j\text{-}Dep \leftarrow O_j$ s.t. $O_i \in \{O\}$, $O_i\text{-}Dep == O_j\text{-}Dep$, $POS(O_j) \in \{JJ\}$	$o = O_j$	*If you want to buy a sexy, "cool", accessory-available mp3 player, you can choose iPod.* *sexy→**mod**→player←**mod**←cool*

Explicit and implicit aspects
(Hu and Liu 2004)

- Explicit aspects: Aspects explicitly mentioned as nouns or noun phrases in a sentence
  - The picture quality is of this phone is great.
- Implicit aspects: Aspects not explicitly mentioned in a sentence but are implied
  - "This car is so expensive."
  - "This phone will not easily fit in a pocket.
  - "Included 16MB is stingy"
- Not much work has been done on mining or mapping implicit aspects.

Implicit aspect mapping

- There are many types of implicit aspect expressions. Adjectives and adverbs are perhaps the most common type.
  - Most adjectives modify or describe some specific attributes of entities.
  - “expensive” $\Rightarrow$ aspect “price,” “beautiful” $\Rightarrow$ aspect “appearance”, “heavy” $\Rightarrow$ aspect “weight”
- Although manual mapping is possible, in different contexts, the meaning can be different.
  - E.g., “The computation is expensive”.

A mutual reinforcement method

(Su et al. 2009)

- It proposed an unsupervised approach which exploits the mutual reinforcement relationship between aspects and opinion words.
  - Specifically, it uses the co-occurrence of aspect and opinion word pair in a sentence.
- The algorithm iteratively clusters the set of aspects and the set of opinion words separately,
  - but before clustering each set, clustering results of the other set is used to update the pairwise weight of the set.
  - The model is based on a bipartite graph.

Other papers on aspect extraction

We will discuss topic modeling based methods later.

- Carvalho et al (2011) annotated political debates with aspects and others.
- Choi and Cardie (2010) used a CRF based approach.
- Jin and Ho (2009) proposed a HMM-based method
- Jakob and Gurevych (2010) used anaphora (or coreference) resolution to help find aspects that are mentioned in previous sentences but are referred to as pronouns in the next sentences.
  - E.g., “I took a few pictures yesterday. They look great.”
  - There is almost no improvement with anaphora resolution, higher recall but lower precision.

Other papers on aspect extraction

- Jakob and Gurevych (2010) used CRF to train on review sentences from different domains for a more domain independent extraction. A set of domain independent features were used, e.g. tokens, POS tags, dependency, word distance, and opinion sentences.
- Kobayashi et al (2006) extracted subject-attribute-value
- Kobayashi et al (2007) extracted aspect-evaluation and aspect-of relations using mined patterns.
- Ku et al. (2006a, 2006b) performed the extraction from Chinese reviews and news.

Other papers on aspect extraction

- Li et al (coling-2010) integrated Skip-CRF and Tree-CRF to extract aspects and opinions. It was able to exploit structure features
- Long, Zhang and Zhu (2010) extracted aspects (nouns) based on frequency and the Web, and dependent words (adjectives). These words are then used to select reviews which discuss an aspect most.
- Ma and Wan (2010) used centering theory for extraction in news comments. It also exploited aspects in the news title and contents.
- Meng and Wang (2009) extracted aspects from product specifications, which are usually structured data.

Other papers on aspect extraction

- Scaffidi et al (2007) extracted frequent nouns and noun phrases but compare their frequency in a review corpus with their occurrence rates in generic English to identify true aspects
- Somasundaran and Wiebe (2009) also used syntactic dependency for aspect and opinion extraction.
- Toprak, Jakob and Gurevych (2010) designed a comprehensive annotation scheme for aspect-based opinion annotation. Earlier annotations are partial and mainly for individual papers.
- Yi et al (2003) used language models to extract product features.

Other papers on aspect extraction

- Yu et al (2011) ranked aspects by considering their frequency and contribution to the overall review rating
- Zhu et al (CIKM-2009) used a method for finding multi-word terms, called cvalue, to find aspects.
  - The method also segments a sentence with multiple aspects.

Identify aspect synonyms (Carenini et al 2005)

- Once aspect expressions are discovered, group them into aspect categories.
  - E.g., power usage and battery life are the same.
- It proposed a method based on some similarity metrics, but it needs a taxonomy of aspects.
  - The system merges each discovered aspect to a aspect node in the taxonomy.
  - Similarity metrics: string similarity, synonyms and other distances measured using WordNet.
- Many ideas in Web information integration are applicable.

Multilevel latent categorization
(Guo et al 2009)

- This method performs multilevel latent semantic analysis to group aspects expressions.
  - At the first level, all the words in aspect expressions are grouped into a set of concepts using LDA. The results are used to build *latent topic structures* for aspect expressions, e.g.,
    - *touch screen*: topic-1, topic-2
  - At the second level, aspect expressions are grouped by LDA again according to
    - their latent topic structures produced from level 1 and
    - context snippets in reviews.

Group aspect synonyms (Zhai et al. 2011a, b)

- A variety of information/similarities are used to cluster aspect expressions into aspect categories.
  - Lexical similarity based on WordNet
  - Distributional information (surrounding words context)
  - Syntactical constraints (sharing words, in the same sentence)
- Two unsupervised learning methods were used:
  - Clustering: EM-based.
  - Constrained topic modeling: Constrained-LDA
    - By intervening Gibbs sampling.

The EM method

- WordNet similarity

$$Jcn(w_1, w_2) = \frac{1}{IC(w_1) + IC(w_2) - 2 \times Res(w_1, w_2)}$$

- EM-based probabilistic clustering

$$\mathrm{P}(w_t|c_j) = \frac{1 + \sum_{i=1}^{|D|} N_{ti}\mathrm{P}(c_j|d_i)}{|V| + \sum_{m=1}^{|V|} \sum_{i=1}^{|D|} N_{mi}\mathrm{P}(c_j|d_i)}$$

$$\mathrm{P}(c_j) = \frac{1 + \sum_{i=1}^{|D|} \mathrm{P}(c_j|d_i)}{|C| + |D|}$$

$$\mathrm{P}(c_j|d_i) = \frac{\mathrm{P}(c_j) \prod_{\mathrm{k}=1}^{|d_i|} \mathrm{P}(w_{d_{i,k}}|c_j)}{\sum_{\mathrm{r}=1}^{|C|} \mathrm{P}(c_r) \prod_{\mathrm{k}=1}^{|d_i|} \mathrm{P}(w_{d_{i,k}}|c_r)}$$

Aspect sentiment classification

- For each aspect, identify the sentiment or opinion expressed on it.
- Work based on sentences, but also consider,
  - A sentence can have multiple aspects with different opinions.
  - E.g., The battery life and picture quality are *great* (+), but the view founder is *small* (-).
- Almost all approaches make use of opinion words and phrases. But notice:
  - Some opinion words have context independent orientations, e.g., “good” and “bad” (almost)
  - Some other words have context dependent orientations, e.g., “small” and “sucks” (+ve for vacuum cleaner)

Some approaches

- Supervised learning
  - Sentence level classification can be used, but …
  - Need to consider target and thus to segment a sentence (e.g., Jiang et al. 2011)
- Lexicon-based approach (Ding, Liu and Yu, 2008)
  - Need parsing to deal with: Simple sentences, compound sentences, comparative sentences, conditional sentences, questions; different verb tenses, etc.
  - Negation (not), contrary (but), comparisons, etc.
  - A large opinion lexicon, context dependency, etc.
  - *Easy*: "*Apple is doing well in this bad economy*."

A lexicon-based method (Ding, Liu and Yu 2008)

- Input: A set of opinion words and phrases. A pair (a, s), where a is an aspect and s is a sentence that contains a.
- Output: whether the opinion on a in s is +ve, -ve, or neutral.
- Two steps:
  - Step 1: split the sentence if needed based on BUT words (but, except that, etc).
  - Step 2: work on the segment s_f containing a. Let the set of opinion words in s_f be w_1, .., w_n. Sum up their orientations (1, -1, 0), and assign the orientation to (a, s) accordingly.

$$\sum_{i=1}^{n} \frac{w_i.o}{d(w_i, a)}$$

where $w_i.o$ is the opinion orientation of w_i. $d(w_i, a)$ is the distance from a to w_i.

