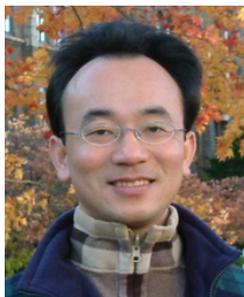


Social Media and Sentiment Analysis

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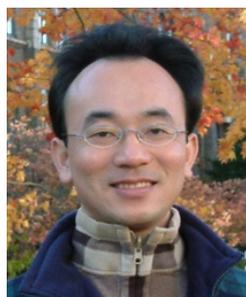
<http://mail.tku.edu.tw/myday/>

2016-11-01



Sentiment Analysis on Social Media

(社群媒體情感分析)



Min-Yuh Day

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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. ...”



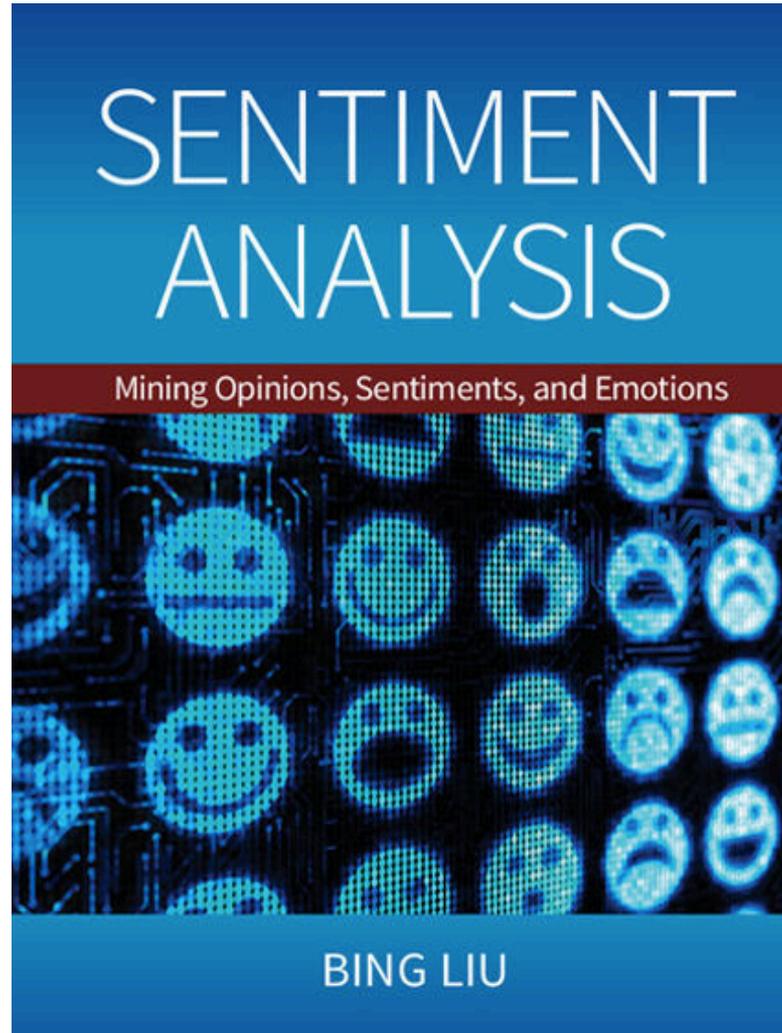
+Positive
Opinion



-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,
ets., 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

Sentiment Analysis	Subjectivity Analysis
Positive	Subjective
Negative	
Neutral	Objective

