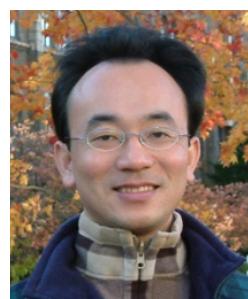




Social Media and Sentiment Analysis (社群媒體與情緒分析)

時間：2016/11/01 (二) (2:10-5:00pm)
地點：政治大學綜合院館270407，北棟407教室
主持人：陳恭主任



Min-Yuh Day
戴敏育
Assistant Professor
專任助理教授

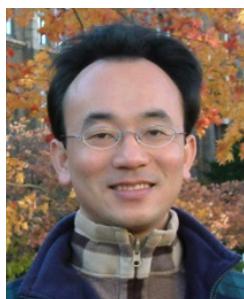
Dept. of Information Management, Tamkang University
淡江大學 資訊管理學系

<http://mail.tku.edu.tw/myday/>

2016-11-01



Sentiment Analysis on Social Media (社群媒體情感分析)



Min-Yuh Day

戴敏育

Assistant Professor

專任助理教授

Dept. of Information Management, Tamkang University

淡江大學 資訊管理學系

<http://mail.tku.edu.tw/myday/>

2016-07

Outline

- Architectures of Sentiment Analytics on Social Media
- Social Media Monitoring/Analysis
- Sentiment Analytics on Social Media:
Tools and Applications

Sentiment Analysis on Social Media



Example of Opinion: review segment on iPhone



“I bought an iPhone a few days ago.
It was such a nice phone.
The touch screen was really cool.
The voice quality was clear too.
However, my mother was mad with me as I did not tell
her before I bought it.
She also thought the phone was too expensive, and
wanted me to return it to the shop. ... ”

Example of Opinion: review segment on iPhone

“(1) I bought an iPhone a few days ago.

(2) It was such a **nice** phone.

(3) The touch screen was really **cool**.

(4) The voice quality was **clear** too.

(5) However, my mother was mad with me as I did not tell her before I bought it.

(6) She also thought the phone was too expensive, and wanted me to return it to the shop. ... ”



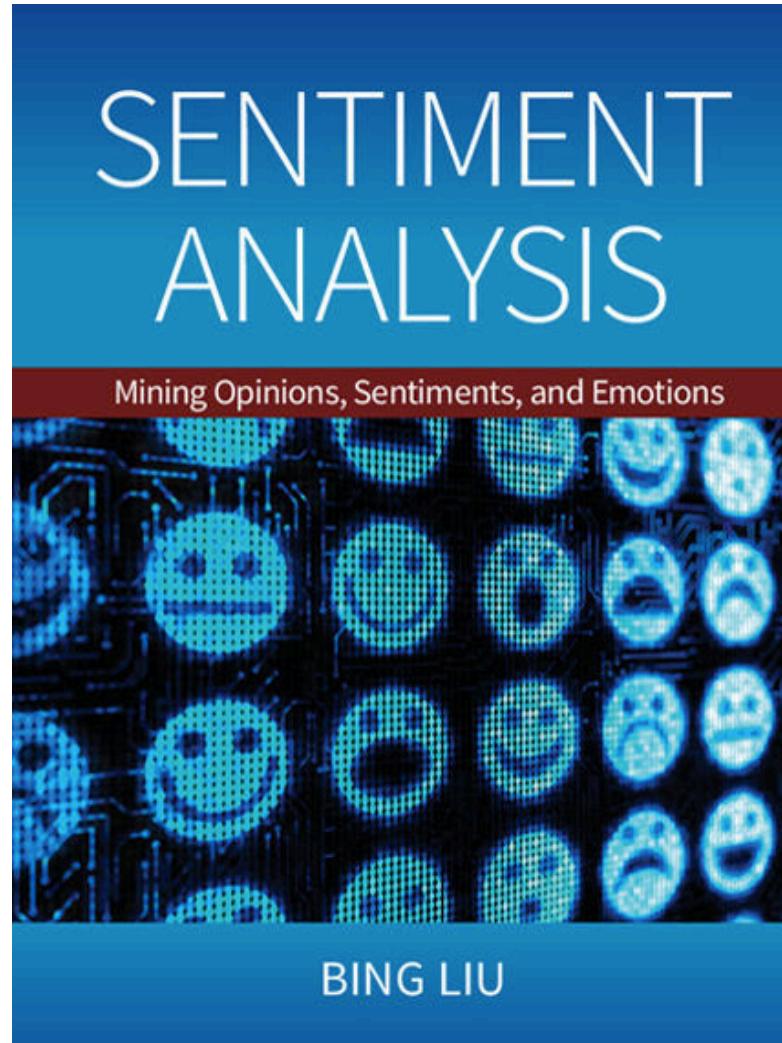
+Positive
Opinion



-Negative
Opinion

Architectures of Sentiment Analytics

Bing Liu (2015),
Sentiment Analysis:
Mining Opinions, Sentiments, and Emotions,
Cambridge University Press



Sentiment Analysis and Opinion Mining

- 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

Research Area of Opinion Mining

- Many names and tasks with difference objective and models
 - Sentiment analysis
 - Opinion mining
 - Sentiment mining
 - Subjectivity analysis
 - Affect analysis
 - Emotion detection
 - Opinion spam detection

Sentiment Analysis

- Sentiment
 - A **thought**, **view**, or **attitude**, especially one based mainly on **emotion** instead of reason
- Sentiment Analysis
 - opinion mining
 - use of natural language processing (NLP) and computational techniques to automate the extraction or classification of sentiment from typically unstructured text

Applications of Sentiment Analysis

- Consumer information
 - Product reviews
- Marketing
 - Consumer attitudes
 - Trends
- Politics
 - Politicians want to know voters' views
 - Voters want to know politicians' stances and who else supports them
- Social
 - Find like-minded individuals or communities

Sentiment detection

- How to interpret features for sentiment detection?
 - Bag of words (IR)
 - Annotated lexicons (WordNet, SentiWordNet)
 - Syntactic patterns
- Which features to use?
 - Words (unigrams)
 - Phrases/n-grams
 - Sentences

Problem statement of Opinion Mining

- Two aspects of abstraction
 - Opinion definition
 - What is an opinion?
 - What is the structured definition of opinion?
 - Opinion summarization
 - Opinion 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.

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
 - Is this review + or -?
 - Sentence level
 - 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 opinion are expressed

Two main types of opinions

- **Regular opinions:** Sentiment/Opinion expressions on some target entities
 - **Direct opinions:** sentiment expressions on one object:
 - “The touch screen is really cool.”
 - “The picture quality of this camera is great”
 - **Indirect opinions:** comparisons, relations expressing similarities or differences (objective or subjective) of more than one object
 - “phone X is cheaper than phone Y.” (objective)
 - “phone X is better than phone Y.” (subjective)
- **Comparative opinions:** comparisons of more than one entity.
 - “iPhone is better than Blackberry.”

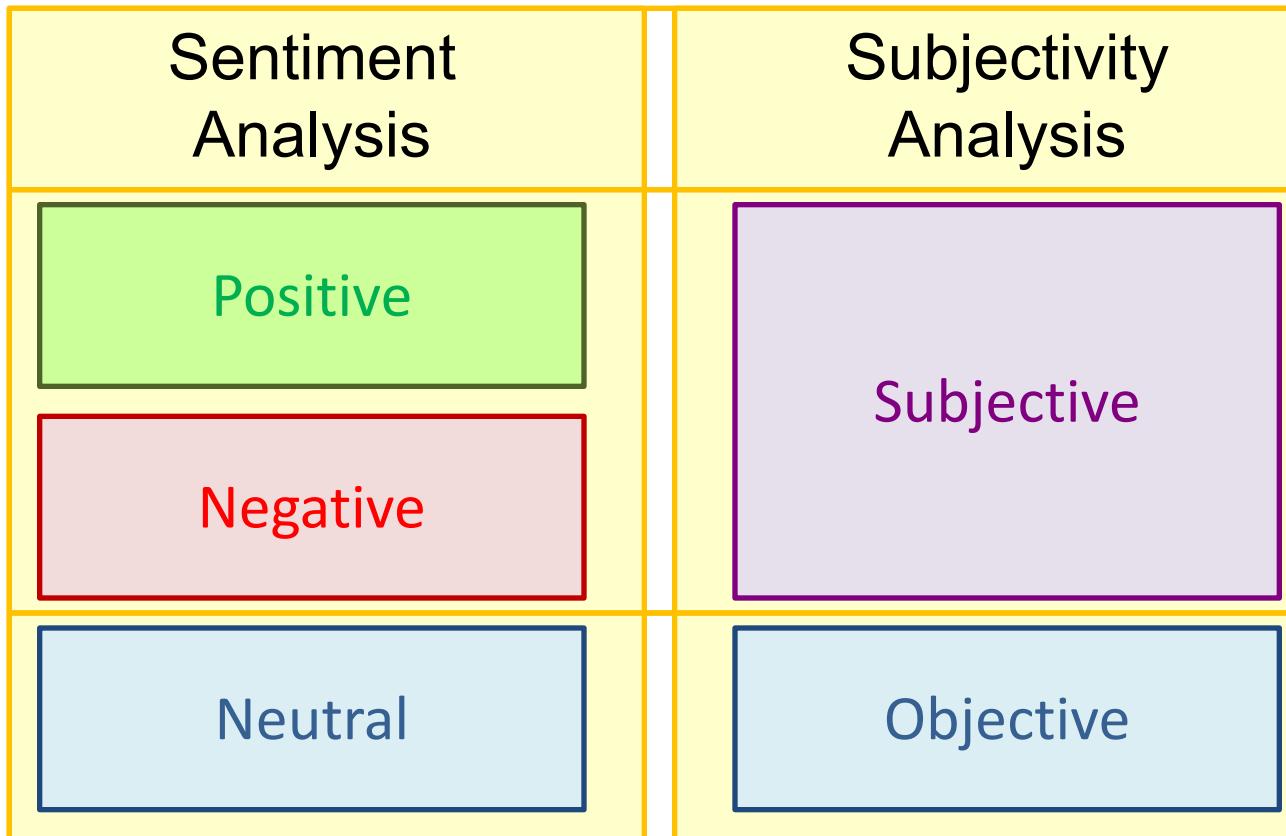
Subjective and Objective

- **Objective**
 - An objective sentence expresses some **factual information** about the world.
 - “I **returned** the phone yesterday.”
 - Objective sentences can implicitly indicate opinions
 - “The **earphone broke** in two days.”
- **Subjective**
 - A subjective sentence expresses some **personal feelings or beliefs**.
 - “The voice on my phone was **not** so **clear**”
 - Not every subjective sentence contains an opinion
 - “I wanted a phone with **good voice quality**”
- → **Subjective analysis**

Sentiment Analysis

vs.

Subjectivity Analysis



A (regular) opinion

- Opinion (a restricted definition)
 - An opinion (regular opinion) is simply a positive or negative sentiment, view, attitude, emotion, or appraisal about an entity or an aspect of the entity from an opinion holder.
- Sentiment orientation of an opinion
 - Positive, negative, or neutral (no opinion)
 - Also called:
 - Opinion orientation
 - Semantic orientation
 - Sentiment polarity

Entity and aspect

- Definition of Entity:
 - An *entity e* is a product, person, event, organization, or topic.
 - e is represented as
 - A hierarchy of components, sub-components.
 - Each node represents a components and is associated with a set of attributes of the components
- An opinion can be expressed on any node or attribute of the node
- Aspects(features)
 - represent both components and attribute

Opinion Definition

- 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 on feature of entity at time.
 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.
- (e_j, a_{jk}) is also called opinion target

Terminologies

- **Entity**: object
- **Aspect**: feature, attribute, facet
- **Opinion holder**: opinion source
- **Topic**: entity, aspect
- Product features, political issues

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**.

Classification Based on Supervised Learning

- Sentiment classification
 - Supervised learning Problem
 - Three classes
 - *Positive*
 - *Negative*
 - *Neutral*

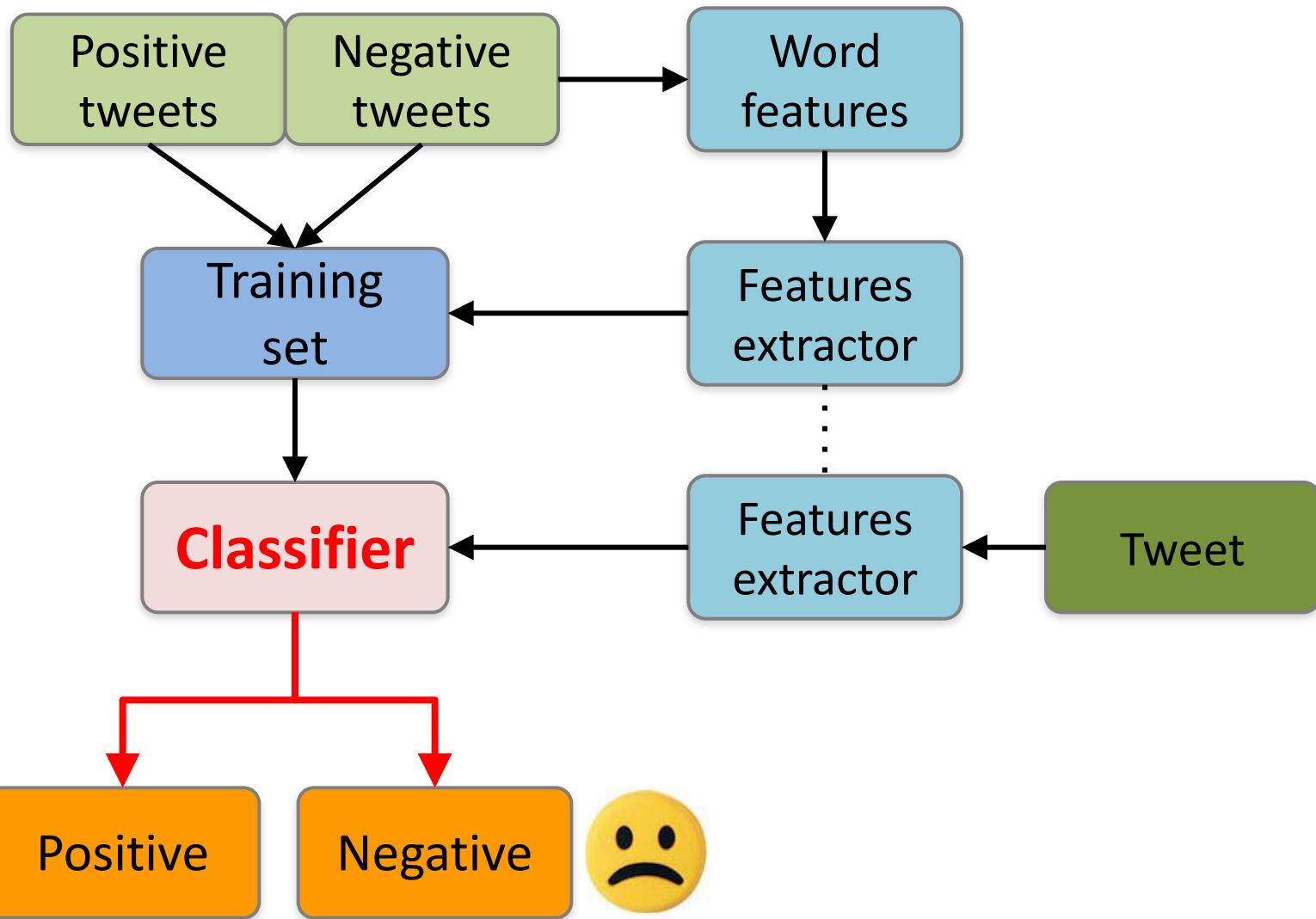
Opinion words in Sentiment classification