Sentiment shifters (e.g., Polanyi and Zaenen 2004)

- Sentiment/opinion shifters (also called **valence shifters** are words and phrases that can shift or change opinion orientations.
- Negation words like *not*, *never*, *cannot*, etc., are the most common type.
- Many other words and phrases can also alter opinion orientations. E.g., modal auxiliary verbs (e.g., *would*, *should*, *could, etc*)
  - "The brake could be improved."

Sentiment shifters (contd)

- Some presuppositional items also can change opinions, e.g., *barely* and *hardly*
  - "It hardly works." (comparing to "it works")
  - It presupposes that better was expected.
- Words like *fail*, *omit*, *neglect* behave similarly,
  - "This camera fails to impress me."
- Sarcasm changes orientation too
  - "What a great car, it did not start the first day."
- Jia, Yu and Meng (2009) designed some rules based on parsing to find the scope of negation.

Basic rules of opinions (Liu, 2010)

- Opinions/sentiments are governed by many rules, e.g.,
  - *Opinion word or phrase, ex: "I love this car"*

    P ::= a positive opinion word or phrase

    N ::= an negative opinion word or phrase
  - *Desirable or undesirable facts, ex:* "After my wife and I slept on it for two weeks, I noticed a mountain in the middle of the mattress"

    P ::= desirable fact

    N ::= undesirable fact

Basic rules of opinions

- *High, low, increased and decreased quantity of a positive or negative potential item*, ex: “The battery life is long.”

PO	::=	no, low, less or decreased quantity of NPI
	|	large, larger, or increased quantity of PPI
NE	::=	no, low, less, or decreased quantity of PPI
	|	large, larger, or increased quantity of NPI
NPI	::=	a negative potential item
PPI	::=	a positive potential item

Basic rules of opinions

- *Decreased and increased quantity of an opinionated item, ex:* "This drug reduced my pain significantly."

  PO ::= less or decreased N
  | more or increased P
  NE ::= less or decreased P
  | more or increased N

- *Deviation from the desired value range*: "This drug increased my blood pressure to 200."

  PO ::= within the desired value range
  NE ::= above or below the desired value range

Basic rules of opinions

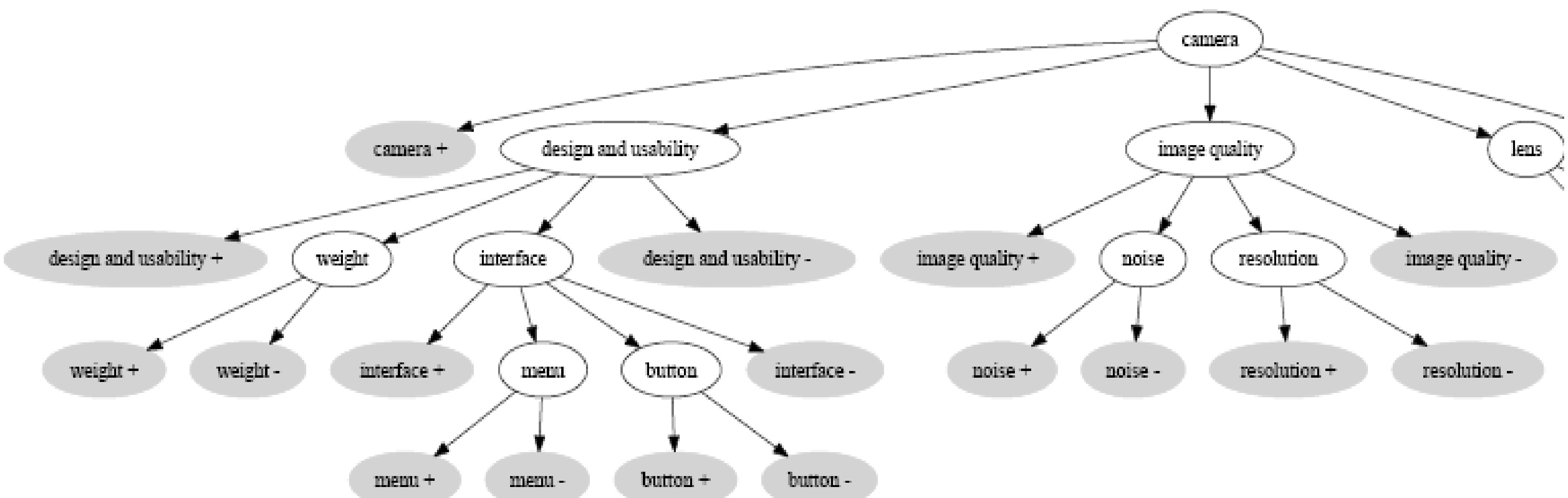
- *Producing and consuming resources and wastes, ex:* "This washer uses a lot of water"

  PO ::= produce a large quantity of or more resource
  | produce no, little or less waste
  | consume no, little or less resource
  | consume a large quantity of or more waste

  NE ::= produce no, little or less resource
  | produce some or more waste
  | consume a large quantity of or more resource
  | consume no, little or less waste

Sentiment ontology tree (Wei and Gulla, 2010)

- Recall in the definition of opinions, we simplified the tree structure to two levels (entity & aspects).
- This paper uses a full tree ontology to denote the relationships of aspects of a product.



Sentiment ontology tree (contd)

- The leaves of the tree are positive or negative sentiments.
- It then uses a hierarchical classification model to learn to assign an sentiment to each node, which is reflected as a child leaf node.
  - Hierarchical classifier is useful here because it considers parents when classifying children.
- However, the ontology for each product has to be built manually.

Aspect-sentiment statistical models

- This direction of research is mainly based on topic models:
  - pLSA: Probabilistic Latent Semantic Analysis (Hofmann 1999)
  - LDA: Latent Dirichlet allocation (Blei, Ng & Jordan, 2003; Griffiths & Steyvers, 2003; 2004)
- Topic models:
  - documents are mixtures of topics
  - a topic is a probability distribution over words.
- A topic model is a document generative model
  - it specifies a simple probabilistic procedure by which documents can be generated.

Aspect-sentiment model (Mei et al 2007)

- This model is based on pLSA (Hofmann, 1999).
- It builds a topic (aspect) model, a positive sentiment model, and a negative sentiment model.
- A training data is used to build the initial models.
  - Training data: topic queries and associated positive and negative sentences about the topics.
- The learned models are then used as priors to build the final models on the target data.
- Solution: log likelihood and EM algorithm

Multi-Grain LDA to extract aspects (Titov and McDonald, 2008a, 2008b)

- Unlike a diverse document set used for traditional topic modeling. All reviews for a product talk about the same topics/aspects. It makes applying PLSA or LDA in the traditional way problematic.
- Multi-Grain LDA (MG-LDA) models global topics and local topics (Titov and McDonald, 2008a).
  - Global topics are entities (based on reviews)
  - Local topics are aspects (based on local context, sliding windows of review sentences)
- MG-LDA was extended to MAS model to give aspect rating (Titov and McDonald, 2008b).

Aspect-rating of short text (Lu et al 2009)

- This work makes use of short phrases, head terms (w_h) and their modifiers (w_m), i.e.
  - (w_m, w_h)
  - E.g., great shipping, excellent seller
- Objective: (1) extract aspects and (2) compute their ratings in each short comment.
- It uses pLSA to extract and group aspects
- It uses existing rating for the full post to help determine aspect ratings.