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*

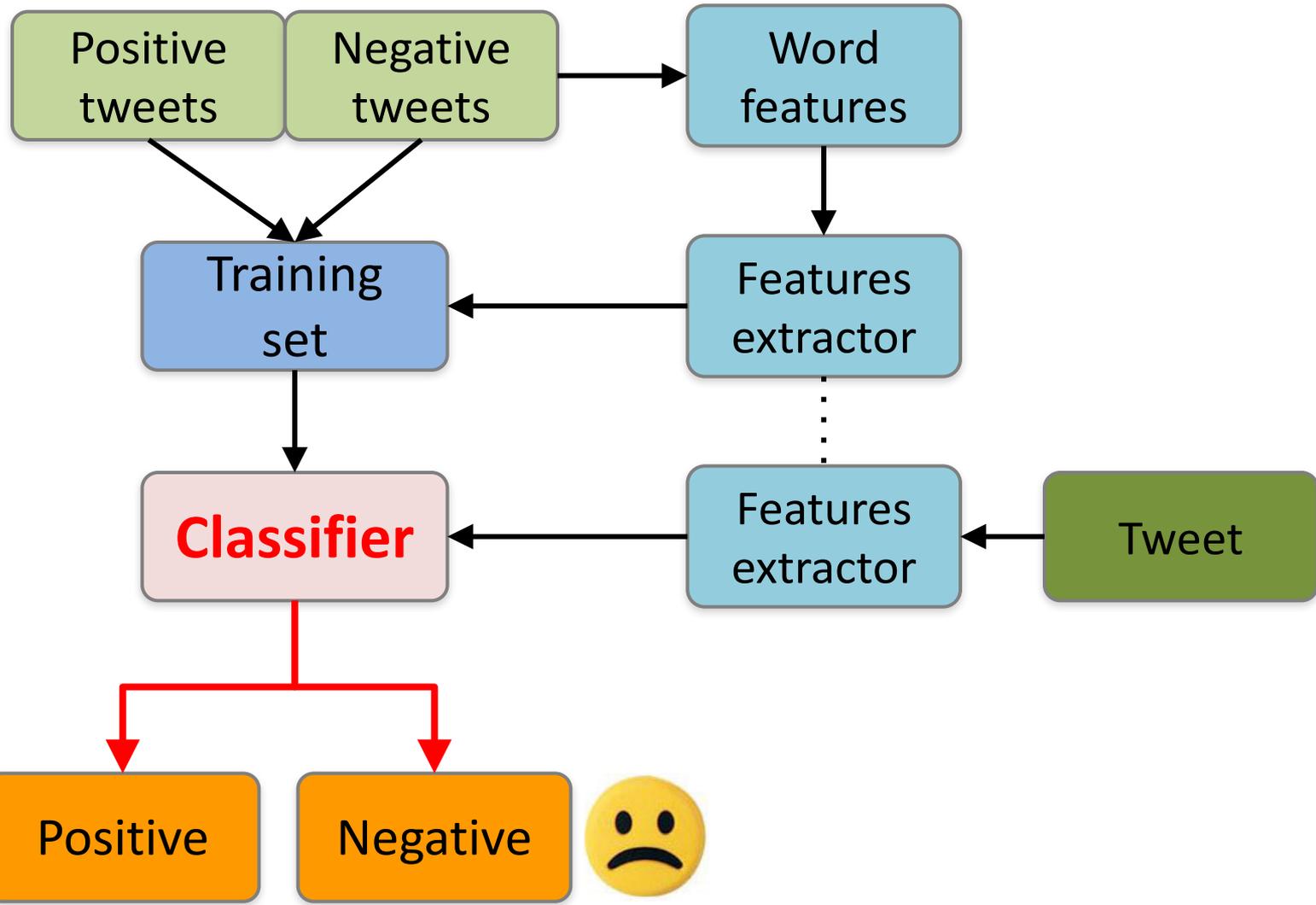
Opinion words in Sentiment classification