- topic-based classification
 - topic-related words are important
 - e.g., *politics, sciences, sports*
- Sentiment classification
 - topic-related words are unimportant
 - **opinion words** (also called **sentiment words**)
 - **that indicate positive or negative opinions** are important,
e.g., *great, excellent, amazing, horrible, bad, worst*

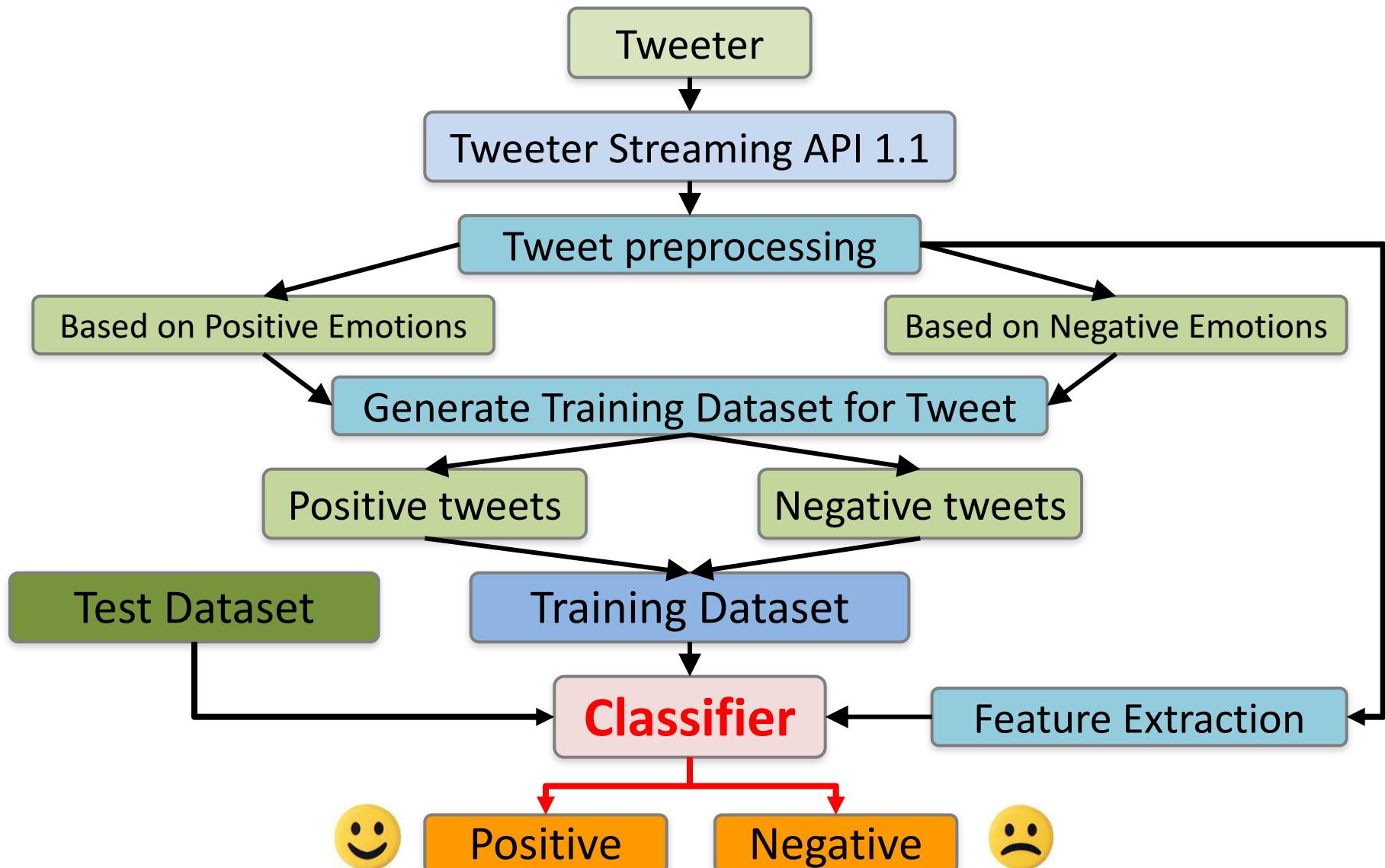
Features in Opinion Mining

- *Terms and their frequency*
 - *TF-IDF*
- *Part of speech (POS)*
 - Adjectives
- *Opinion words and phrases*
 - *beautiful, wonderful, good, and amazing* are *positive opinion words*
 - *bad, poor, and terrible* are *negative opinion words*.
 - opinion phrases and idioms,
e.g., *cost someone an arm and a leg*
- *Rules of opinions*
- *Negations*
- *Syntactic dependency*

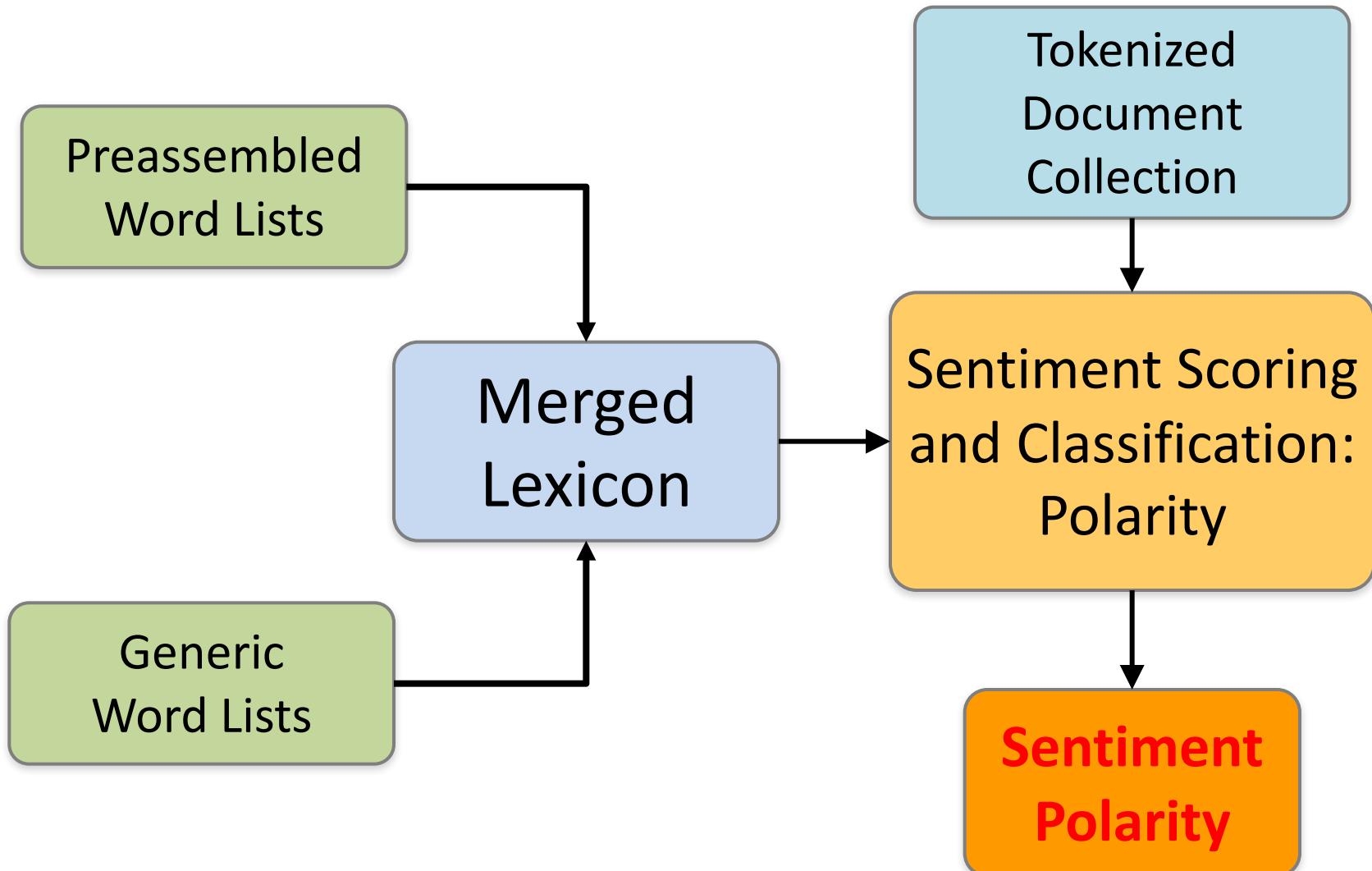
Sentiment Analysis Architecture



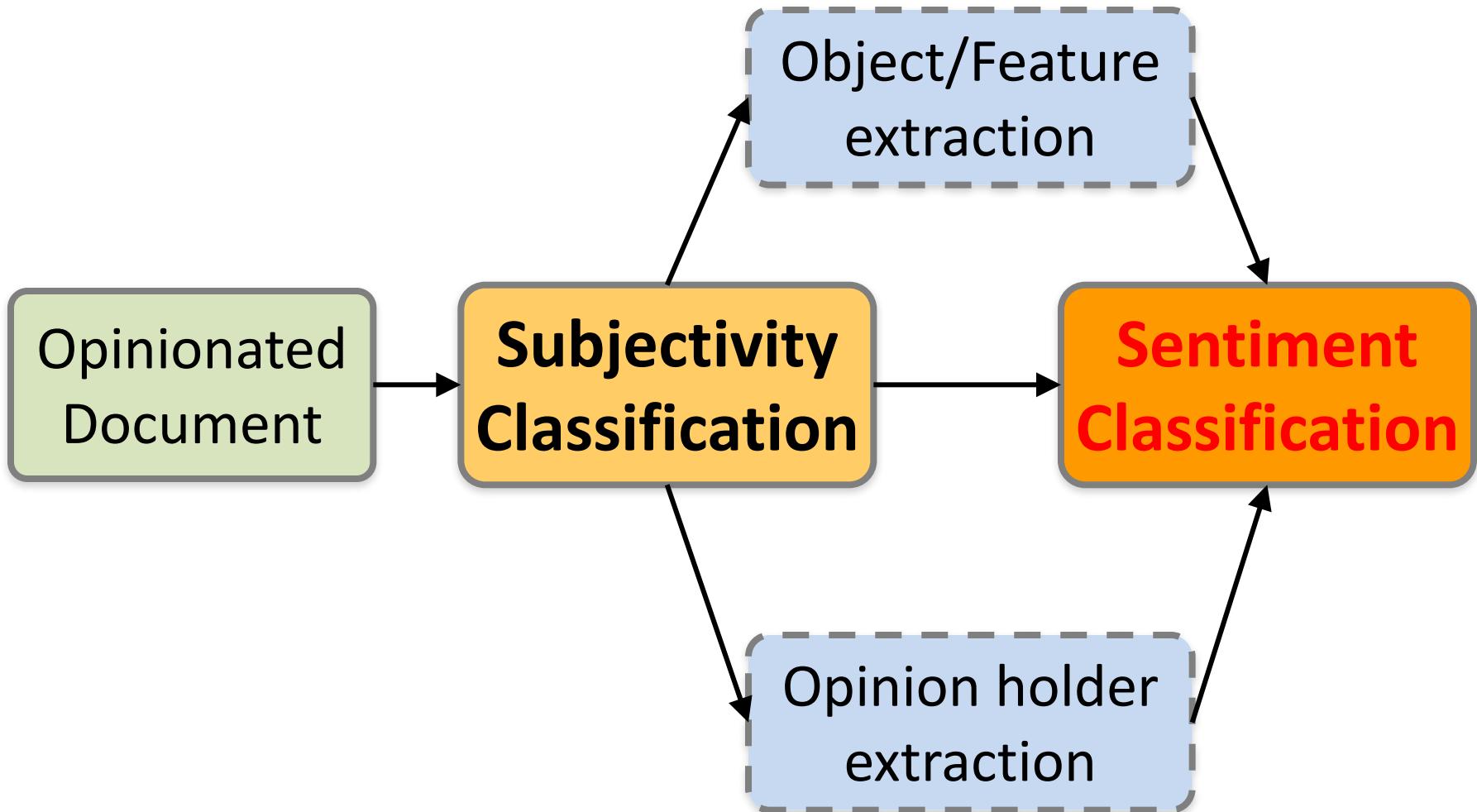
Sentiment Classification Based on Emoticons