Aspect-rating regression

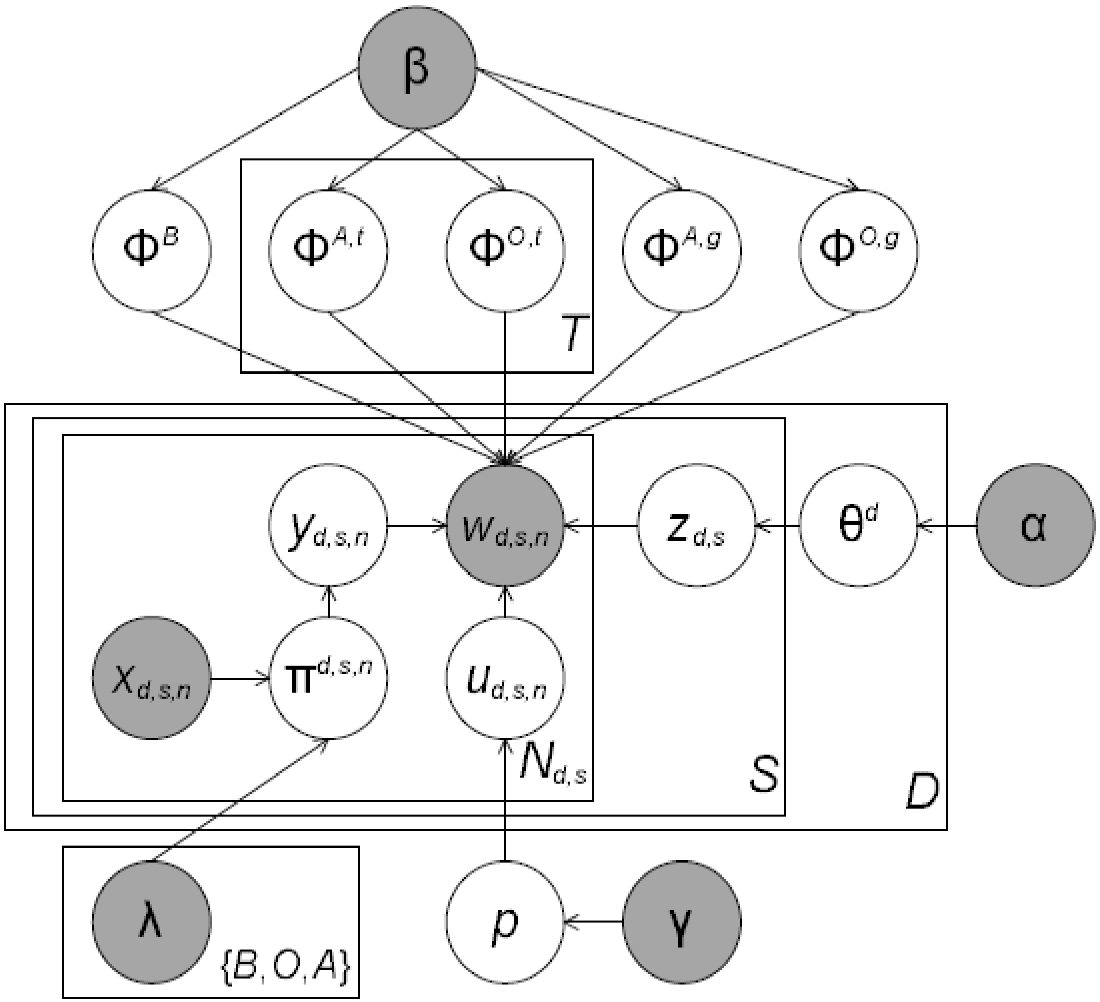
(Wang, Lu, and Zhai, 2010)

- In this work, some seed aspects are given. Its first step finds more aspect words using a heuristic bootstrapping method.
- Its regression model makes use of the review rating and assumes the overall review rating is a linear combination of its aspect ratings.
- The problem is model as a Bayesian regression problem.
  - It is solved using log-likelihood and EM.

MaxEnt-LDA Hybrid (Zhao et al. 2010)

We now describe the generative process of the model. First, we draw several multinomial word distributions from a symmetric Dirichlet prior with parameter β: a background model $\phi^{\mathcal{B}}$, a general aspect model $\phi^{\mathcal{A},g}$, a general opinion model $\phi^{\mathcal{O},g}$, T aspect models $\{\phi^{\mathcal{A},t}\}_{t=1}^{T}$ and T aspect-specific opinion models $\{\phi^{\mathcal{O},t}\}_{t=1}^{T}$. All these are multinomial distributions over the vocabulary, which we assume has V words. Then for each review document d, we draw a topic distribution $\theta^d \sim \text{Dir}(\alpha)$ as in standard LDA. For each sentence s in document d, we draw an aspect assignment $z_{d,s} \sim \text{Multi}(\theta^d)$.

Graphical model (plate)



- $y_{d,s,n}$ indicates
  - Background word
  - Aspect word, or
  - Opinion word
- MaxEnt is used to train a model using training set
  - $\pi^{d,s,n}$
  - $x_{d,s,n}$ feature vector
- $u_{d,s,n}$ indicates
  - General or
  - Aspect-specific

Topic model of snippets
(Sauper, Haghighi and Barzilay, 2011)

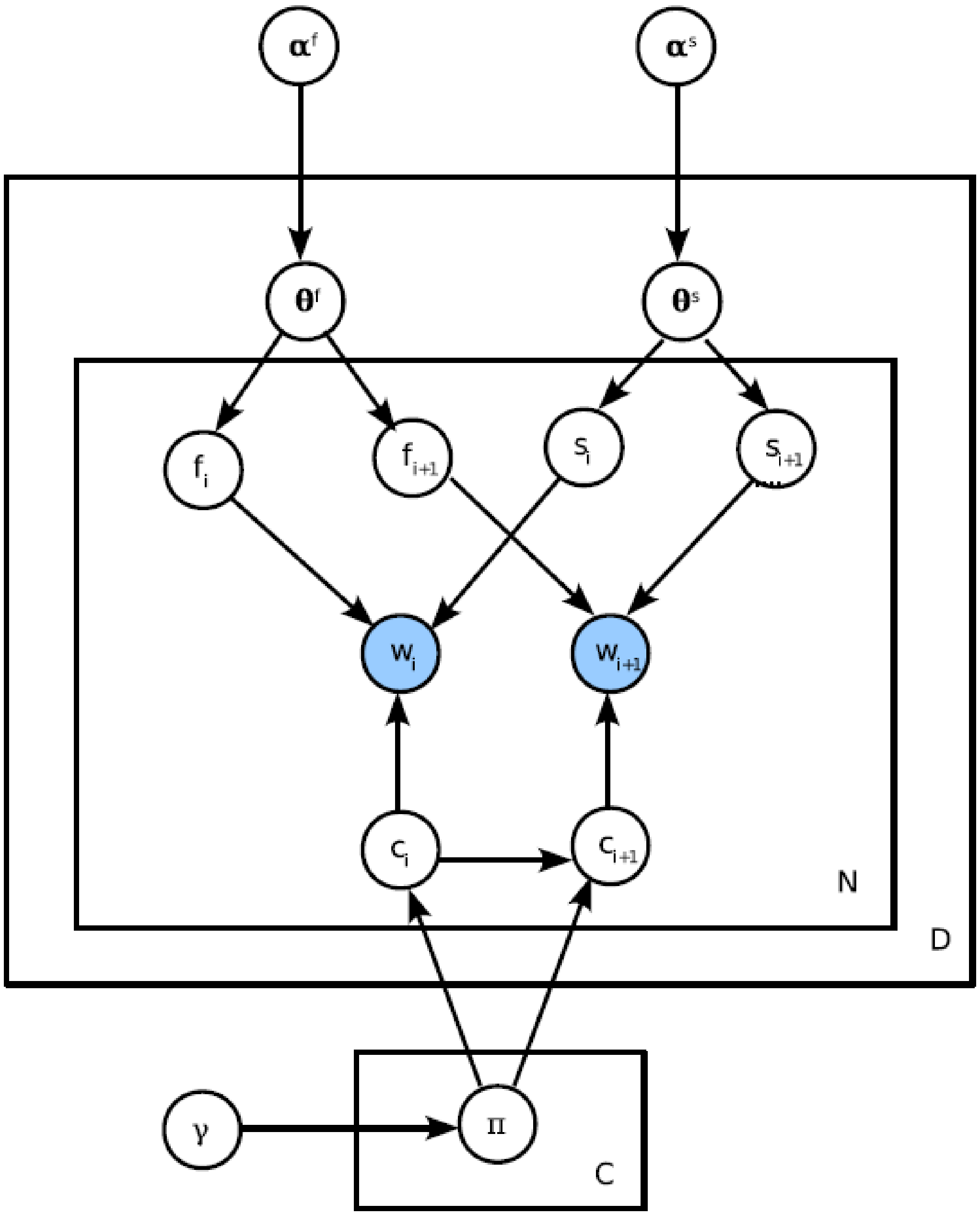
- This method works on short snippets already extracted from reviews.
  - “battery life is the best I’ve found”
- The model is a variation of LDA but with seeds for sentiment words as priors,
  - but it also has HMM for modeling the sequence of words with types (aspect word, sentiment word, or background word).
- Inference: variational technique

Considering both syntax and semantics (Lakkaraju et al. 2011)

- This work is based the composite model of HMM-LDA of Griffiths et al. (2005), which consider both word sequence and word-bag
- It captures both syntactic structure and semantic dependencies (similar to the previous paper)
- A class label is used for each word to represent the syntactic category of the word, whether it is
  - an aspect word,
  - a sentiment word, or
  - some other category.