- 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*

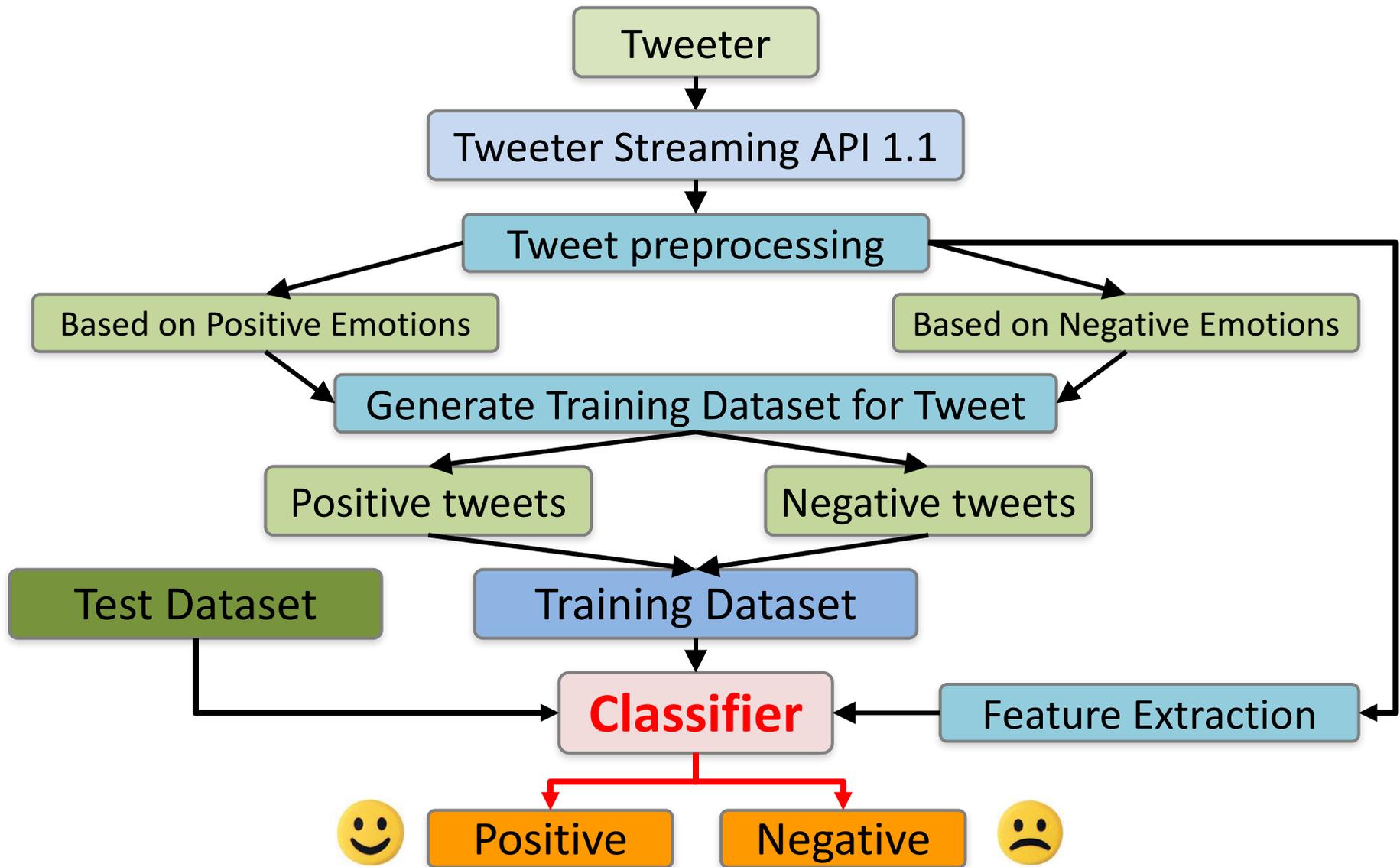
Features in Opinion Mining