Lexicon-Based Model



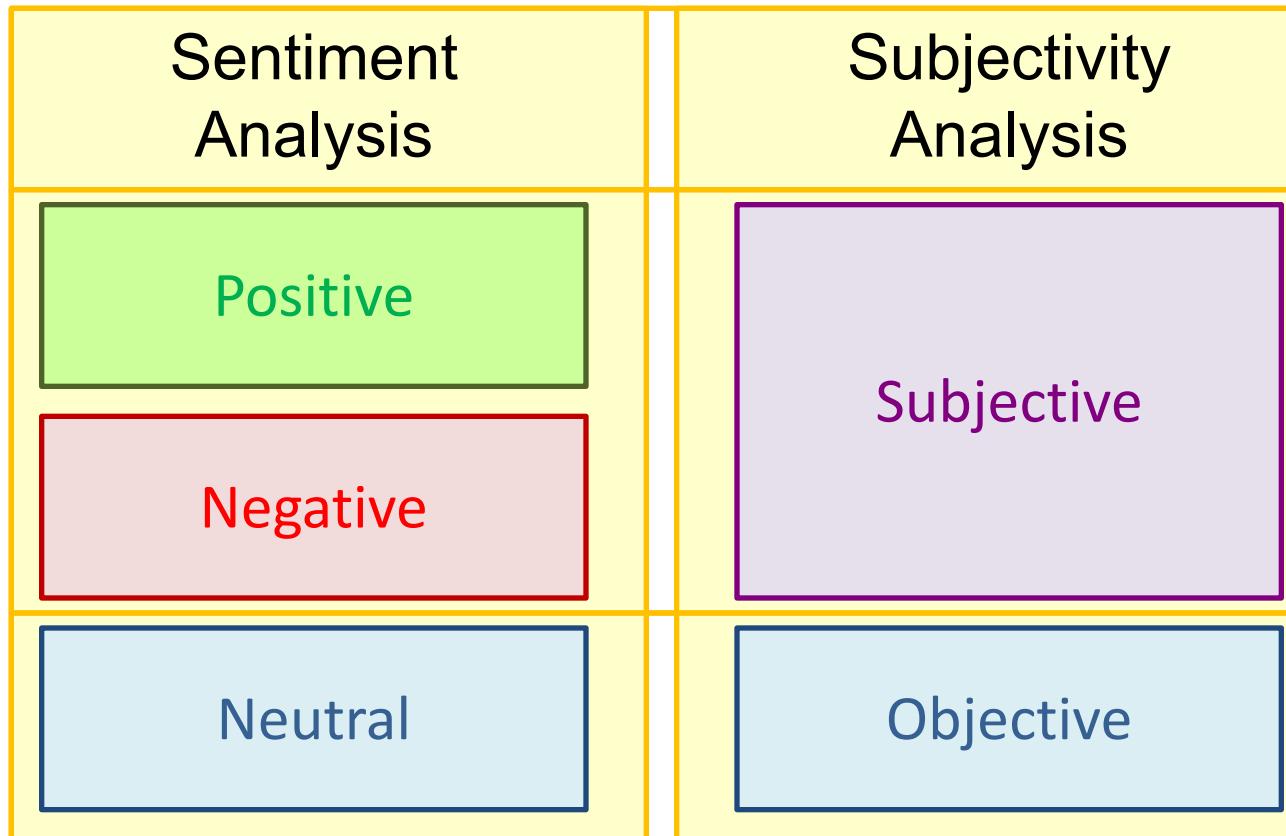
Sentiment Analysis Tasks



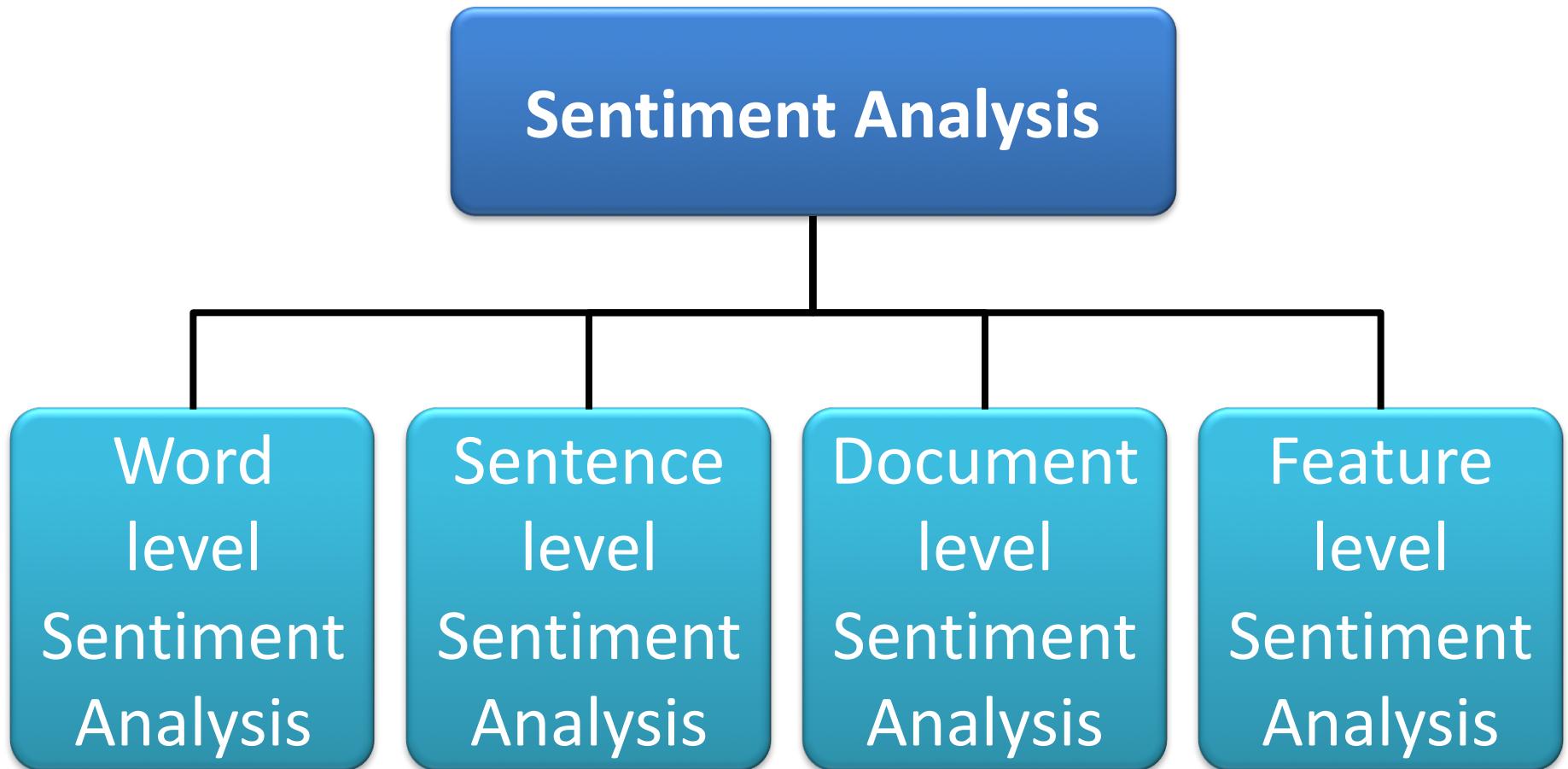
Sentiment Analysis

vs.