FACTS model

- *Words: $w_{d,1}, w_{d,2} \dots w_{d,N}$*
- Hidden variables
  - *Class: $c_{d,i}$*
    - *1: appect word*
    - *2: sentiment word*
    - *others*
  - *Aspect cat.: $f_{d,i}$*
  - *Sentiment cat.: $s_{d,i}$*
- *It also has more sophsticated models*
  - *CFACTS: consider neighboring windows*
  - *CFACTS-R: consider ratings*



About topic model based methods

- There several other similar topic model based methods (e.g., Brody and Elhadad, 2010; Lu et al. 2011; Jo and Oh, 2011; Lin and He 2009; Liu et al, 2007).
- These methods tend to need a large number reviews (10000 and more) to make it statistically stable. They are hard to use for most specific products, which often have <100 reviews.
- They also need a lot of parameter tuning.
- The results usually are quite coarse, not precise enough for practical needs.

Roadmap

- Opinion Mining Problem
- Document sentiment classification
- Sentence subjectivity & sentiment classification
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- **Aspect-based opinion summarization**
- Opinion lexicon generation
- Mining comparative opinions
- Some other problems
- Opinion spam detection
- Utility or helpfulness of reviews
- Summary

Aspect-based opinion summarization

- A multi-document summarization problem.
  - An opinion from a single person is usually not sufficient for action unless from a VIP (e.g., President)
- Key Idea: Use aspects as basis for a summary
  - Not done in traditional multi-document summarization.
- We have discussed the aspect-based summary using quintuples earlier (Hu and Liu 2004; Liu, 2010).
  - Also called: *Structured Summary*
- Similar approaches are also taken in
  - (e.g., Ku et al 2006; Carenini, Ng and Paul 2006) and
  - By most topic model based methods

Text summary of opinions

- One can also generate a summary in the tradition fashion, e.g., producing a short text summary (Lerman et al 2009), by extracting some important sentences, etc.
  - Weakness: It is only qualitative but not quantitative.
- One can generate sentences based on aspects and opinions using some templates.
  - E.g., 60% of the people like the picture quality.

Select and order sentences

(Tata and Di Eugenio, 2010)

- If we produce summary as a list of sentences for each aspect and each sentiment (+ or –), it is useful to
  - Select a representative sentence for each group: it selects a sentence that mention fewest aspects (the sentence is focused).
  - Order the sentences: It uses an ontology to map sentences to the ontology nodes (domain concepts).

Informativeness and Readability

(Nishikawa et al. 2010)

- It summarizes by considering both informativeness and readability.
- It uses frequency f(.) of (aspect, opinion), but it is more like a traditional summary.
- It is not quantitative. Note: Lerman et al (2009) used +ve/-ve proportions.

- S* is the summary

$$S^* = \operatorname*{argmax}_{S \in T}[\mathrm{Info}(S) + \lambda \mathrm{Read}(S)]$$

$$\text{s.t. length}(S) \leq K$$

$$\mathrm{Info}(S) = \sum_{e \in E(S)} f(e)$$

$$\mathrm{Read}(S) = \sum_{i=0}^{n} \mathbf{w}^\top \phi(s_i, s_{i+1})$$

Summarization using an ontology
(Lu et al. Coling-2010)

- This work uses existing online ontologies of entities and aspects to organize opinions
  - Given an entity and an online ontology of the entity
  - Goal: Generate a structured summary of opinions.
- It performs
  - Aspect selection to capture major opinions
  - Aspect ordering that is natural for human viewing
  - Suggest new aspects to add to ontology

Summarization using an ontology (contd)

- Aspect selection
  - E.g., by frequency, by opinion coverage (no redundancy), or by conditional entropy
- Ordering aspects and their corresponding sentences based on their appearance in their original posts, called coherence

$$Co(A_i, A_j) = \frac{\sum_{S_{i,k} \in S_i, S_{j,l} \in S_j} Co(S_{i,k}, S_{j,l})}{|S_i||S_j|}$$

$$\hat{\pi}(A') = \arg\max_{\pi(A')} \sum_{A_i, A_j \in A', A_i \prec A_j} Co(A_i, A_j)$$

Some other summarization papers

- Carenini, Ng and Pauls (2006) evaluated different summarization methods using human judges.
- Huang, Wan and Xiao (2011) generated contrast summaries of news.
- Kim and Zhai (2009) generated contrast opinion sentence pairs.
- Lerman and McDonald (2009) generated summaries to contrast opinions about two different products.
- Lerman, Blair-Goldensohn and McDonald (2009) designed three summarizers and evaluated them with human raters.
- Paul, Zhai and Girju (2010) found opposing views.
- Park, Lee and Song (2011) also found opposing views
- Wang and Liu (2011) generated opinion summary for conversations.

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Opinion (or sentiment) lexicon

- Opinion lexicon: lists of words and expressions used to express people's subjective feelings and sentiments/opinions.
  - Not just individual words, but also phrases and idioms, e.g., "cost an arm and a leg"
- They are instrumental for opinion mining.
- There seems to be endless variety of sentiment bearing expressions.
  - We have compiled more than 6,700 individual words.
  - There are also a large number of phrases.

Opinion lexicon

- Opinion words or phrases (also called polar words, opinion bearing words, etc). E.g.,
  - Positive: beautiful, wonderful, good, amazing,
  - Negative: bad, poor, terrible, cost an arm and a leg.
- Many of them are context dependent, not just application domain dependent.
- Three main ways to compile such lists:
  - Manual approach: not a bad idea, only an one-time effort
  - Corpus-based approach
  - Dictionary-based approach

Corpus-based approaches

- Rely on syntactic patterns in large corpora. (Hazivassiloglou and McKeown, 1997; Turney, 2002; Yu and Hazivassiloglou, 2003; Kanayama and Nasukawa, 2006; Ding, Liu and Yu, 2008)
  - Can find domain dependent orientations (positive, negative, or neutral).
- (Turney, 2002) and (Yu and Hazivassiloglou, 2003) are similar.
  - Assign opinion orientations (polarities) to words/phrases.
  - (Yu and Hazivassiloglou, 2003) is slightly different from (Turney, 2002)
    - use more seed words (rather than two) and use log-likelihood ratio (rather than PMI).

Corpus-based approaches (contd)

- Sentiment consistency: Use conventions on connectives to identify opinion words (Hazivassiloglou and McKeown, 1997). E.g.,
  - Conjunction: conjoined adjectives usually have the same orientation.
    - E.g., “This car is *beautiful* **and** *spacious*.” (conjunction)
  - AND, OR, BUT, EITHER-OR, and NEITHER-NOR have similar constraints.
  - Learning using
    - log-linear model: determine if two conjoined adjectives are of the same or different orientations.
    - Clustering: produce two sets of words: positive and negative

Find domain opinion words

- A similar approach was also taken in (Kanayama and Nasukawa, 2006) but for Japanese words:
  - Instead of only based on intra-sentence sentiment consistency, the new method also looks at the previous and next sentence, i.e., inter-sentence sentiment consistency.
  - Have an initial seed lexicon of positive and negative words.

Context dependent opinion

- Find domain opinion words is insufficient. A word may indicate different opinions in same domain.
  - "The battery life is *long*" (+) and "It takes a *long* time to focus" (-).
- Ding, Liu and Yu (2008) and Ganapathibhotla and Liu (2008) exploited sentiment consistency (both inter and intra sentence) based on contexts
  - It finds context dependent opinions.
  - Context: (adjective, aspect), e.g., (long, battery_life)
  - It assigns an opinion orientation to the pair.