- *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*

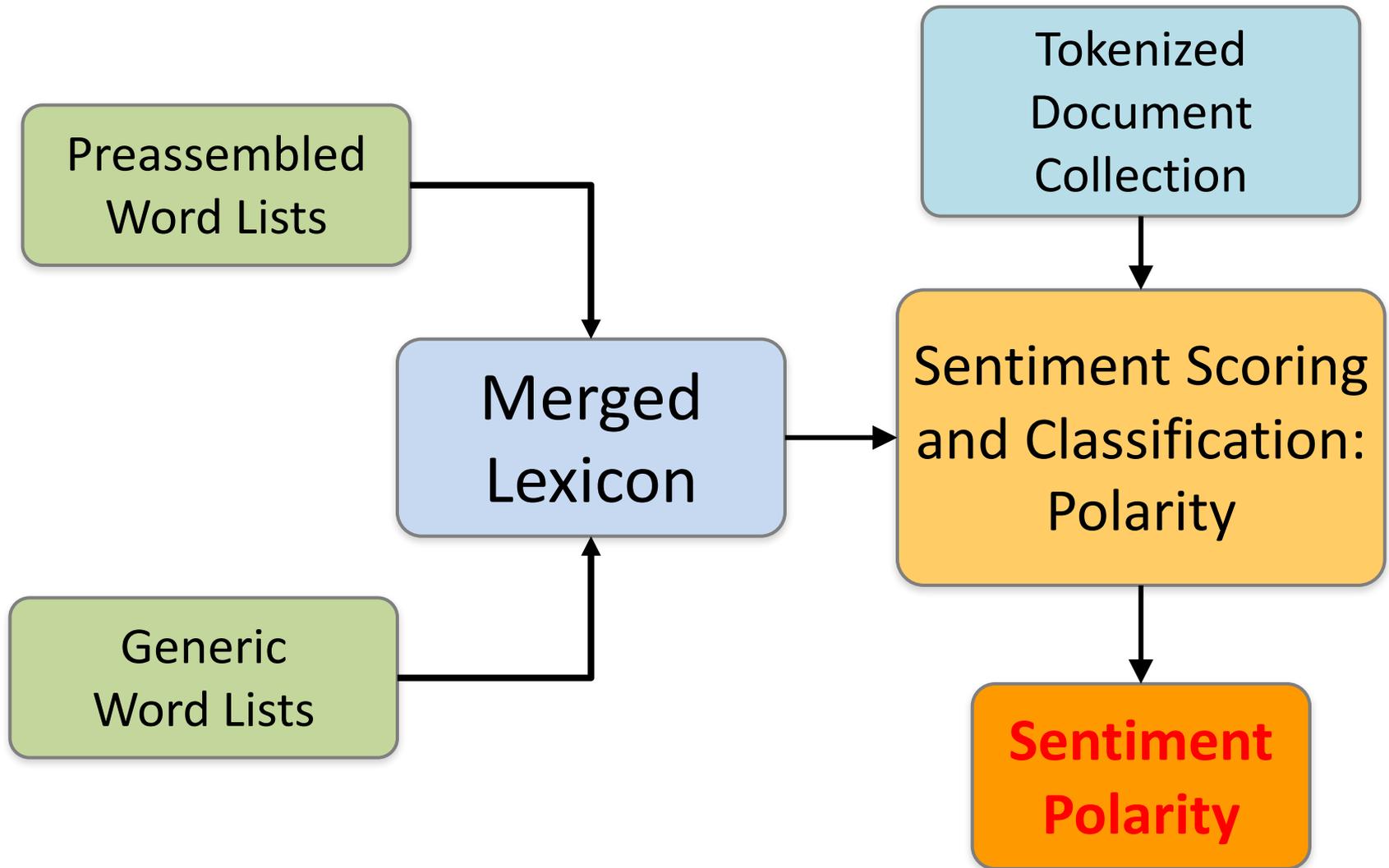
Sentiment Analysis Architecture