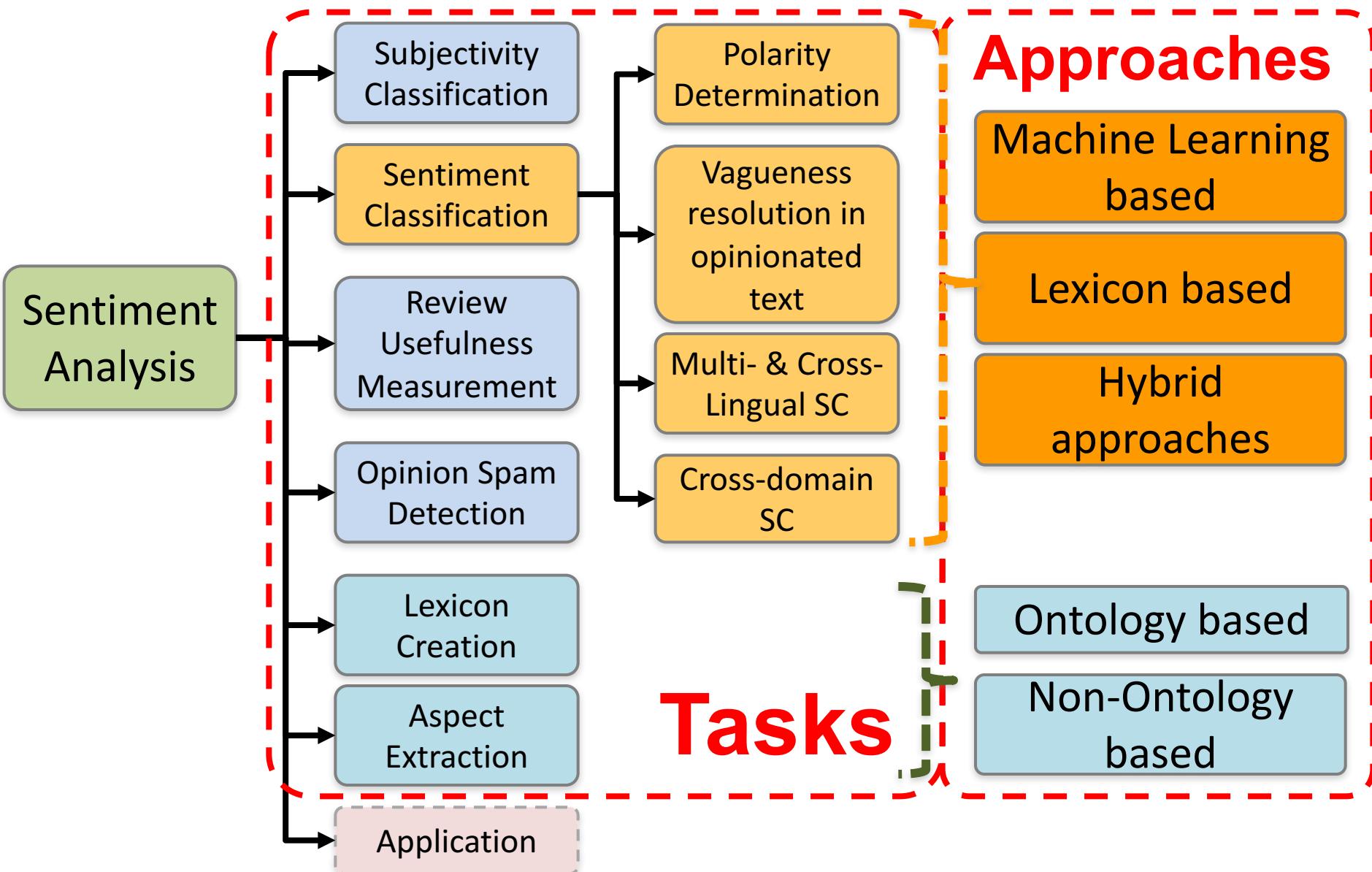
Subjectivity Analysis



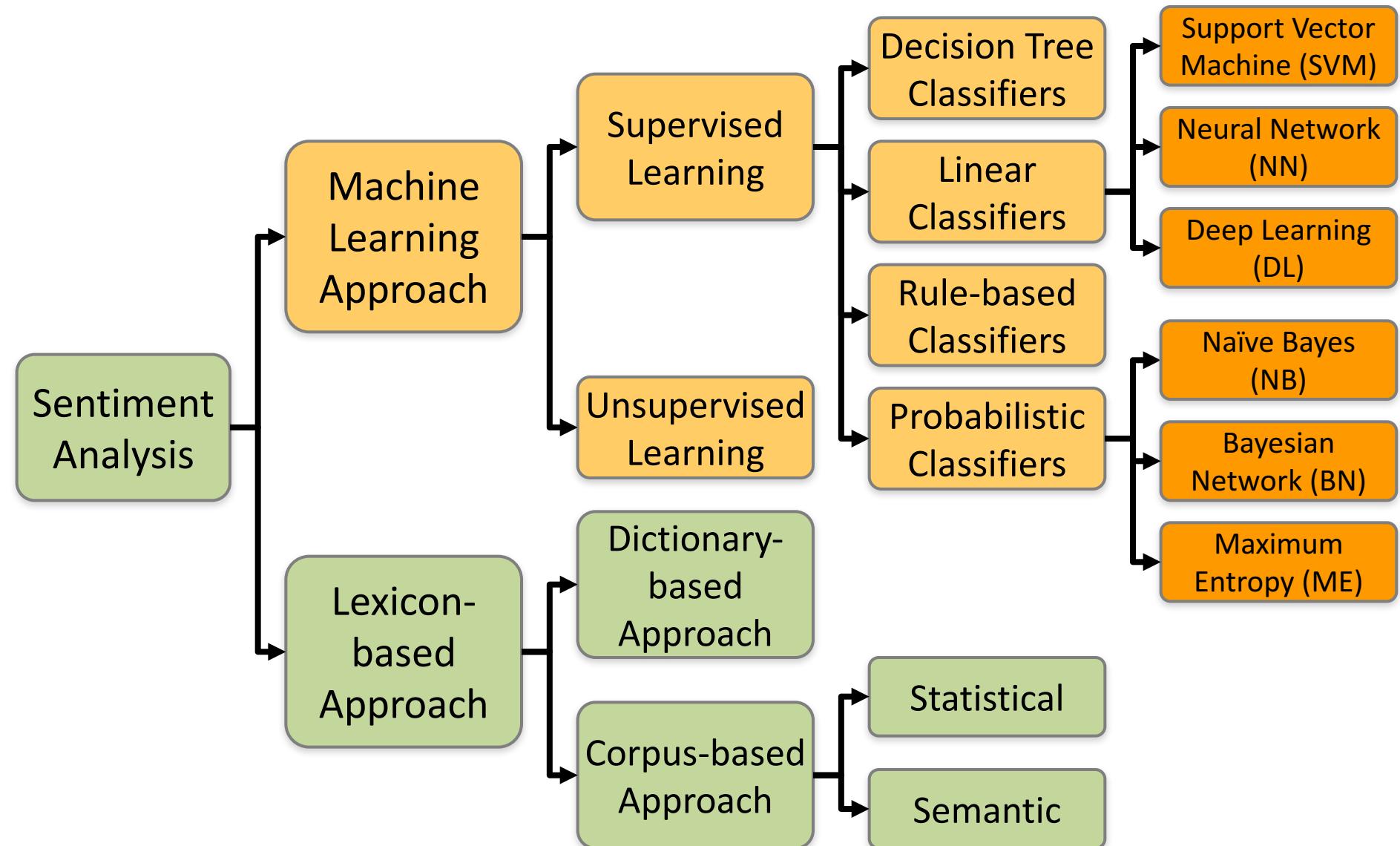
Levels of Sentiment Analysis



Sentiment Analysis



Sentiment Classification Techniques



A Brief Summary of Sentiment Analysis Methods

| Study | Analysis Task | Sentiment Identification | | Sentiment Aggregation | | Nature of Measure |
|-----------------------------------|---------------|-----------------------------------|----------|-----------------------|----------|-------------------|
| | | Method | Level | Method | Level | |
| Hu and Li, 2011 | Polarity | ML (Probabilistic model) | Snippet | | | Valence |
| Li and Wu, 2010 | Polarity | Lexicon/Rule | Phrase | Sum | Snippet | Valence |
| Thelwall et al., 2010 | Polarity | Lexicon/Rule | Sentence | Max & Min | Snippet | Range |
| Boiy and Moens, 2009 | Both | ML (Cascade ensemble) | Sentence | | | Valence |
| Chung 2009 | Polarity | Lexicon | Phrase | Average | Sentence | Valence |
| Wilson, Wiebe, and Hoffmann, 2009 | Both | ML (SVM, AdaBoost, Rule, etc.) | Phrase | | | Valence |
| Zhang et al., 2009 | Polarity | Lexicon/Rule | Sentence | Weighted average | Snippet | Valence |
| Abbasi, Chen, and Salem, 2008 | Polarity | ML (GA + feature selection) | Snippet | | | Valence |
| Subrahmanian and Reforgiato, 2008 | Polarity | Lexicon/Rule | Phrase | Rule | Snippet | Valence |
| Tan and Zhang 2008 | Polarity | ML (SVM, Winnow, NB, etc.) | Snippet | | | Valence |
| Airoldi, Bai, and Padman, 2007 | Polarity | ML (Markov Blanket) | Snippet | | | Valence |
| Das and Chen, 2007 | Polarity | ML (Bayesian, Discriminate, etc.) | Snippet | Average | Daily | Valence |
| Liu et al., 2007 | Polarity | ML (PLSA) | Snippet | | | Valence |
| Kennedy and Inkpen, 2006 | Polarity | Lexicon/Rule, ML (SVM) | Phrase | Count | Snippet | Valence |
| Mishne 2006 | Polarity | Lexicon | Phrase | Average | Snippet | Valence |
| Liu et al., 2005 | Polarity | Lexicon/Rule | Phrase | Distribution | Object | Range |
| Mishne 2005 | Polarity | ML (SVM) | Snippet | | | Valence |
| Popescu and Etzioni 2005 | Polarity | Lexicon/Rule | Phrase | | | Valence |
| Efron 2004 | Polarity | ML (SVN, NB) | Snippet | | | Valence |
| Wilson, Wiebe, and Hwa, 2004 | Both | ML (SVM, AdaBoost, Rule, etc.) | Sentence | | | Valence |
| Nigam and Hurst 2004 | Polarity | Lexicon/Rule | Chunk | Rule | Sentence | Valence |
| Dave, Lawrence, and Pennock, 2003 | Polarity | ML (SVM, Rainbow, etc.) | Snippet | | | Valence |
| Nasukawa and Yi 2003 | Polarity | Lexicon/Rule | Phrase | Rule | Sentence | Valence |
| Yi et al., 2003 | Polarity | Lexicon/Rule | Phrase | Rule | Sentence | Valence |
| Yu and Hatzivassiloglou 2003 | Both | ML (NB) + Lexicon/Rule | Phrase | Average | Sentence | Valence |
| Pang, Lee, and Vaithyanathan 2002 | Polarity | ML (SVM, MaxEnt, NB) | Snippet | | | Valence |
| Subasic and Huettner 2001 | Polarity | Lexicon/Fuzzy logic | Phrase | Average | Snippet | Valence |
| Turney 2001 | Polarity | Lexicon/Rule | Phrase | Average | Snippet | Valence |

(Both = Subjectivity and Polarity; ML= Machine Learning; Lexicon/Rule= Lexicon enhanced by linguistic rules)

Source: Zhang, Z., Li, X., and Chen, Y. (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.,

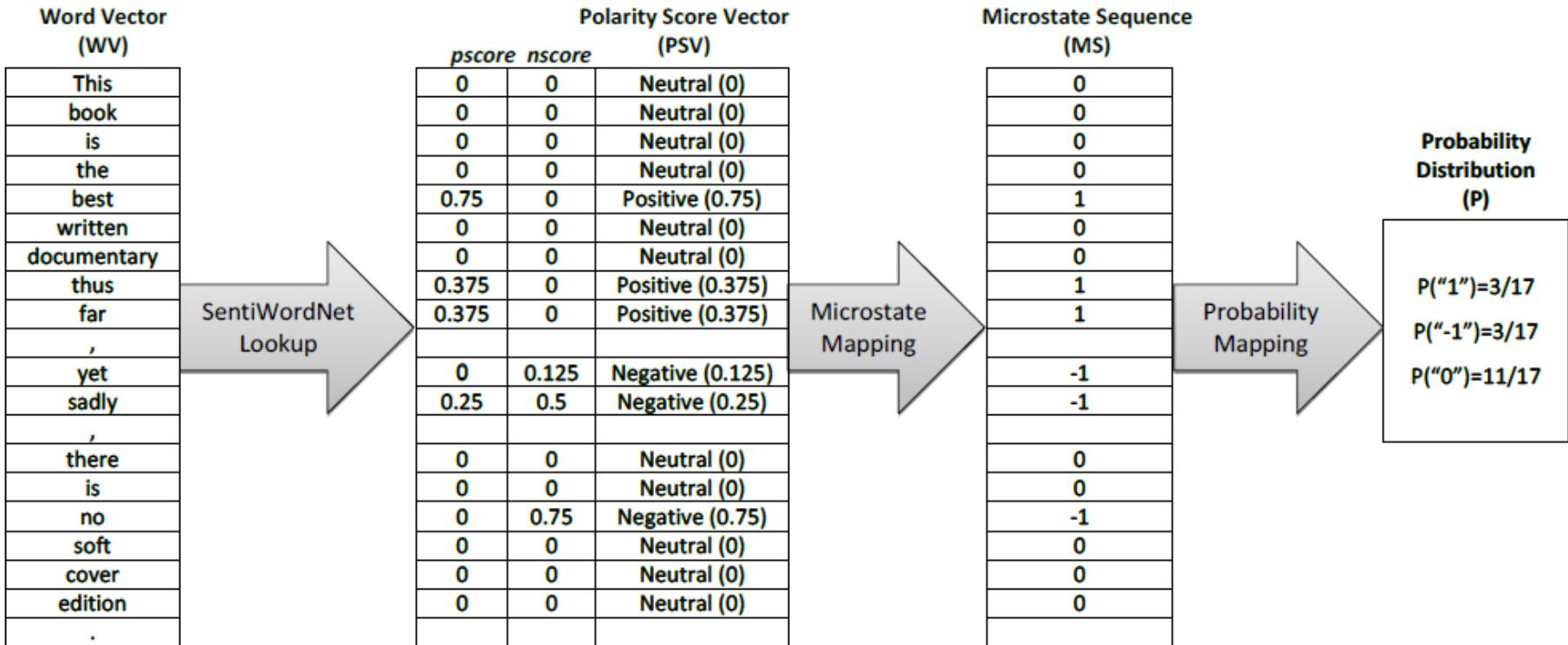
Word-of-Mouth (WOM)

- “This book is the best written documentary thus far, yet sadly, there is no soft cover edition.”
- “This book is the **best** written documentary thus far, **yet** sadly, there is **no** soft cover edition.”

| | Word | POS |
|-------------|-------------|-----|
| This | This | DT |
| book | book | NN |
| is | is | VBZ |
| the | the | DT |
| best | best | JJS |
| written | written | VBN |
| documentary | documentary | NN |
| thus | thus | RB |
| far | far | RB |
| , | , | , |
| yet | yet | RB |
| sadly | sadly | RB |
| , | , | , |
| there | there | EX |
| is | is | VBZ |
| no | no | DT |
| soft | soft | JJ |
| cover | cover | NN |
| edition | edition | NN |
| . | . | . |

Source: Zhang, Z., Li, X., and Chen, Y. (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.,

Conversion of text representation



Example of SentiWordNet

| POS | ID | PosScore | NegScore | SynsetTerms | Gloss |
|-----|----------|----------|----------|--|---|
| a | 00217728 | 0.75 | 0 | beautiful#1 | delighting the senses or exciting intellectual or emotional admiration; "a beautiful child"; "beautiful country"; "a beautiful painting"; "a beautiful theory"; "a beautiful party" |
| a | 00227507 | 0.75 | 0 | best#1 | (superlative of `good') having the most positive qualities; "the best film of the year"; "the best solution"; "the best time for planting"; "wore his best suit" |
| r | 00042614 | 0 | 0.625 | unhappily#2 sadly#1 | in an unfortunate way; "sadly he died before he could see his grandchild" |
| r | 00093270 | 0 | 0.875 | woefully#1 sadly#3 lamentably#1 deplorably#1 | in an unfortunate or deplorable manner; "he was sadly neglected"; "it was woefully inadequate" |
| r | 00404501 | 0 | 0.25 | sadly#2 | with sadness; in a sad manner; ``She died last night,' he said sadly" |



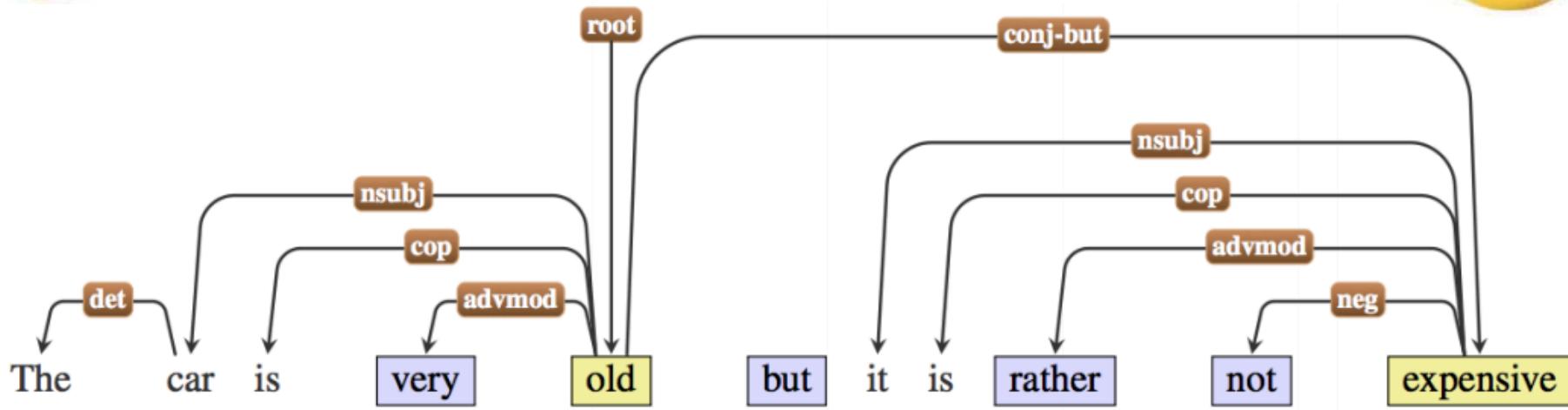
SenticNet

The car is very old but it is rather not expensive.

The car is very **old** but it is rather not **expensive**.

The car is very **old** but it is rather **not** **expensive**.

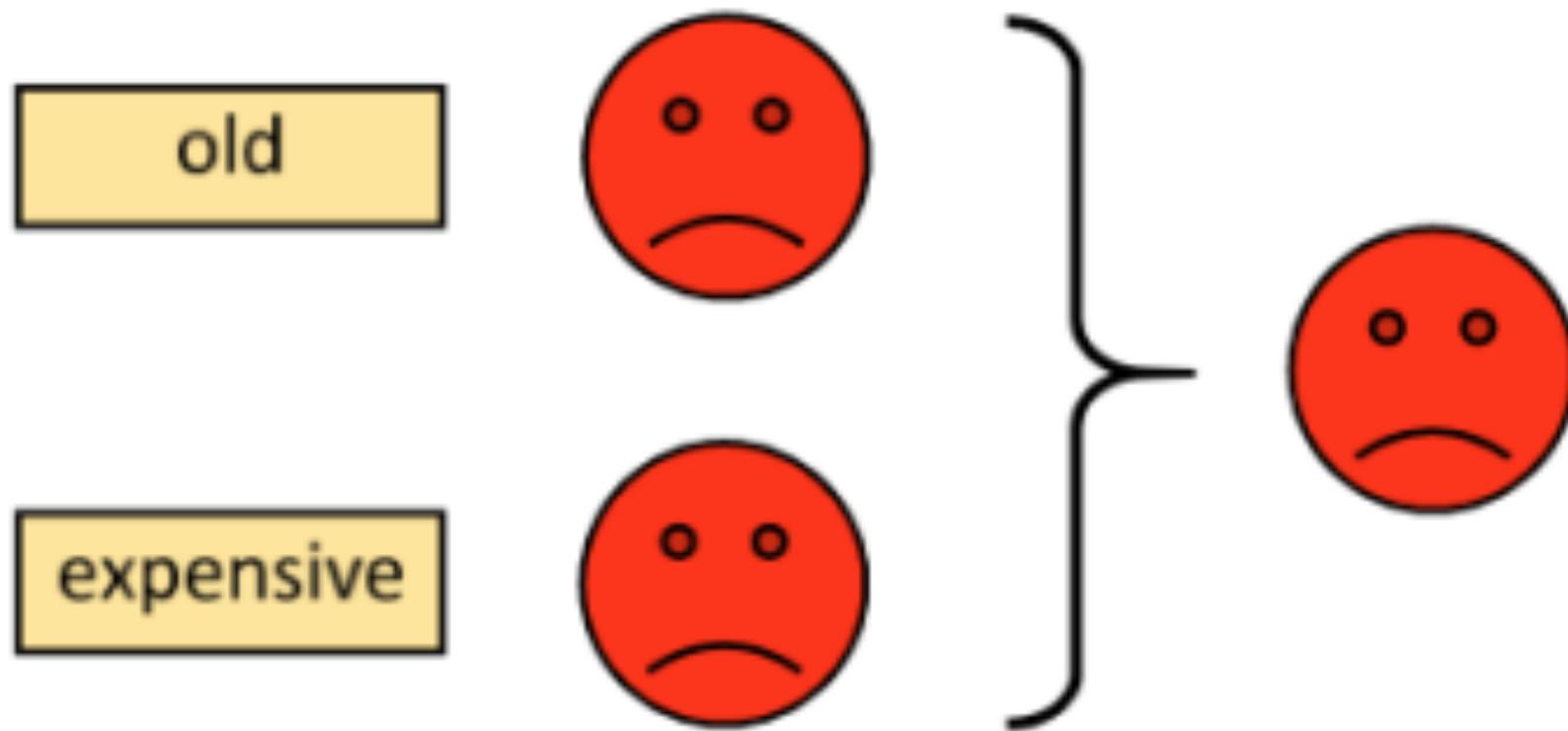
Polarity Detection with SenticNet



The car is **very old** but it is rather not **expensive**.