The Double Propagation method
(Qiu et al 2009, 2011)

- The same DP method can also use dependency of opinions & aspects to extract new opinion words.
- Based on dependency relations
  - Knowing an aspect can find the opinion word that modifies it
    - E.g., "The rooms are spacious"
  - Knowing some opinion words can find more opinion words
    - E.g., "The rooms are spacious and beautiful"

Opinions implied by objective terms (Zhang and Liu, 2011a)

- Most opinion words are adjectives and adverbs, e.g., good, bad, etc
  - There are also many subjective and opinion verbs and nouns, e.g., hate (VB), love (VB), crap (NN).
- But objective nouns can imply opinions too.
  - E.g., “After sleeping on the mattress for one month, a valley/body impression has formed in the middle.”
- How to discover such nouns in a domain or context?

The technique

- Sentiment analysis to determine whether the context is +ve or –ve.
  - E.g., “I saw a valley in two days, which is terrible.”
  - This is a negative context.
- Statistical test to find +ve and –ve candidates.

$$Z = \frac{p - p_0}{\sqrt{\frac{p_0(1 - p_0)}{n}}}$$

- Pruning to move those unlikely ones though *sentiment homogeneity*.

Pruning

- For an aspect with an implied opinion, it has a fixed opinion, either +ve or –ve, but not both.
- We find two direct modification relations using a dependency parser.
  - Type 1: $O \rightarrow O\text{-}Dep \rightarrow A$
    - e.g. " *This TV has good picture quality*."
  - Type 2: $O \rightarrow O\text{-}Dep \rightarrow H \leftarrow A\text{-}Dep \leftarrow A$
    - e.g. " *The springs of the mattress are bad*. "
- If an aspect has mixed opinions based on the two dependency relations, prune it.

Opinions implied by resource usage
(Zhang and Liu, 2011b)

- Resource usage descriptions may also imply opinions (as mentioned in rules of opinions)
  - E.g., “This washer uses a lot of water.”
- Two key roles played by resources usage:
  - An important aspect of an entity, e.g., water usage.
  - Imply a positive or negative opinion
- Resource usages that imply opinions can often be described by a triple.

  (verb, quantifier, noun_term),

  - Verb: uses, quantifier: “a lot of “, noun_term: water

The proposed technique

- The proposed method is graph-based.
  - Stage 1: Identifying Some Global Resource Verbs
    - Identify and score common resource usage verbs used in almost any domain, e.g., “use” and “consume”
  - Stage 2: Discovering Resource Terms in each Domain Corpus
    - Use a graph-based method considering occurrence probabilities.
    - With resource verbs identified from stage 1 as the seeds.
    - Score domain specific resource usage verbs and resource terms.

Dictionary-based methods

- Typically use WordNet's synsets and hierarchies to acquire opinion words
  - Start with a small seed set of opinion words.
  - Bootstrap the set to search for synonyms and antonyms in WordNet iteratively (Hu and Liu, 2004; Kim and Hovy, 2004; Kamps et al 2004).
- Use additional information (e.g., glosses) from WordNet (Andreevskaia and Bergler, 2006) and learning (Esuti and Sebastiani, 2005). (Dragut et al 2010) uses a set of rules to infer orientations.

Semi-supervised learning
(Esuti and Sebastiani, 2005)

- Use supervised learning
  - Given two seed sets: positive set P, negative set N
  - The two seed sets are then expanded using synonym and antonymy relations in an online dictionary to generate the expanded sets P' and N'.
- P' and N' form the training sets.
- Using all the glosses in a dictionary for each term in P' $\cup$ N' and converting them to a vector
- Build a binary classifier
  - Tried various learners.

Multiple runs of bootstrapping (Andreevskaia and Bergler, 2006)

- Basic bootstrapping with given seeds sets (adjectives)
  - First pass: seed sets are expanded using synonym, antonymy, and hyponyms relations in WordNet.
  - Second pass: it goes through all WordNet glosses and identifies the entries that contain in their definitions the sentiment-bearing words from the extended seed set and adds these head words to the corresponding category (+ve, -ve, neutral)
  - Third pass: clean up using a POS tagger to make sure the words are adjectives and remove contradictions.

Multiple runs of bootstrapping (contd)

- Each word is then assigned a fuzzy score reflecting the degree of certainty that the word is opinionated (+ve/-ve).
- The method performs multiple runs of bootstrapping using non-overlapping seed sets.
  - A net overlapping score for each word is computed based on how many times the word is discovered in the runs as +ve (or –ve)
  - The score is normalized based on the fuzzy membership.

Which approach to use?

- Both corpus and dictionary based approaches are needed.
- Dictionary usually does not give domain or context dependent meaning
  - Corpus is needed for that
- Corpus-based approach is hard to find a very large set of opinion words
  - Dictionary is good for that
- In practice, corpus, dictionary and manual approaches are all needed.

Some other related papers

- Choi and Cardie (2009) adapting a lexicon to domain specific need using integer linear programming
- Du and Tan (2009) and Du, Tan, Cheng and Yun (2010) clustered sentiment words
- Hassan and Radev (2010) built a word graph based on synonyms and then used a number of random walks to hit known seed words
- Hassan et al. (2011) found sentiment orientations of foreign words. It first created a multilingual word network and then did random walk similar to the above paper.
- Jijkoun, Rijke and Weerkamp (2010) used target and sentiment word relationship. Similar to that in (Qiu et al 2009).

Some other related papers

- Kaji and Kitsuregawa (2006, 2007) and Velikovich et al (2010) used text on the web to generate lexicons.
- Lu et al (2011) dealt with the same problem as (Ding et al 2008) but used various constraints in optimization.
- Mohammad, Dunne, and Dorr, (2009) used seeds and thesaurus.
- Rao and Ravichandran (2009) used WordNet and OpenOffice thesaurus and semi-supervised learning
- Wu and Wen (2010) found context adjectives like *large* and *small* by mining the web using lexico-syntactic patterns. They solved the same problem as (Ding et al 2008)

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Comparative Opinions
(Jindal and Liu, 2006)

- *Gradable*
  - *Non-Equal Gradable*: Relations of the type *greater* or *less than*
    - *Ex: "optics of camera A is better than that of camera B"*
  - *Equative*: Relations of the type *equal to*
    - Ex: "*camera A and camera B both come in 7MP*"
  - *Superlative*: Relations of the type *greater* or *less than all others*
    - Ex: "*camera A is the cheapest in market*"

Analyzing Comparative Opinions

- Objective: Given an opinionated document *d*, Extract comparative opinions:

  (E_1, E_2, *A*, *po*, *h*, *t*),

  where E_1 and E_2 are the entity sets being compared based on their shared aspects *A*, *po* is the preferred entity set of the opinion holder *h*, and *t* is the time when the comparative opinion is expressed.

- Note: not positive or negative opinions.

An example

- Consider the comparative sentence
  - "*Canon's optics is better than those of Sony and Nikon*."
  - Written by John in 2010.
- The extracted comparative opinion/relation:
  - ({Canon}, {Sony, Nikon}, {optics}, *preferred*:{Canon}, John, 2010)

Common comparatives

- In English, comparatives are usually formed by adding -*er* and superlatives are formed by adding -*est* to their base adjectives and adverbs
- Adjectives and adverbs with two syllables or more and not ending in *y* do not form comparatives or superlatives by adding -*er* or -*est*.
  - Instead, *more*, *most*, *less*, and *least* are used before such words, e.g., *more beautiful*.
- Irregular comparatives and superlatives, i.e., *more most*, *less*, *least*, *better*, *best*, *worse*, *worst*, etc

Some techniques (Jindal and Liu, 2006, Ding et al, 2009)

- Identify comparative sentences
  - Using class sequential rules as attributes in the data, and then perform
  - Supervised learning
- Extraction of different items
  - Label sequential rules
  - conditional random fields
- Determine preferred entities (opinions)
  - Parsing and opinion lexicon

Analysis of comparative opinions

- Gradable comparative sentences can be dealt with *almost* as normal opinion sentences.
  - E.g., "*optics of camera A is better than that of camera B*"
  - Positive: *"optics of camera A"*
  - Negative: *"optics of camera B"*
- Difficulty: recognize non-standard comparatives
  - E.g., "I am so happy because my new iPhone is nothing like my old slow ugly Droid."
  - ?

Identifying preferred entities
(Ganapathibhotla and Liu, 2008)

- The following rules can be applied

  Comparative Negative ::= increasing comparative N
  | decreasing comparative P
  Comparative Positive ::= increasing comparative P
  | decreasing comparative N

  - E.g., "Coke tastes better than Pepsi"
  - "Nokia phone's battery life is longer than Moto phone"
- Context-dependent comparative opinion words
  - Using context pair: (aspect, JJ/JJR)
  - Deciding the polarity of (battery_life, longer) in a corpus

Some other work

- Bos and Nissim (2006) proposed a method to extract items from superlative sentences, but does not study sentiments.
- Fiszman et al (2007) tried to identify which entity has more of a certain property in comparisons.
- Li et al (2010) finds comparative questions and compared entities using sequence patterns.
- Yang and Ko (2009, 2011) worked on Korean comparative sentences.
- Zhang, Narayanan and Choudhary (2010) found comparative sentences based on a set of rules, and the sentences must also mention at least two product names explicitly or implicitly (comparing with the product being reviewed).

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Coreference resolution: semantic level?

- Coreference resolution (Ding and Liu, 2010)
  - "I bought the Sharp tv a month ago. The picture quality is so bad. Our other Sony tv is much better than this Sharp. ***It*** is also so expensive".
    - "it" means "Sharp"
  - "I bought the Sharp tv a month ago. The picture quality is so bad. Our other Sony tv is much better than this Sharp. ***It*** is also very reliable."
    - "it" means "Sony
- Sentiment consistency.

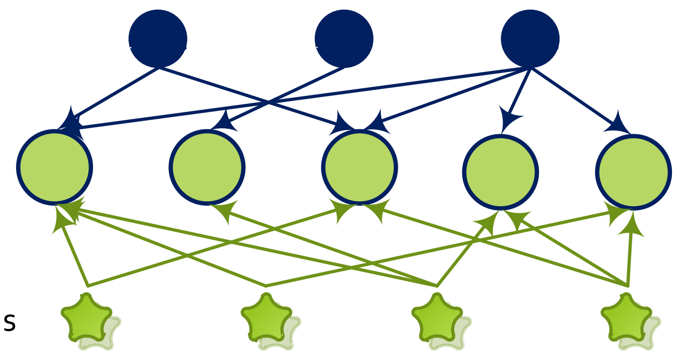
Coreference resolution (contd)

- "The picture quality of this Canon camera is very good. ***It*** is not expensive either."
  - Does "it" mean "Canon camera" or "Picture Quality"?
    - Clearly it is Canon camera because picture quality cannot be expensive.
    - Commonsense knowledge, but can be discovered.
- For coreference resolution, we actually need to
  - do sentiment analysis first, and
  - mine adjective-noun associations using dependency
- Finally, use supervised learning

Find evaluative opinions in discussions (Zhai et al. 2011c)

- Existing research focuses on product reviews
  - reviews are opinion-rich and
  - contain little irrelevant information.
- Not true for online discussions.
  - Many postings express no opinions about the topic, but emotional statements and others.
  - Evaluative opinions, "*The German defense is strong.*"
  - Non-evaluative opinions, "*I feel so sad for Argentina.*" "*you know nothing about defense*"
- Goal: identify evaluative opinion sentences.

Aspects, evaluation words and emotion words interaction



$$asp(a_i) = \lambda \times \sum_{(i,j)\epsilon E_{va-a}} eva(va_j) - (1-\lambda) \times \sum_{(i,k)\epsilon E_{mo-a}} emo(mo_k) \quad (1)$$

$$eva(va_j) = \sum_{(i,j)\epsilon E_{va-a}} asp(a_i) \quad (2)$$

- An extracted aspect that is modified by many *evaluation words* is more likely to indicate an evaluative sentence.
- An extracted aspect that is modified by many *emotion words* is not a good indicator of an evaluative sentence.
- An evaluation word that does not modify *good* (high scored) aspects are likely to be a wrong evaluation word.
- The more evaluative the aspects are, the less emotional their associated emotion words should be.

$$tmp(mo_k) = \sum_{(i,k)\epsilon E_{mo-a}} asp(a_i) \quad (3)$$

$$emo(mo_k) \propto -tmp(mo_k) \quad (4)$$

$$emo(mo_k) = -tmp(mo_k) + max = max - tmp(mo_k) \quad (5)$$

$$max = \max\{tmp(mo_1), tmp(mo_2), \dots, tmp(mo_{|V_{mo}|})\} \quad (6)$$

Some interesting sentences

- "Trying out Google chrome because Firefox keeps crashing."
  - The opinion about Firefox is clearly negative, but for Google chrome, there is no opinion.
  - We need to segment the sentence into clauses to decide that "crashing" only applies to Firefox.
  - "Trying out" also indicates no opinion.
- How about this
  - "I changed to Audi because BMW is so expensive."

Some interesting sentences (contd)

- Conditional sentences are hard to deal with (Narayanan et al. 2009)
  - "If I can find a good camera, I will buy it."
  - But conditional sentences can have opinions
    - "If you are looking for a good phone, buy Nokia"
- Questions may or may not have opinions
  - No sentiment
    - "Are there any great perks for employees?"
  - With sentiment
    - "Any idea how to repair this lousy Sony camera?"

Some interesting sentences (contd)

- Sarcastic sentences
  - “What a great car, it stopped working in the second day.”
- Sarcastic sentences are very common in political blogs, comments and discussions.
  - They make political blogs difficult to handle
  - Many political aspects can also be quite complex and hard to extract because they cannot be described using one or two words.
- Some initial work by (Tsur, Davidov, Rappoport 2010)

Some interesting sentences (contd)

- See these two sentences in a medical domain:
  - "I come to see my doctor because of severe pain in my stomach"
  - "After taking the drug, I got severe pain in my stomach"
- If we are interested in opinions on a drug, the first sentence has no opinion, but the second implies negative opinion on the drug.
  - Some understanding seems to be needed?

Some interesting sentences (contd)

- The following two sentences are from reviews in the paint domain.
  - “For paint_X, one coat can cover the wood color.”
  - “For paint_Y, we need three coats to cover the wood color.
- We know that paint_X is good and Paint_Y is not, but how by a system.
  - Do we need commonsense knowledge and understanding of the text?

Some more interesting/hard sentences

- “My goal is to have a high quality tv with decent sound”
- “The top of the picture was much brighter than the bottom.”
- “Google steals ideas from Bing, Bing steals market shares from Google.”
- “When I first got the airbed a couple of weeks ago it was wonderful as all new things are, however as the weeks progressed I liked it less and less.”

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Opinion spam detection

(Jindal and Liu 2007, 2008)

- Opinion spamming refers to people giving fake or untruthful opinions, e.g.,
  - Write undeserving positive reviews for some target entities in order to promote them.
  - Write unfair or malicious negative reviews for some target entities in order to damage their reputations.
- Opinion spamming has become a business in recent years.
- Increasing number of customers are wary of fake reviews (biased reviews, paid reviews)

Problem is wide-spread

Professional Fake Review Writing Services

- Post positive reviews
- Fake review writer
- Product review writer for hire
- Hire a content writer

Manipulating Social Media (sock puppets - fake identities - fake personas)

- Revealed: US spy operation that manipulates social media, Guardian.co.uk, Thursday 17 March 2011.
- America's absurd stab at systematising sock puppetry, Guardian.co.uk, Thursday 17 March 2011.

China's Internet "Water Army" (Shuijun) - Opinion Spammers

- You can hire people to write and post fake reviews or comments, and even bribe staff at review, forum
- 'Water Army' Whistleblower Threatened, January 7, 2011, People's Daily.
- The Chinese Online "Water Army", June 25, 2010, Wired.com.
- If you read Chinese, see this description from Baidu Baike at baidu.com.