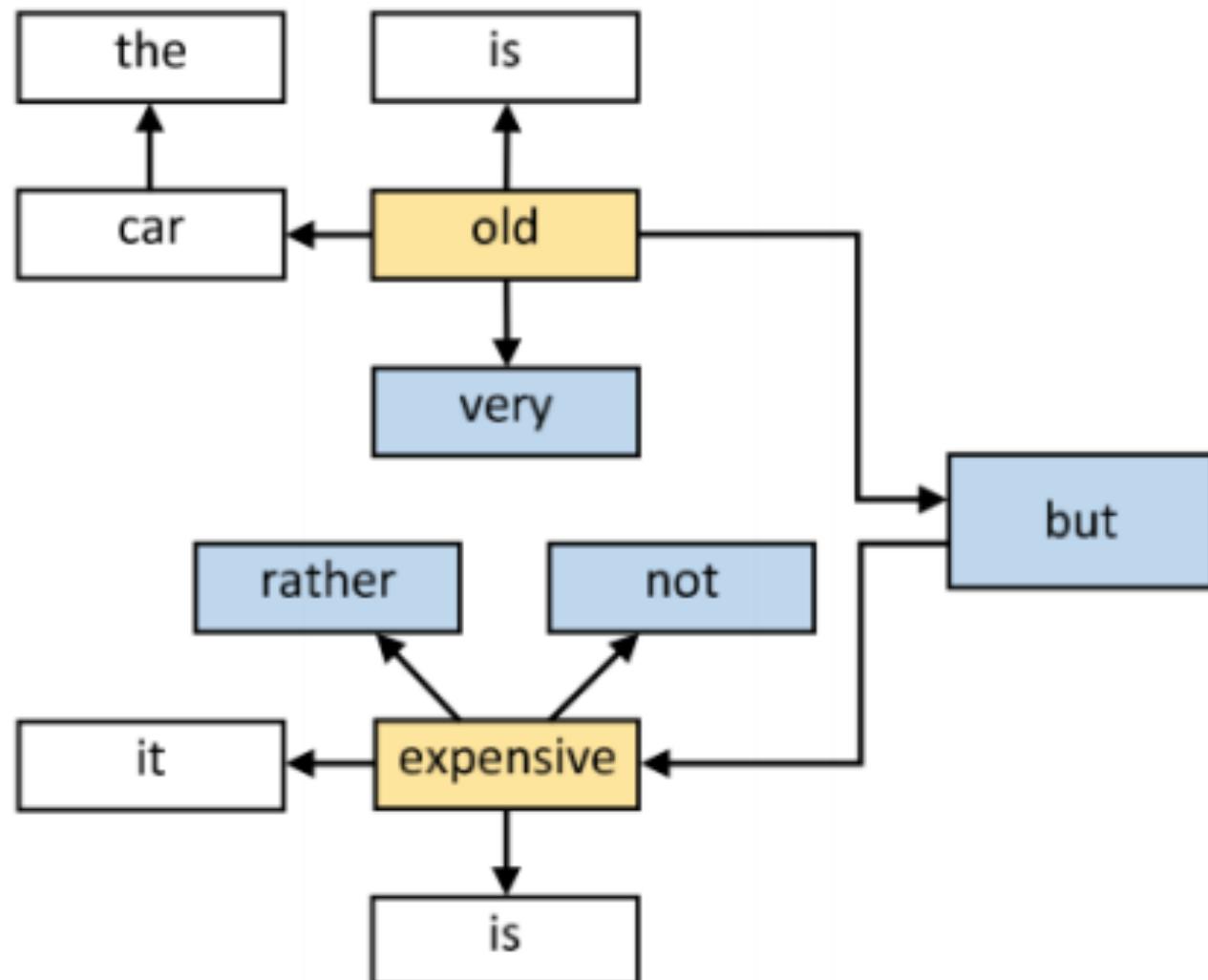
The car is very old but it is rather not **expensive**.

Polarity Detection with SenticNet



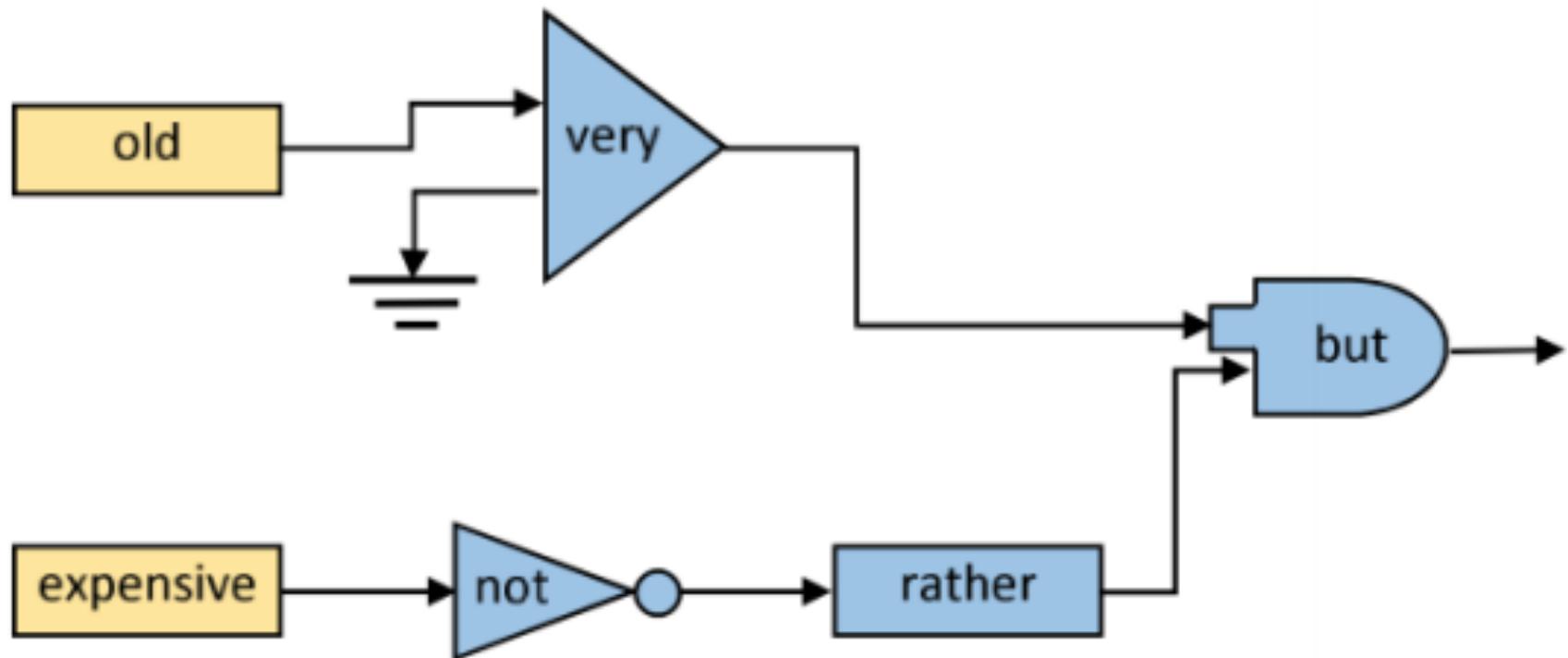
Source: Cambria, Erik, Soujanya Poria, Rajiv Bajpai, and Björn Schuller. "SenticNet 4: A semantic resource for sentiment analysis based on conceptual primitives." In *the 26th International Conference on Computational Linguistics (COLING)*, Osaka. 2016.

Polarity Detection with SenticNet



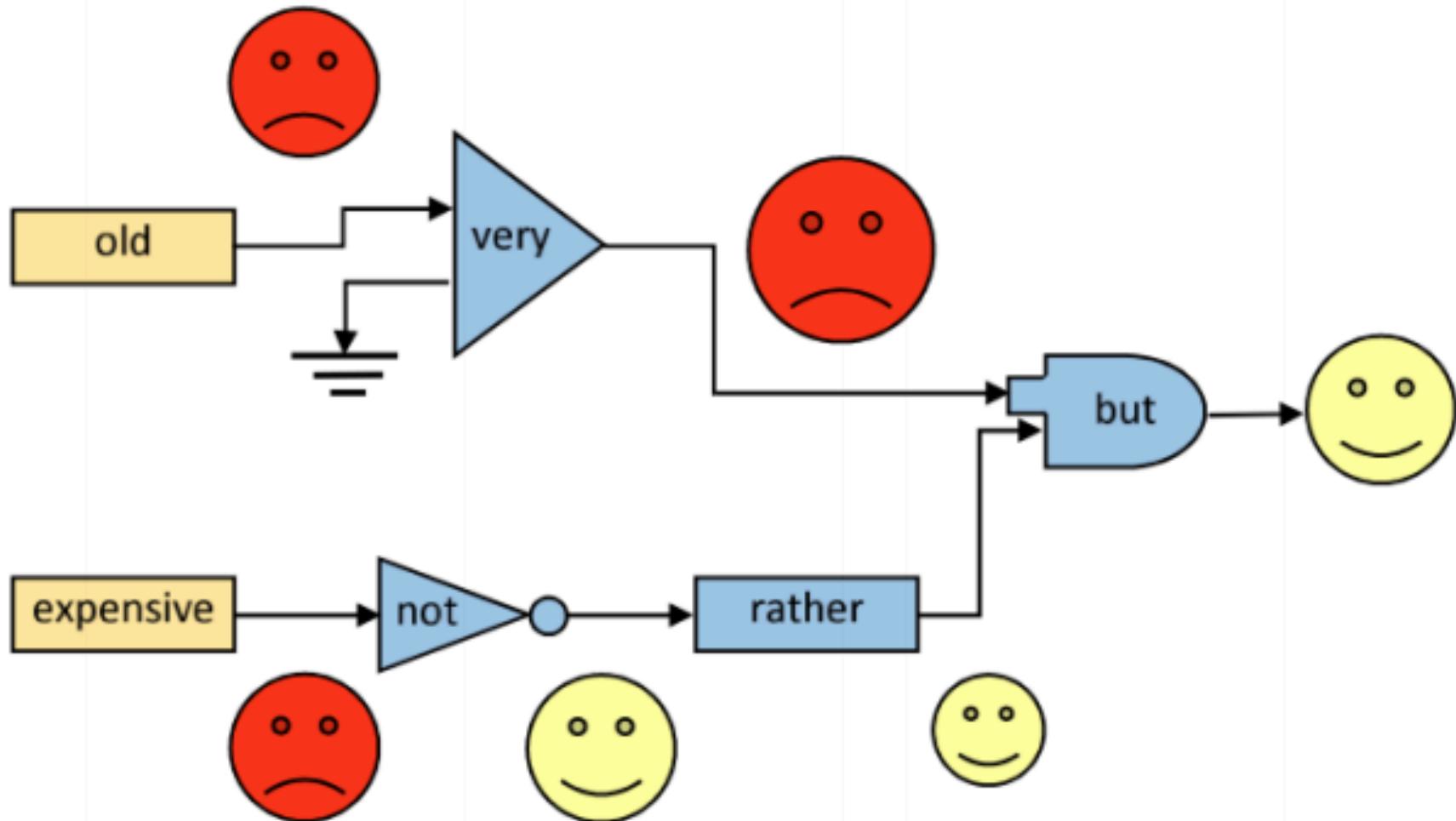
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Polarity Detection with SenticNet



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Evaluation of Text Mining and Sentiment Analysis

- Evaluation of Information Retrieval
- Evaluation of Classification Model (Prediction)
 - Accuracy
 - Precision
 - Recall
 - F-score

Deep Learning for Sentiment Analytics

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang,
Christopher D. Manning, Andrew Y. Ng and Christopher Potts

Stanford University, Stanford, CA 94305, USA

richard@socher.org, {aperelyg, jcchuang, ang}@cs.stanford.edu
{jeaneis, manning, cgpotts}@stanford.edu

Abstract

Semantic word spaces have been very useful but cannot express the meaning of longer phrases in a principled way. Further progress towards understanding compositionality in tasks such as sentiment detection requires richer supervised training and evaluation resources and more powerful models of composition. To remedy this, we introduce a Sentiment Treebank. It includes fine grained sentiment labels for 215,154 phrases in the parse trees of 11,855 sentences and presents new challenges for sentiment compositionality. To address them, we introduce the Recursive Neural Tensor Network. When trained on the new treebank, this model out-