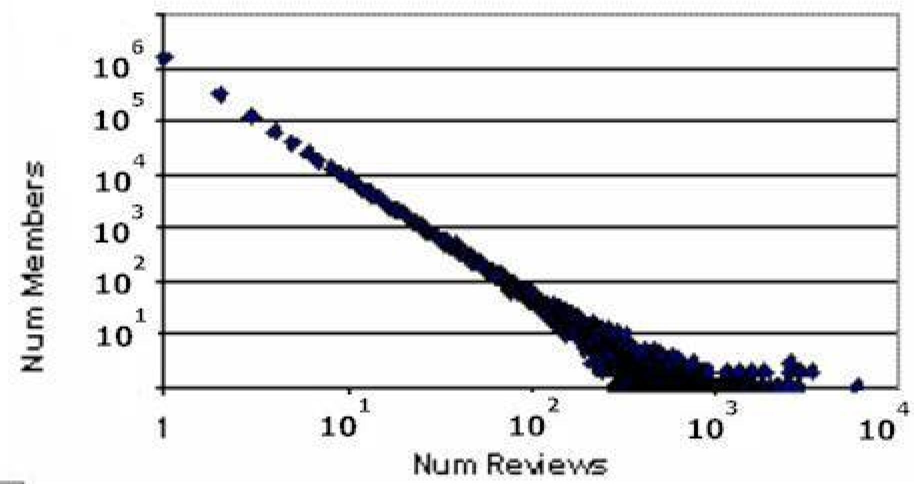
An example practice of review spam

Belkin International, Inc

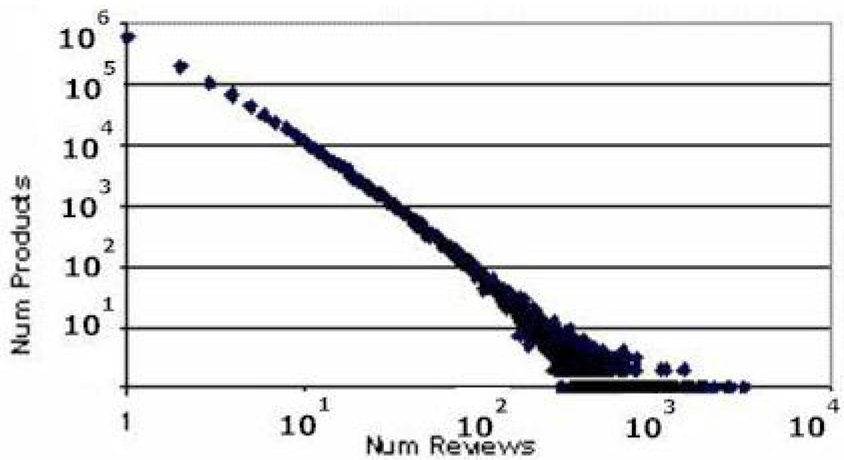
- Top networking and peripherals manufacturer | Sales ~ $500 million in 2008
- Posted an ad for writing fake reviews on amazon.com (65 cents per review)

Log-log plot

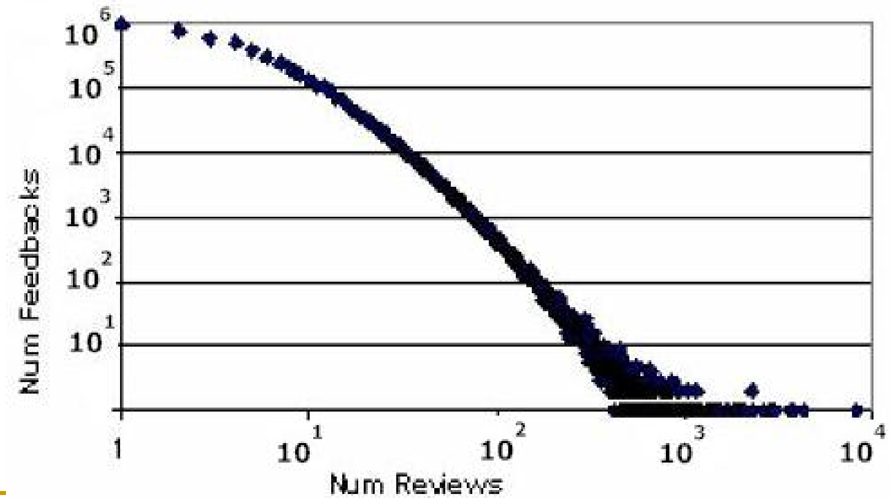
Amazon reviews, reviewers and products



- Fig. 1 reviews and reviewers



- Fig. 2 reviews and products



- Fig. 3 reviews and feedbacks

Categorization of opinion spam

(Jindal and Liu 2008)

- Type 1 (fake reviews)

  Ex:
- Type 2 (Reviews on Brands Only) (?)

  Ex: "*I don't trust HP and never bought anything from them*"
- Type 3 (Non-reviews)
  - Advertisements

    Ex: "*Detailed product specs: 802.11g, IMR compliant, …*"

    "*…buy this product at: compuplus.com*"
  - Other non-reviews

    Ex: "*What port is it for*"

    "*The other review is too funny*"

    "*Go Eagles go*"

Type 1 Spam Reviews

- Hype spam – promote one's own products
- Defaming spam – defame one's competitors' products

Table 4. Spam reviews vs. product quality

	Positive spam review	Negative spam review
Good quality product	1	**2**
Bad quality product	**3**	4
Average quality product	**5**	**6**

Harmful Regions

- Very hard to detect manually

Harmful spam are outlier reviews?

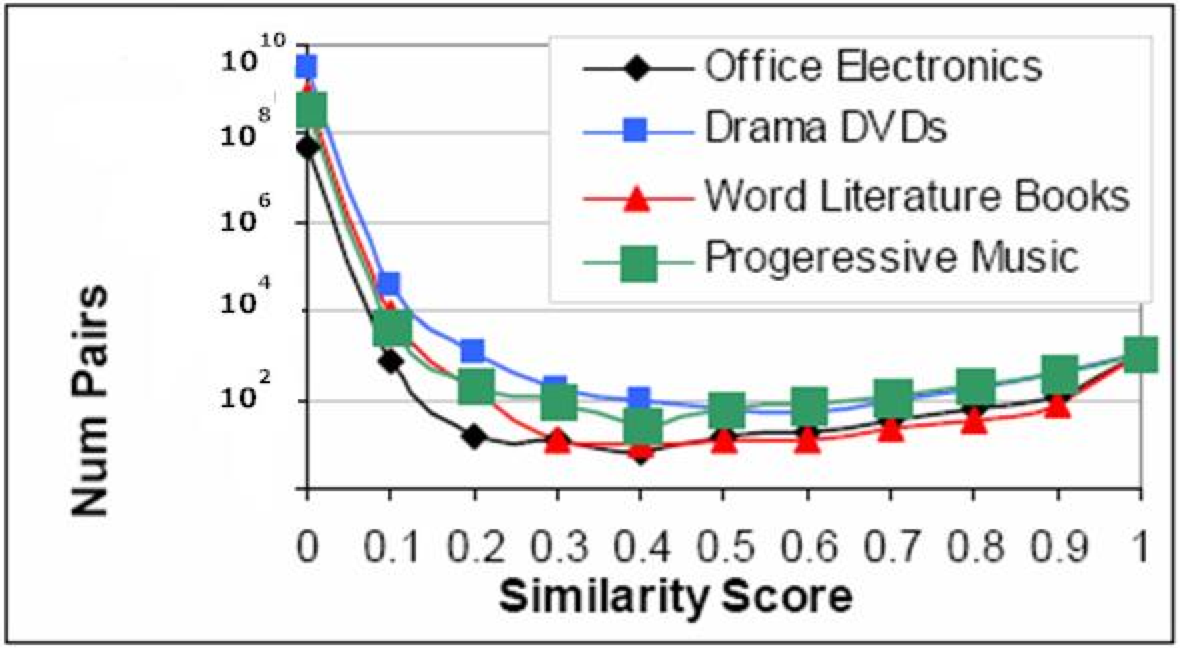
- Assumption: Most reviewers and reviews are honest,
  - Not true when a group of people spam on a product (called group spam, discussed later).
- Outliers reviews: Reviews which deviate a great deal from the average product rating
- Harmful spam reviews:
  - Outliers are necessary but not sufficient condition for harmful spam reviews.
  - This idea helps us identify learning features.

Spam detection

- Type 2 and Type 3 spam reviews are relatively easy to detect
  - Supervised learning, e.g., logistic regression
  - It performs quite well, and not discuss it further.
- Type 1 spam (fake) reviews
  - Manual labeling is extremely hard
  - Propose to use duplicate and near-duplicate reviews as positive training data

Duplicate reviews

Two reviews which have similar contents are called duplicates



Four types of duplicates

1. Same userid, same product
2. Different userid, same product
3. Same userid, different products
4. Different userid, different products

- The last three types are very likely to be fake!