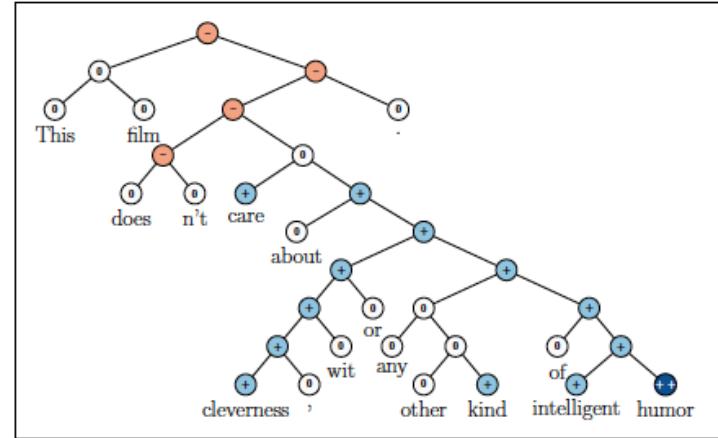
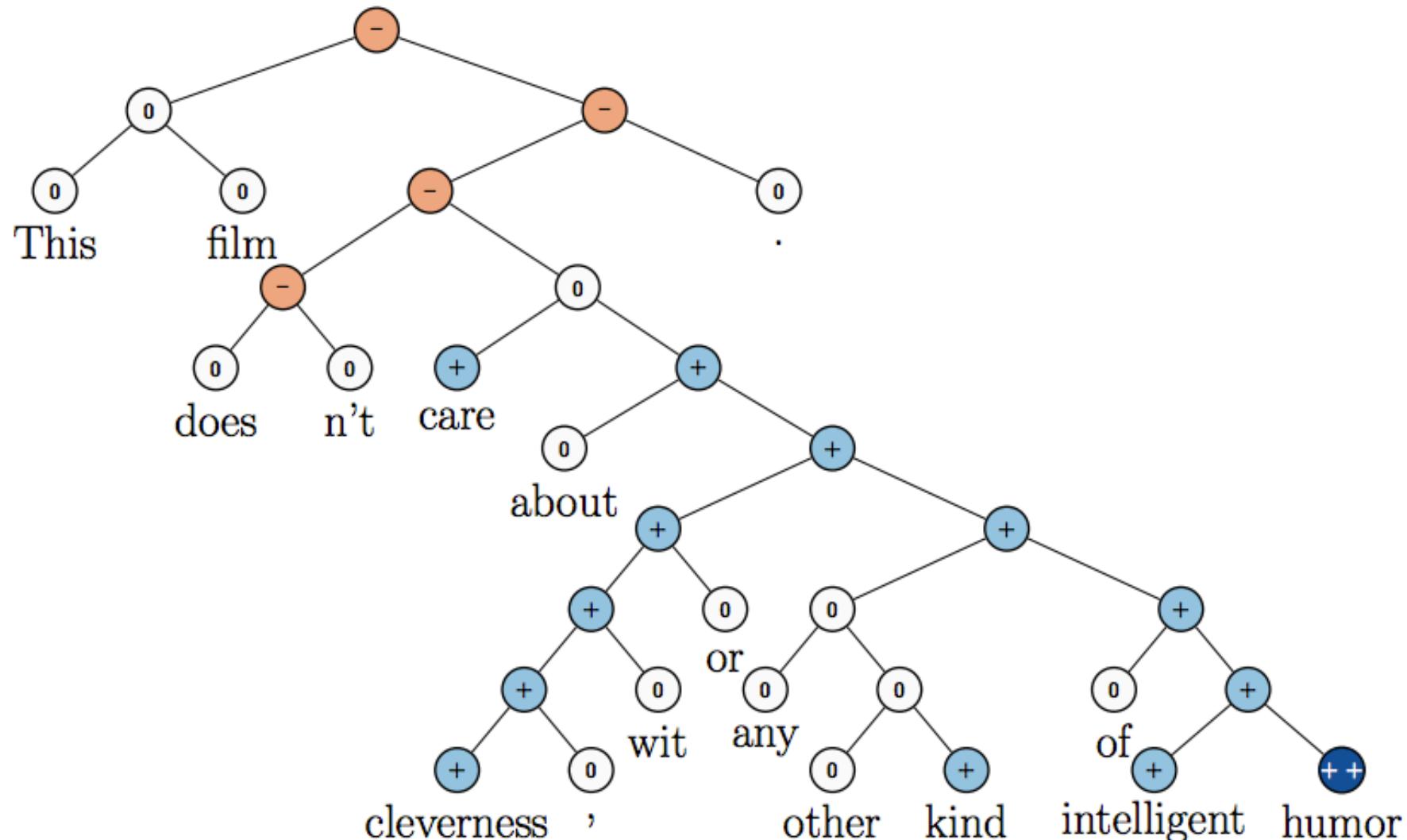


Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (−−, −, 0, +, ++), at every node of a parse tree and capturing the negation and its scope in this sentence.

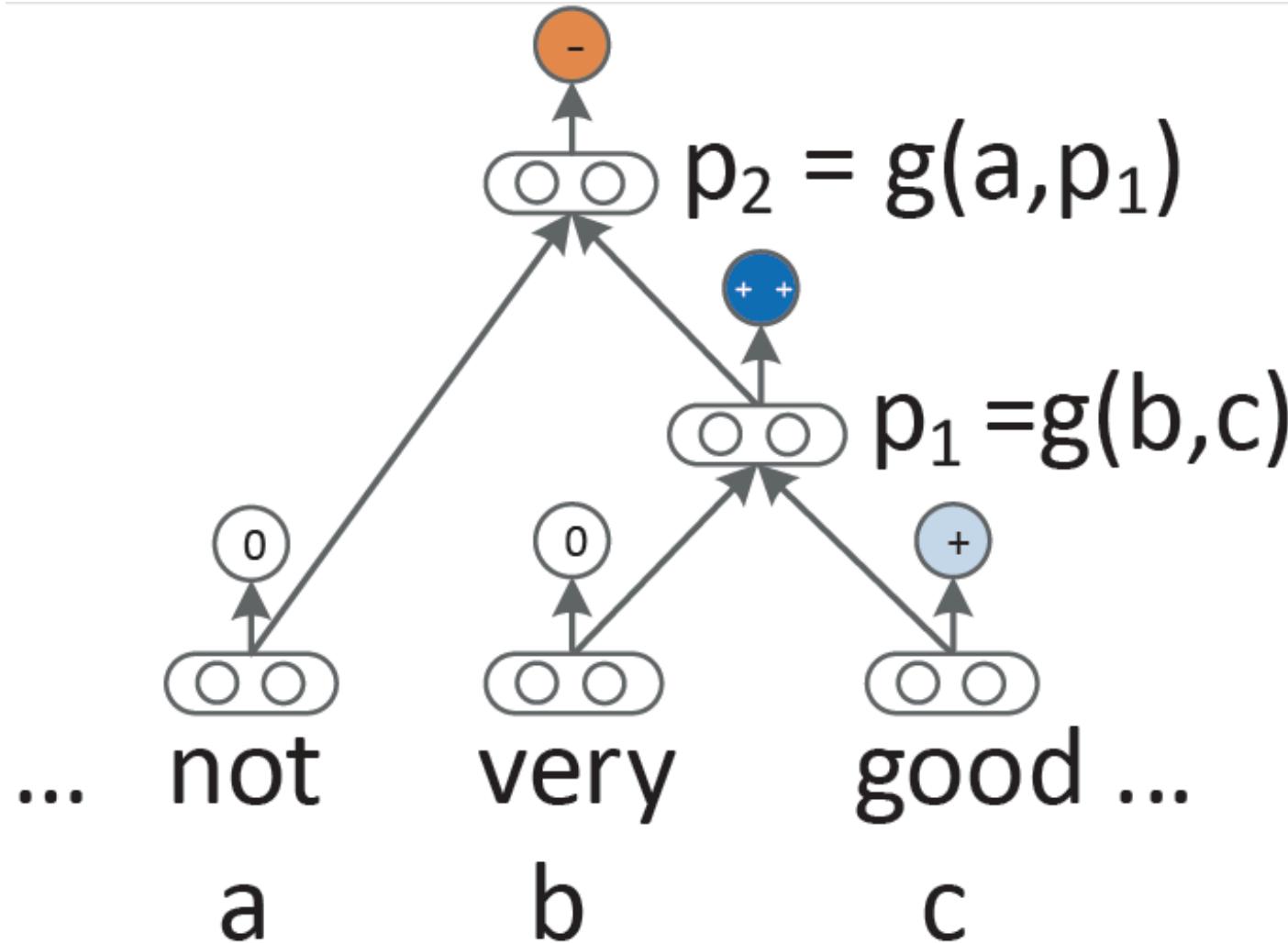
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Tensor Network (RNTN)



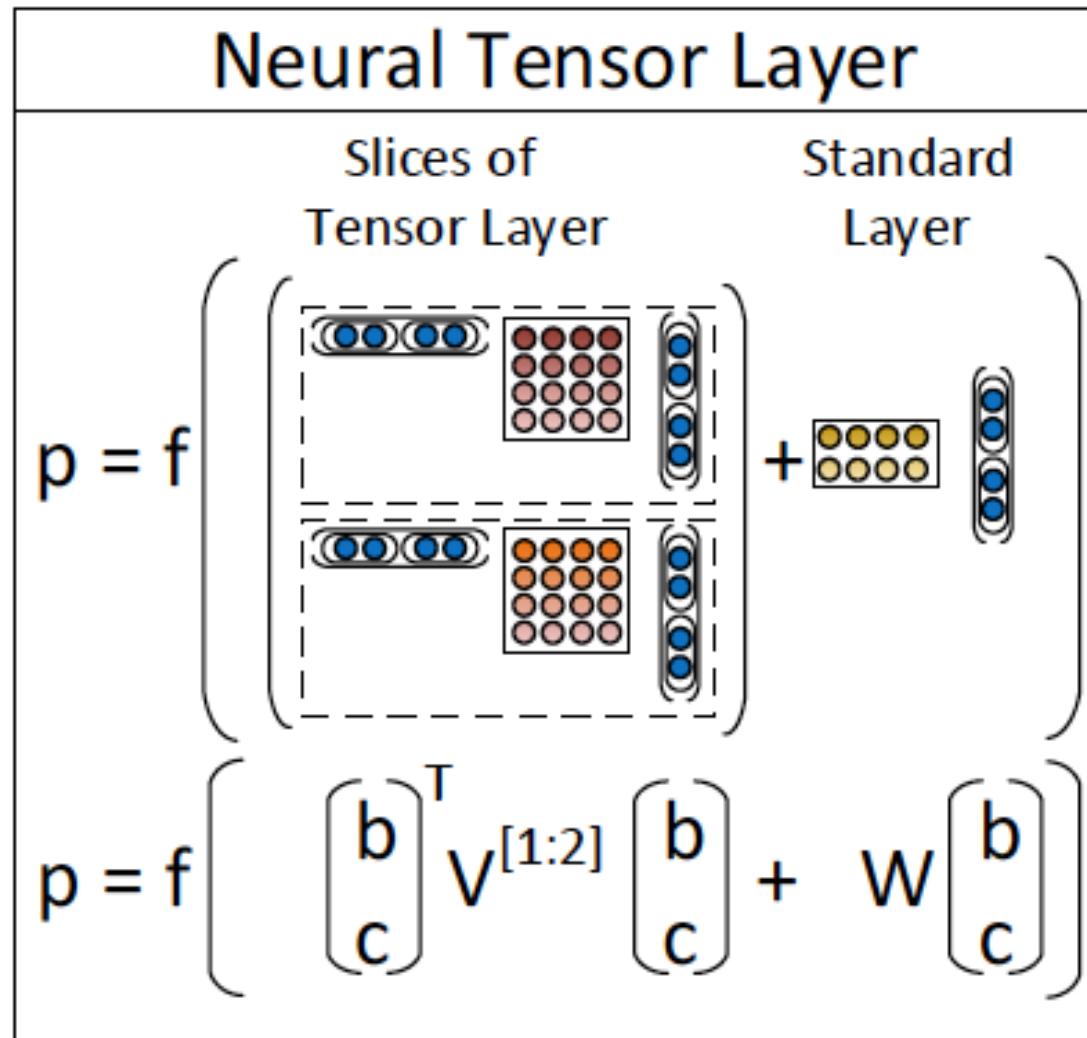
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Network (RNN) models for sentiment



Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Tensor Network (RNTN)

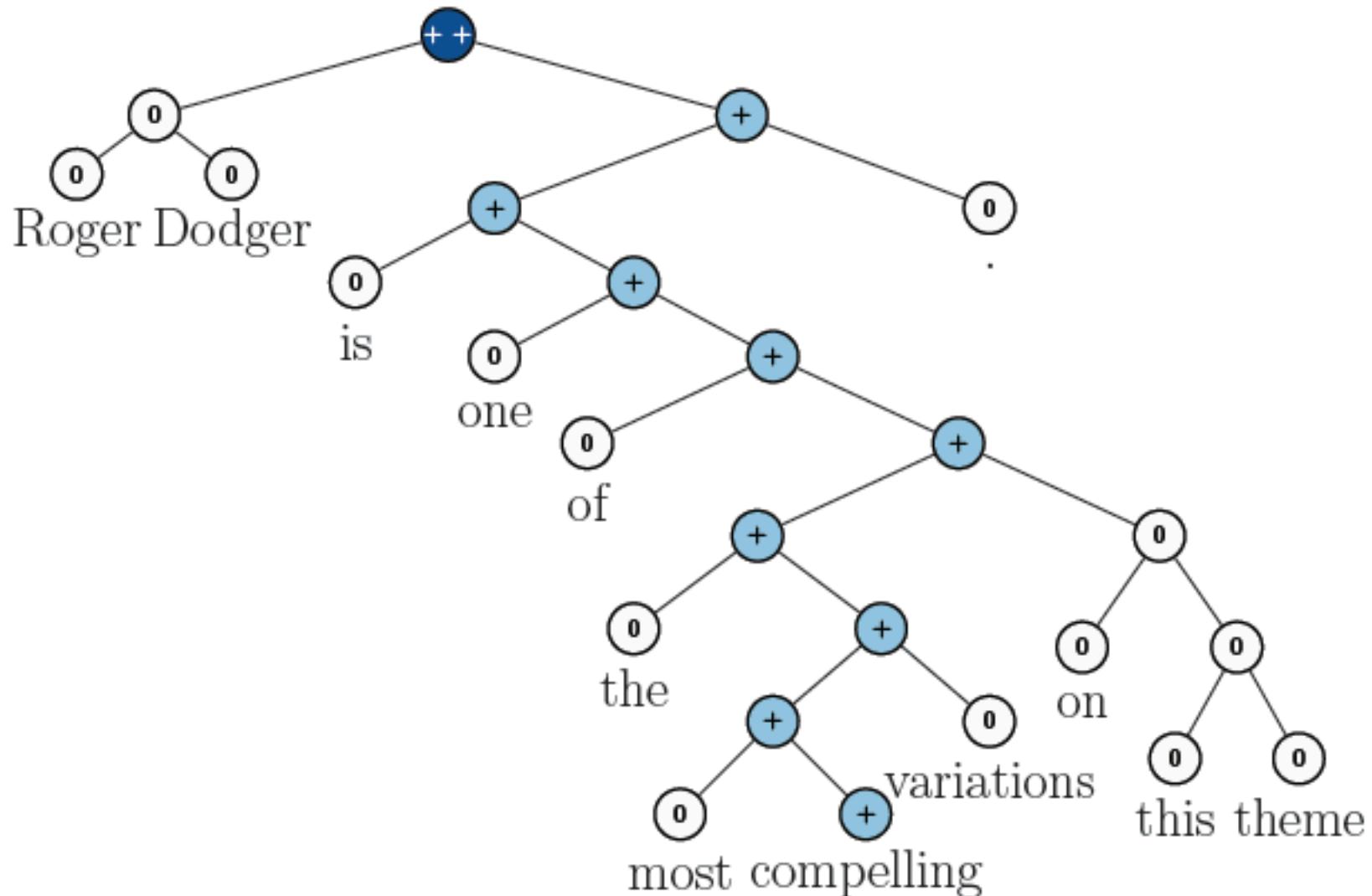


Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Roger Dodger is one of the **most** compelling variations on this theme.

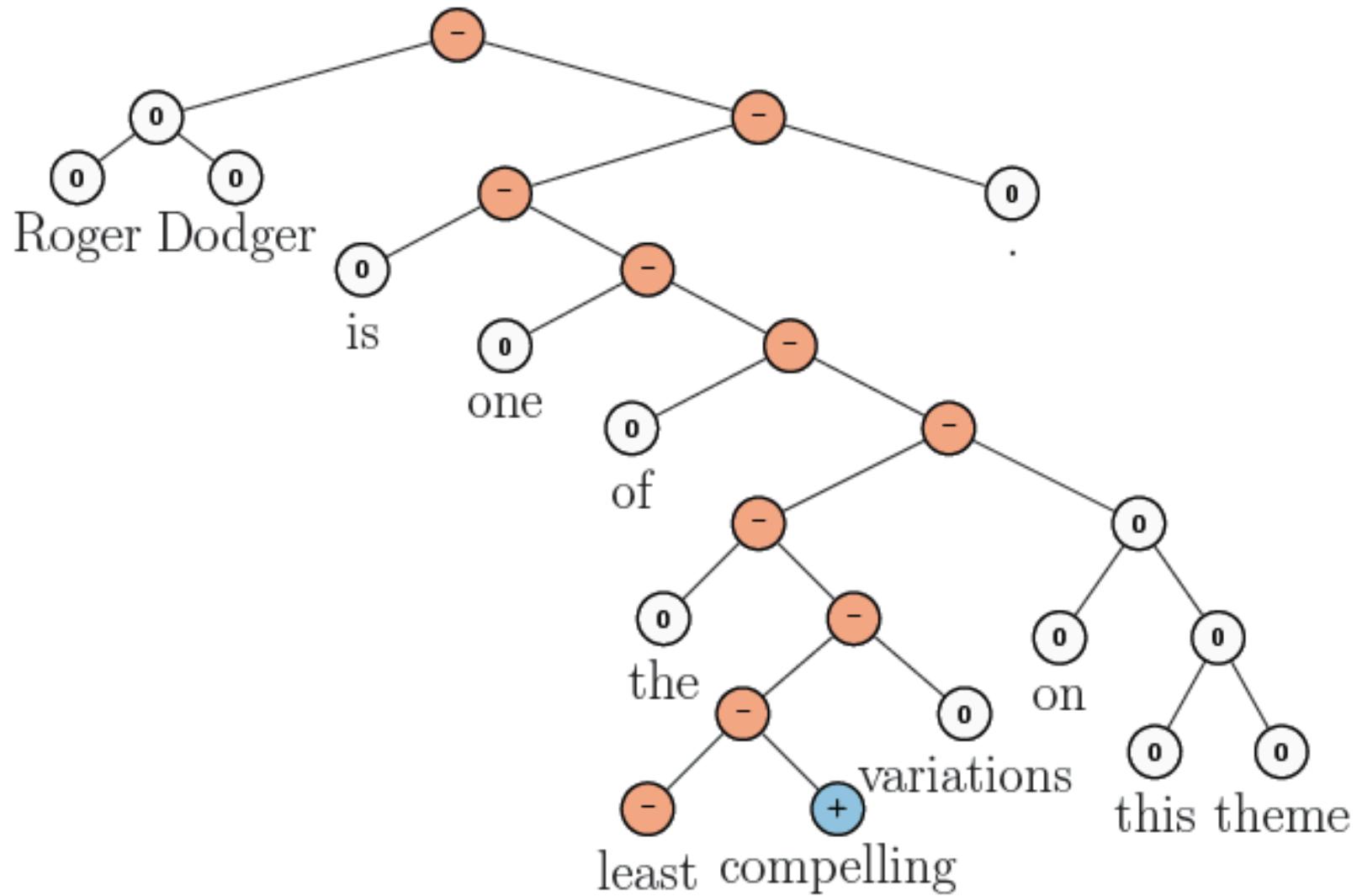
Roger Dodger is one of the **least** compelling variations on this theme.

RNTN for Sentiment Analysis



Roger Dodger is one of the **most** compelling variations on this theme.

RNTN for Sentiment Analysis



Roger Dodger is one of the **least** compelling variations on this theme.

Accuracy for fine grained (5-class) and binary predictions at the sentence level (root) and for all nodes

| Model | Fine-grained | | Positive/Negative | |
|--------|--------------|-------------|-------------------|-------------|
| | All | Root | All | Root |
| NB | 67.2 | 41.0 | 82.6 | 81.8 |
| SVM | 64.3 | 40.7 | 84.6 | 79.4 |
| BiNB | 71.0 | 41.9 | 82.7 | 83.1 |
| VecAvg | 73.3 | 32.7 | 85.1 | 80.1 |
| RNN | 79.0 | 43.2 | 86.1 | 82.4 |
| MV-RNN | 78.7 | 44.4 | 86.8 | 82.9 |
| RNTN | 80.7 | 45.7 | 87.6 | 85.4 |

Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Accuracy of negation detection

| Model | Accuracy | |
|--------|------------------|------------------|
| | Negated Positive | Negated Negative |
| biNB | 19.0 | 27.3 |
| RNN | 33.3 | 45.5 |
| MV-RNN | 52.4 | 54.6 |
| RNTN | 71.4 | 81.8 |

Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Deep Learning for Sentiment Analysis

CNN RNTN LSTM

| Model | Fine (5-class) | Binary |
|---|----------------|--------|
| DCNN (Blunsom, et al. 2014) | 0.485 | 0.868 |
| RNTN (Socher, et al. 2013) | 0.457 | 0.854 |
| CNN-non-static (Kim, 2014) | 0.480 | 0.872 |
| CNN-multi-channel (Kim, 2014) | 0.474 | 0.881 |
| DRNN w. pretrained word-embeddings (Irsoy and Cardie, 2014) | 0.498 | 0.866 |
| Paragraph Vector (Le and Mikolov. 2014) | 0.487 | 0.878 |
| Dependency Tree-LSTM (Tai, et al, 2015) | 0.484 | 0.857 |
| Constituency Tree-LSTM (Tai, et al, 2015) | 0.439 | 0.820 |
| Constituency Tree-LSTM (Glove vectors) (Tai, et al, 2015) | 0.510 | 0.880 |
| Paragraph Vector | 0.391 | 0.798 |
| LSTM | 0.456 | 0.843 |
| Deep Recursive-NN | 0.469 | 0.847 |

Performance Comparison of Sentiment Analysis Methods

| | Method | Data Set | Acc. | Author |
|------------------|-----------------|---------------------------------|-----------|----------------|
| Machine Learning | SVM | Movie reviews | 86.40% | Pang, Lee[23] |
| | CoTraining SVM | Twitter | 82.52% | Liu[14] |
| | Deep learning | Stanford Sentiment Treebank | 80.70% | Richard[18] |
| Lexical based | Corpus | Product reviews | 74.00% | Turkey |
| | Dictionary | Amazon's Mechanical Turk | --- | Taboada[20] |
| Cross-lingual | Ensemble | Amazon | 81.00% | Wan,X[16] |
| | Co-Train | Amazon, ITI68 | 81.30% | Wan,X.[16] |
| | EWGA | IMDb movie review | >90% | Abbasi,A. |
| | CLMM | MPQA, NTCIR, ISI | 83.02% | Mengi |
| Cross-domain | Active Learning | Book, DVD, Electronics, Kitchen | 80% (avg) | Li, S |
| | Thesaurus | | | Bollegrala[22] |
| | SFA | | | Pan S J[15] |

Social Media Monitoring/Analysis

Existing Tools

("Social Media Monitoring/Analysis")

- Radian 6
- Social Mention
- Overtone OpenMic
- Microsoft Dynamics Social Networking Accelerator
- SAS Social Media Analytics
- Lithium Social Media Monitoring
- RightNow Cloud Monitor

Word-of-mouth

Voice of the Customer

- 1. Attensity
 - Track social sentiment across brands and competitors
 - <http://www.attensity.com/home/>
- 2. Clarabridge
 - Sentiment and Text Analytics Software
 - <http://www.clarabridge.com/>

Attensity: Track social sentiment across brands and competitors

<http://www.attensity.com/>

The screenshot shows the Attensity Home Page. At the top, there's a navigation bar with links for "Select your language" (set to English), "Contact", "Resources", "Support", "Blog", and a search bar. Below the navigation is a main menu with "Products", "Solutions", "Services", "Customers", and "Partners". On the left, a sidebar lists "Social Analytics", "Social Response", "Customer Analytics", "Industry Solutions", and "Why Attensity". The central area features a large banner with the text "Your real-time window into the social web." and a quote from Yahoo!: "Teaming with a leading analytics provider like Attensity offers Yahoo! a great opportunity to deliver the key news and analysis that matter." Below the banner is a green "Learn More" button. To the right of the banner, there are several screenshots of Attensity's software interface, including a dashboard with a circular gauge and various charts, and a "ATTENSITY RESPOND" module showing social media mentions and metrics. At the bottom, there are sections for "About Attensity" (describing Attensity as the leading provider of social analytics and engagement solutions) and "Watch Video" (linking to a Command Center Video). The footer includes links for "Attensity for Marketing", "Attensity for Customer Service", and "Attensity for IT".

<http://www.youtube.com/watch?v=4goxmBEg2lw#>

Clarabridge: Sentiment and Text Analytics Software

<http://www.clarabridge.com/>

The screenshot shows the homepage of the Clarabridge website. At the top, there's a navigation bar with links for Home, About Us, News & Events, Blog, Login, and Contact Us. Below the navigation is a main banner with the text "The First Sentiment and Text Analytics Solution Built Specifically for Business." A central paragraph states: "The Clarabridge sentiment and text analytics software provides enterprises with a universal view of their customers." To the right of this text is a link "Learn more about how Clarabridge works >". Below the banner, there's a section titled "Customers" featuring logos for Nissan, Best Buy, Marriott, Sage, H&R Block, Choice Hotels International, Wendy's, Lord Hotels, AT&T, and Dell. There are also three call-to-action buttons: "Clarabridge Text Analytics", "Choose Your Edition", and "Clarabridge Webinar". The "Clarabridge Webinar" button includes the text "Hypatia Research Group presents on Social".

<http://www.youtube.com/watch?v=IDHudt8M9P0>

<http://www.radian6.com/>

The screenshot shows the Radian6 website homepage. At the top, there's a navigation bar with links for "Country", "1 888 672 3426", "About Radian6", "Contact", "CUSTOMER LOGIN", "Search", and "GO". Below the navigation is a main banner featuring a cartoon illustration of a man sitting in an orange armchair, looking at a tablet. The text in the banner reads "The Social Enterprise. Get closer to your customer. Learn how >". To the right of the banner are several call-to-action buttons: "Have Us Contact You" (orange), "Live Demo" (green), "Free Trial" (blue), and "Chat & find out more." (green). On the far right, there's a sidebar with social media icons for Facebook, Twitter, YouTube, Google+, and LinkedIn, along with a "radian6 Community" link. The main content area below the banner contains four sections: "Sales" (The social web is a goldmine of untapped sales opportunities. Let us help you realize your potential. [Learn more >](#)), "Marketing" (Brands are now the sum of the conversations about them. We can help you hear what's being said. [Learn more >](#)), "Customer Service" (Take your customer service where your consumers are gathering. Respond to issues voiced on the social web. [Learn more >](#)), and "Newsletter" (Sign up and get the regular Radian6 goods. [Enter email address GO](#)). At the bottom, there's a footer with links for "JUST Get the Skinny", "WEBINAR / June 7th at 2pm est", "CASE STUDY", and "Mashable named Radian6's Co-founder Chris Ramsey one of five masterminds redefining social media".

http://www.youtube.com/watch?feature=player_embedded&v=8i6Exg3Urg0

Social Media Monitoring x

www.sas.com/software/customer-intelligence/social-media-analytics/

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SEARCH

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PRODUCTS & SOLUTIONS / SOCIAL MEDIA ANALYTICS

Products and Solutions

- Industries
- Small and Midsize Business
- Nonprofit Organizations
- Analytics
- Business Analytics
- Business Intelligence
- Customer Intelligence
 - ↳ Strategy & Planning
 - ↳ Information & Analytics
 - ↳ Orchestration & Interaction
 - ↳ Customer Experience
 - Customer Experience Analytics
 - Social Media Analytics
 - Web Analytics
- Financial Intelligence
- Foundation Tools
- Fraud & Financial Crimes
- Governance, Risk & Compliance
- High-Performance Analytics
- Human Capital Intelligence
- Information Management
- IT & CIO Enablement

SAS® Social Media Analytics

Integrate, archive, analyze and act on online conversations

Overview Benefits Features Demos & Screenshots System Requirements

SAS Social Media Analytics is an enterprise-hosted, on-demand solution that integrates, archives, analyzes and enables organizations to act on intelligence gleaned from online conversations on professional and consumer-generated media sites. It enables you to attribute online conversations to specific parts of your business, allowing accelerated responses to marketplace shifts.

Based on your unique business challenges and enterprise goals, SAS can provide a tailored implementation that's hosted and managed by [SAS Solutions OnDemand](#).