Supervised model building

- Logistic regression
  - Training: duplicates as spam reviews (positive) and the rest as non-spam reviews (negative)
- Use the follow data attributes
  - Review centric features (content)
    - About reviews (contents (n-gram), ratings, etc)
  - Reviewer centric features
    - About reviewers (different unusual behaviors, etc)
  - Product centric features
    - Features about products reviewed (sale rank, etc)

Predictive power of duplicates

- Representative of all kinds of spam
- Only 3% duplicates accidental
- Duplicates as positive examples, rest of the reviews as negative examples

Table 5. AUC values on duplicate spam reviews.

Features used	**AUC**
All features	78%
Only review features	75%
Only reviewer features	72.5%
Without feedback features	77%
Only text features	63%

  - reasonable predictive power
  - Maybe we can use duplicates as type 1 spam reviews(?)

Tentative classification results

- Negative outlier reviews tend to be heavily spammed
- Those reviews that are the only reviews of products are likely to be spammed
- Top-ranked reviewers are more likely to be spammers
- Spam reviews can get good helpful feedbacks and non-spam reviews can get bad feedbacks

Detecting deceptive reviews (Ott et al 2011)

- Detecting deceptive language has been studied in psychology, communication and linguistics (Newman et al 2003; Zhou, Shi and Zhang 2008; Mihalcea and Strapparava 2009).
- Ott et al (2011) used the idea to detect deceptive opinion spam reviews with supervised learning.
  - Manually labeled a dataset
  - Various features on genre, psycholinguistic, n-grams
- Yoo and Gretzel (2009) also studied deceptive reviews.

Finding unexpected reviewer behavior

- Since in general it is hard to manually label spam review for learning, it is thus difficult to detect fake reviews based on review contents.
- Lim et al (2010) and Nitin et al (2010) analyze the behavior of reviewers
    - identifying *unusual review patterns* which may indicate suspicious behaviors of reviewers.
- The problem is formulated as finding unexpected rules and rule groups.

Spam behavior models (Lim et al 2010)

- Several unusual reviewer behavior models were identified.
  - Targeting products
  - Targeting groups
  - General rating deviation
  - Early rating deviation
- Their scores for each reviewer are then combined to produce the final spam score.
- Ranking and user evaluation

Finding unexpected rules (Jindal, Liu, Lim 2010)

- For example, if a reviewer wrote all positive reviews on products of a brand but all negative reviews on a competing brand …
- Finding unexpected rules,
  - Data: *reviewer-id*, *brand-id*, *product-id*, and a *class*.
  - Mining: class association rule mining
  - Finding unexpected rules and rule groups, i.e., showing atypical behaviors of reviewers.

Rule1: Reviewer-1, brand-1 -> positive (confid=100%)

Rule2: Reviewer-1, brand-2 -> negative (confid=100%)

The example (cont.)

Expectation: Let the subset of data with $A_j = v_{jk}$ be D^{jk}. We have

$$E(v_{jk}, A_g \rightarrow C) = \text{entropy}(D^{jk}) \qquad (24)$$

Attribute unexpectedness: To compute attribute unexpectedness, we first compute the entropy after adding the A_g attribute:

$$entropy_{A_g}(D^{jk}) = -\sum_{h=1}^{|A_g|} \frac{|D^{jk}{}_h|}{|D^v|} entropy(D^{jk}{}_h) \qquad (25)$$

The unexpectedness is computed as follows (information gain):

$$Au(v_{jk}, A_g \rightarrow C) = entropy(D^{jk}) - entropy_{A_g}(D^{jk}) \qquad (26)$$

Confidence unexpectedness

Rule: reviewer-1, brand-1 $\rightarrow$ positive [sup = 0.1, conf = 1]

- If we find that on average reviewers give brand-1 only 20% positive reviews (expectation), then reviewer-1 is quite unexpected.

$$Cu(v_{jk} \rightarrow c_i) = \frac{\Pr(c_i \mid v_{jk}) - E(\Pr(c_i \mid v_{jk}))}{E(\Pr(c_i \mid v_{jk}))}$$

$$E(\Pr(c_i \mid v_{jk}, v_{gh})) = \frac{\Pr(c_i \mid v_{jk})\Pr(c_i \mid v_{gh})}{\Pr(c_i)\sum_{r=1}^{m} \frac{\Pr(c_r \mid v_{jk})\Pr(c_r \mid v_{gh})}{\Pr(c_r)}}$$

Support unexpectedness

Rule: reviewer-1, product-1 -> positive [sup = 5]

- Each reviewer should write only one review on a product and give it a positive or negative rating (expectation).
- This unexpectedness can detect those reviewers who review the same product multiple times, which is unexpected.
  - These reviewers are likely to be spammers.
- Can be defined probabilistically as well.

Detecting group spam (Mukherjee et al 2011)

- A group of people (could be a single person with multiple ids, *sockpuppets*) work together to promote a product or to demote a product.
- Such spam can be very harmful as
  - they can take control of sentiment on a product
- The algorithm has three steps
  - Frequent pattern mining: find groups of people who reviewed a number of products together.
  - A set of feature indicators are identified
  - Ranking is performed with a learning to rank algo.

Roadmap

- Opinion Mining Problem
- Document sentiment classification
- Sentence subjectivity & sentiment classification
- Aspect-based sentiment analysis
- Aspect-based opinion summarization
- Opinion lexicon generation
- Mining comparative opinions
- Some other problems
- Opinion spam detection
- **Utility or helpfulness of reviews**
- Summary

Utility or quality of reviews

- Goal: Determining the usefulness, helpfulness, or utility of each review.
  - It is desirable to rank reviews based on utilities or qualities when showing them to users, with the highest quality review first.
- Many review aggregation sites have been practicing this, e.g., amazon.com.
  - "*x of y people found the following review helpful*."
  - Voted by user - "*Was the review helpful to you?*"

Application motivations

- Although review sites use helpfulness feedback to rank,
  - A review takes a long time to gather enough feedback.
    - New reviews will not be read.
  - Some sites do not provide feedback information.
- It is thus beneficial to score each review once it is submitted to a site.

Regression formulation

(Zhang and Varadarajan, 2006; Kim et al. 2006)

- Formulation: Determining the utility of reviews is usually treated as a regression problem.
  - A set of features is engineered for model building
  - The learned model assigns an utility score to each review, which can be used in review ranking.
- Unlike fake reviews, the ground truth data used for both training and testing are available
  - Usually the user-helpfulness feedback given to each review.

Features for regression learning

- Example features include
  - review length, review rating, counts of some POS tags, opinion words, tf-idf scores, wh-words, product aspect mentions, comparison with product specifications, timeliness, etc (Zhang and Varadarajan, 2006; Kim et al. 2006; Ghose and Ipeirotis 2007; Liu et al 2007)
- Subjectivity classification was applied in (Ghose and Ipeirotis 2007).
- Social context was used in (O'Mahony and Smyth 2009; Lu et al. 2010).

Classification formulation

- Binary classification: Instead of using the original helpfulness feedback as the target or dependent variable,
  - Liu et al (2007) performed manual annotation of two classes based on whether the review evaluates many product aspects or not.
- Binary class classification is also used in (O'Mahony and Smyth 2009)
  - Classes: Helpful and not helpful
  - Features: helpfulness, content, social, and opinion

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Summary

- This tutorial presented
  - The problem of sentiment analysis and opinion mining
    - It provides a structure to the unstructured text.
    - It shows that summarization is crucial.
  - Main research directions and their representative techniques.
  - By no means exhaustive, a large body of work.
- Still many problems not attempted or studied.
- None of the problem is solved.

Summary (contd)

- It is a fascinating NLP or text mining problem.
  - Every sub-problem is highly challenging.
  - But it is also highly restricted (semantically).
- Despite the challenges, applications are flourishing!
  - It is useful to every organization and individual.
- The general NLP is probably too hard, but can we solve this highly restricted problem?
  - I am optimistic

References

- The references will be available from this link
  - http://www.cs.uic.edu/~liub/FBS/AAAI-2011-tutorial-references.pdf
- The main content is from Chapter 11 of the following book,
  - B. Liu. Web Data Mining: Exploring Hyperlinks, Contents and Usage Data. *Second Edition*, Springer, July 2011.
  - But updated based on 2011 papers.