Benefits

- Analyze conversation data.
- Identify advocates of, and threats to, corporate reputation and brand.
- Quantify interaction among traditional media/campaigns and social media activity.
- Establish a platform for social CRM strategy.

Product Demo

“ The great thing about SAS is that it's so powerful and has such a broad offering. ”

—Jonathan Prantner
Manager of Statistics
Organic

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Questions?

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White Paper

Text Analytics for Social Media: Evolving Tools for an Evolving Environment

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RESOURCES

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» Solution Brief (PDF)

» White Papers

What do tweeples think about iPhone4s

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iPhone4s

Search

Try some Twitter trends: [Tomorrow is June](#) [H&M Defense of Marriage Act](#) [Diddy's Bloomberg](#) [UCLA](#) [ESPN](#)

 40  41 = 51%

Those are all the results available right now. Try again or try another term to see how people feel towards it.
Got questions? [Read our FAQ](#).

RT @jigglinjello: This 12 year old has an iPhone4s wtf

So my 9 year old little sister has a iPhone4s . Wtf bruh?!

This 12 year old has an iPhone4s wtf

So my sister has a android and i dont even have a phone and she gets a brand new iPhone4s -___- #Wtf

iPhone4s is funny ass a bitch

-Ohwell .. a new iPhone4s won't hurt , aha.

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OpView

<http://www.opview.com.tw/>



OpView 介紹 ▾ 產業應用 ▾ 新聞與活動 分析報告 資源與課程 ▾ 聯絡資訊



社群大數據
觀測 · 分析 · 探索 · 預警



FOCUS

i-Buzz
VOC口碑分析平台
自動化海量資料分析
迅速掌握網路口碑動態



母親節好禮大比拼 聽聽網友怎麼說

這個周末就是母親節了，大家有想好要如何慶祝了嗎？吃大餐、送好禮已成了節慶的基本盤，再加上百貨針對母親節紛紛推出特賣優惠，不僅讓孝子孝女省下荷包，也讓平常有在觀望檔期活動的網友殺紅了眼，更增添了其口碑豐富性...

i-Buzz
專業口碑客服團隊

公關危機處理，扭轉話題關鍵
提供具有科學性的策略方針



熱門文章



iPhone 6S
唯一不同，就是一切都不一樣。

Resources of Opinion Mining

Datasets of Opinion Mining

- Blog06
 - 25GB TREC test collection
 - <http://ir.dcs.gla.ac.uk/test collections/access to data.html>
- Cornell movie-review datasets
 - <http://www.cs.cornell.edu/people/pabo/movie-review-data/>
- Customer review datasets
 - <http://www.cs.uic.edu/~liub/FBS/CustomerReviewData.zip>
- Multiple-aspect restaurant reviews
 - <http://people.csail.mit.edu/bsnyder/naacl07>
- NTCIR multilingual corpus
 - NTCIR Multilingual Opinion-Analysis Task (MOAT)

Lexical Resources of Opinion Mining

- SentiWordnet
 - <http://sentiwordnet.isti.cnr.it/>
- General Inquirer
 - <http://www.wjh.harvard.edu/~inquirer/>
- OpinionFinder's Subjectivity Lexicon
 - <http://www.cs.pitt.edu/mpqa/>
- NTU Sentiment Dictionary (NTUSD)
 - <http://nlg18.csie.ntu.edu.tw:8080/opinion/>
- Hownet Sentiment
 - http://www.keenage.com/html/c_bulletin_2007.htm

Example of SentiWordNet

| POS | ID | PosScore | NegScore | SynsetTerms | Gloss |
|-----|----------|----------|----------|--|---|
| a | 00217728 | 0.75 | 0 | beautiful#1 | delighting the senses or exciting intellectual or emotional admiration; "a beautiful child"; "beautiful country"; "a beautiful painting"; "a beautiful theory"; "a beautiful party" |
| a | 00227507 | 0.75 | 0 | best#1 | (superlative of `good') having the most positive qualities; "the best film of the year"; "the best solution"; "the best time for planting"; "wore his best suit" |
| r | 00042614 | 0 | 0.625 | unhappily#2 sadly#1 | in an unfortunate way; "sadly he died before he could see his grandchild" |
| r | 00093270 | 0 | 0.875 | woefully#1 sadly#3 lamentably#1 deplorably#1 | in an unfortunate or deplorable manner; "he was sadly neglected"; "it was woefully inadequate" |
| r | 00404501 | 0 | 0.25 | sadly#2 | with sadness; in a sad manner; ``She died last night,' he said sadly" |

《知網》情感分析用詞語集 (beta版)

- “中英文情感分析用詞語集”
 - 包含詞語約 17887
- “中文情感分析用詞語集”
 - 包含詞語約 9193
- “英文情感分析用詞語集”
 - 包含詞語 8945

中文情感分析用詞語集

| | |
|----------|------|
| 中文正面情感詞語 | 836 |
| 中文負面情感詞語 | 1254 |
| 中文正面評價詞語 | 3730 |
| 中文負面評價詞語 | 3116 |
| 中文程度級別詞語 | 219 |
| 中文主張詞語 | 38 |
| Total | 9193 |

中文情感分析用詞語集

- “正面情感” 詞語

- 如：

- 愛，讚賞，快樂，感同身受，好奇，
喝彩，魂牽夢縈，嘉許 ...

- “負面情感” 詞語

- 如：

- 哀傷，半信半疑，鄙視，不滿意，不是滋味兒，後悔，大失所望 ...

中文情感分析用詞語集

- “正面評價” 詞語

- 如：

- 不可或缺，部優，才高八斗，沉魚落雁，
催人奮進，動聽，對勁兒...

- “負面評價” 詞語

- 如：

- 醜，苦，超標，華而不實，荒涼，混濁，
畸輕畸重，價高，空洞無物 ...

中文情感分析用詞語集

- “程度級別” 詞語
 - 1. “極其 |extreme / 最 |most”
 - 非常，極，極度，無以倫比，最為
 - 2. “很 |very”
 - 多麼，分外，格外，著實
 - ...
- “主張” 詞語
 - 1. {perception |感知}
 - 感覺，覺得，預感
 - 2. {regard |認為}
 - 認為，以為，主張

Opinion Spam Detection

Opinion Spam Detection

- Opinion Spam Detection: Detecting Fake Reviews and Reviewers
 - Spam Review
 - Fake Review
 - Bogus Review
 - Deceptive review
 - Opinion Spammer
 - Review Spammer
 - Fake Reviewer
 - Shill (Stooge or Plant)

Opinion Spamming

- Opinion Spamming
 - "illegal" activities
 - e.g., writing fake reviews, also called shilling
 - try to mislead readers or automated opinion mining and sentiment analysis systems by giving undeserving positive opinions to some target entities in order to promote the entities and/or by giving false negative opinions to some other entities in order to damage their reputations.

Forms of Opinion spam

- fake reviews (also called bogus reviews)
- fake comments
- fake blogs
- fake social network postings
- deceptions
- deceptive messages

Fake Review Detection

- Methods
 - supervised learning
 - pattern discovery
 - graph-based methods
 - relational modeling
- Signals
 - Review content
 - Reviewer abnormal behaviors
 - Product related features
 - Relationships

Professional Fake Review Writing Services (some Reputation Management companies)

- Post positive reviews
- Sponsored reviews
- Pay per post
- Need someone to write positive reviews about our company (budget: \$250-\$750 USD)
- Fake review writer
- Product review writer for hire
- Hire a content writer
- Fake Amazon book reviews (hiring book reviewers)
- People are just having fun (not serious)

SponsoredReviews.com x

www.sponsoredreviews.com

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Bloggers Earn Cash, Advertisers Build Buzz!

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SponsoredReviews connects bloggers with SEO's, Marketers, and Advertisers looking to build Links, Traffic and Buzz.

Direct Traffic.
Millions of people read blogs every day. Paying for posts puts the spotlight on your company and will generate tons of targeted traffic.

Buzz & Branding.
The more bloggers talk about your site the better. Many blogs syndicate stories they see on other sites. A couple well timed sponsored posts has the potential to generate a flurry of other post being written.

Search Engine Rankings.
Every post has links back to your site. Getting links from quality blogs will increase your link popularity and will help your site rank better in the search engines.

Valuable Feedback.
Getting Reviewed by bloggers will provide you with valuable feedback that you can use to better understand your audience and customers.

Advertisers
Start Here.

A

- Announce your products, services, websites, and ideas to the world!
- Tap into the power of the blogosphere to build traffic, links and valuable feedback.

Free Sign Up Read More

Bloggers
Earn Cash.

B

- Earn cash by writing honest posts about our advertiser's products and services.
- Write posts in your own tone and style, and gear them to your audience's interest.

Free Sign Up Read More

How it works •  Advertiser  Blogger

PayPerPost : Blog Market <https://payperpost.com>

payperpost

advertisers bloggers ethics about login



advertisers

Hire bloggers to blog about your company, service or website. PayPerPost gives you access to a diverse pool of bloggers from all over the world. Make offers, negotiate deals and approve posts.

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bloggers

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see how it *works*

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customer testimonial

 "PayPerPost has been instrumental in helping our company streamline our various product awareness campaigns."
-C. Litchfield



Help

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Search for Freelancers, Projects...



Need someone to write and post positive reviews

[f Like 0](#) [f Send](#) [Twitter Tweet 0](#) [+1 0](#) [Share](#)Bids
10Avg Bid (USD)
N/AProject Budget (USD)
\$250 - \$750**CLOSED****Project Description:**

We need someone to write and post positive reviews about our company on websites. Please send an example of a review you would post for any company. We can also send examples of comments our customers have sent us to use and refer to as well.

This is a long term project, so if it works out there will be a healthy amount of work. Please reply back with all your experience and how much you would charge per post.

thank you.

Skills required:

Publicación en foros, Opiniones

[Follow](#)

Project posted by:

dvel

5.0 (1 Review)



Papers on Opinion Spam Detection

1. Arjun Mukherjee, Bing Liu, and Natalie Glance. Spotting Fake Reviewer Groups in Consumer Reviews. International World Wide Web Conference (WWW-2012), Lyon, France, April 16-20, 2012.
2. Guan Wang, Sihong Xie, Bing Liu, Philip S. Yu. Identify Online Store Review Spammers via Social Review Graph. ACM Transactions on Intelligent Systems and Technology, accepted for publication, 2011.
3. Guan Wang, Sihong Xie, Bing Liu, Philip S. Yu. Review Graph based Online Store Review Spammer Detection. ICDM-2011, 2011.
4. Arjun Mukherjee, Bing Liu, Junhui Wang, Natalie Glance, Nitin Jindal. Detecting Group Review Spam. WWW-2011 poster paper, 2011.
5. Nitin Jindal, Bing Liu and Ee-Peng Lim. "Finding Unusual Review Patterns Using Unexpected Rules" Proceedings of the 19th ACM International Conference on Information and Knowledge Management (CIKM-2010, short paper), Toronto, Canada, Oct 26 - 30, 2010.
6. Ee-Peng Lim, Viet-An Nguyen, Nitin Jindal, Bing Liu and Hady Lauw. "Detecting Product Review Spammers using Rating Behaviors." Proceedings of the 19th ACM International Conference on Information and Knowledge Management (CIKM-2010, full paper), Toronto, Canada, Oct 26 - 30, 2010.
7. Nitin Jindal and Bing Liu. "Opinion Spam and Analysis." Proceedings of First ACM International Conference on Web Search and Data Mining (WSDM-2008), Feb 11-12, 2008, Stanford University, Stanford, California, USA.
8. Nitin Jindal and Bing Liu. "Review Spam Detection." Proceedings of WWW-2007 (poster paper), May 8-12, Banff, Canada.

Summary

- Architectures of Sentiment Analytics on Social Media
- Social Media Monitoring/Analysis
- Sentiment Analytics on Social Media:
Tools and Applications

References

- Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” 2nd Edition, Springer.
<http://www.cs.uic.edu/~liub/WebMiningBook.html>
- Bing Liu (2013), Opinion Spam Detection: Detecting Fake Reviews and Reviewers,
<http://www.cs.uic.edu/~liub/FBS/fake-reviews.html>
- Bo Pang and Lillian Lee (2008), "Opinion mining and sentiment analysis," Foundations and Trends in Information Retrieval 2(1-2), pp. 1–135, 2008.
- Wiltrud Kessler (2012), Introduction to Sentiment Analysis,
http://www.ims.uni-stuttgart.de/~kesslewd/lehre/sentimentanalysis12s/introduction_sentimentanalysis.pdf
- Z. Zhang, X. Li, and Y. Chen (2012), "Deciphering word-of-mouth in social media: Text-based metrics of consumer reviews," ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.
- Efraim Turban, Ramesh Sharda, Dursun Delen (2011), Decision Support and Business Intelligence Systems, Ninth Edition, 2011, Pearson.
- Guandong Xu, Yanchun Zhang, Lin Li (2011), Web Mining and Social Networking: Techniques and Applications, 2011, Springer

References

- Cambria, Erik, Soujanya Poria, Rajiv Bajpai, and Björn Schuller. "SenticNet 4: A semantic resource for sentiment analysis based on conceptual primitives." In the 26th International Conference on Computational Linguistics (COLING), Osaka. 2016.
- Richard Socher, Alex Perelygin, Jean Y. Wu, Jason Chuang, Christopher D. Manning, Andrew Y. Ng, and Christopher Potts (2013), "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank," In Proceedings of the conference on empirical methods in natural language processing (EMNLP), vol. 1631, p. 1642
http://nlp.stanford.edu/~socherr/EMNLP2013_RNTN.pdf
- Kumar Ravi and Vadlamani Ravi (2015), "A survey on opinion mining and sentiment analysis: tasks, approaches and applications." Knowledge-Based Systems, 89, pp.14-46.
- Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, vol 139, no. 11, 2016. pp.5-15.
- Jesus Serrano-Guerrero, Jose A. Olivas, Francisco P. Romero, and Enrique Herrera-Viedma (2015), "Sentiment analysis: A review and comparative analysis of web services," Information Sciences, 311, pp. 18-38.
- Steven Struhl (2015), Practical Text Analytics: Interpreting Text and Unstructured Data for Business Intelligence (Marketing Science), Kogan Page
- Bing Liu (2015), Sentiment Analysis: Mining Opinions, Sentiments, and Emotions, Cambridge University Press