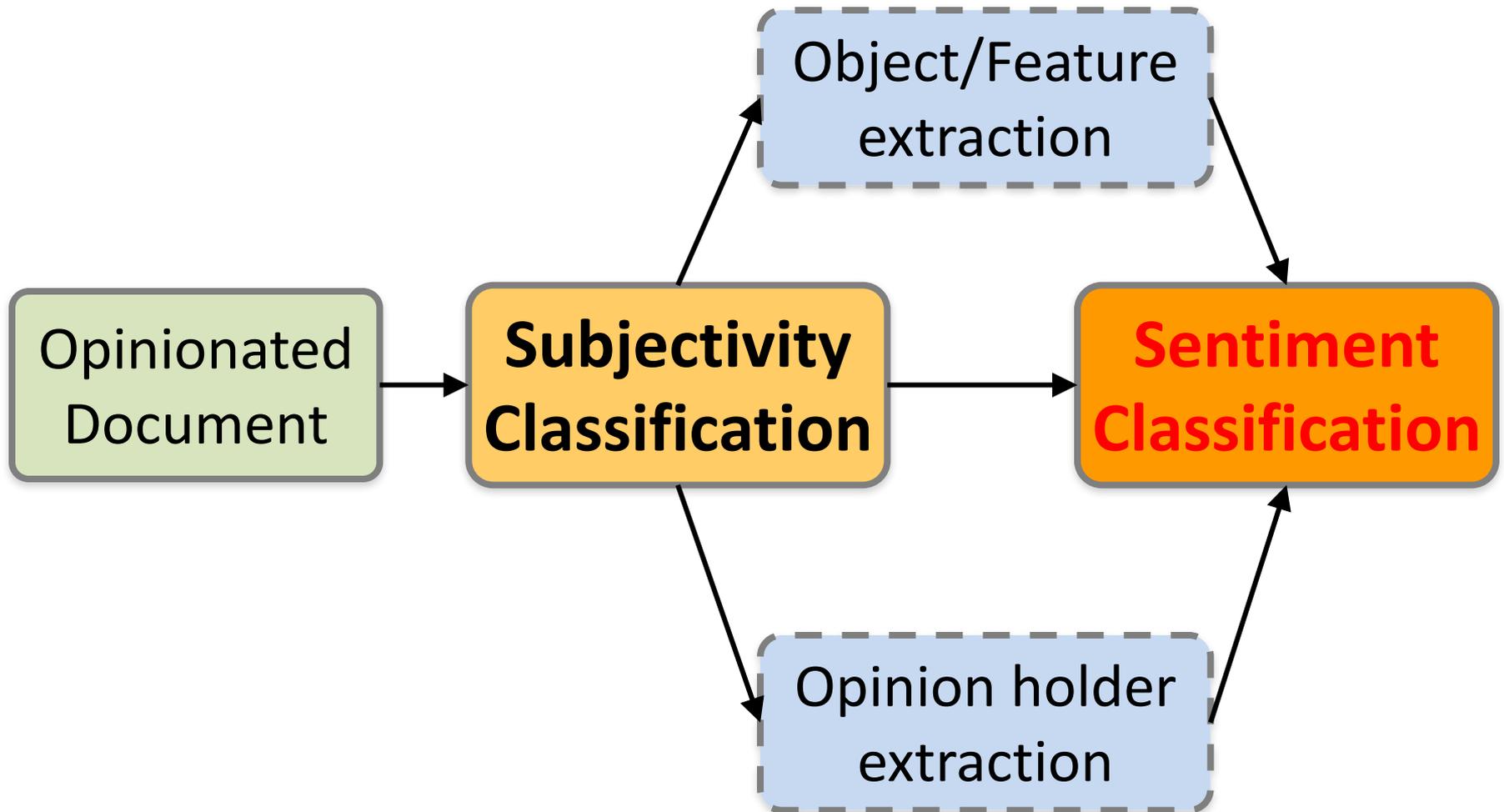
Sentiment Classification Based on Emoticons



Lexicon-Based Model



Sentiment Analysis Tasks



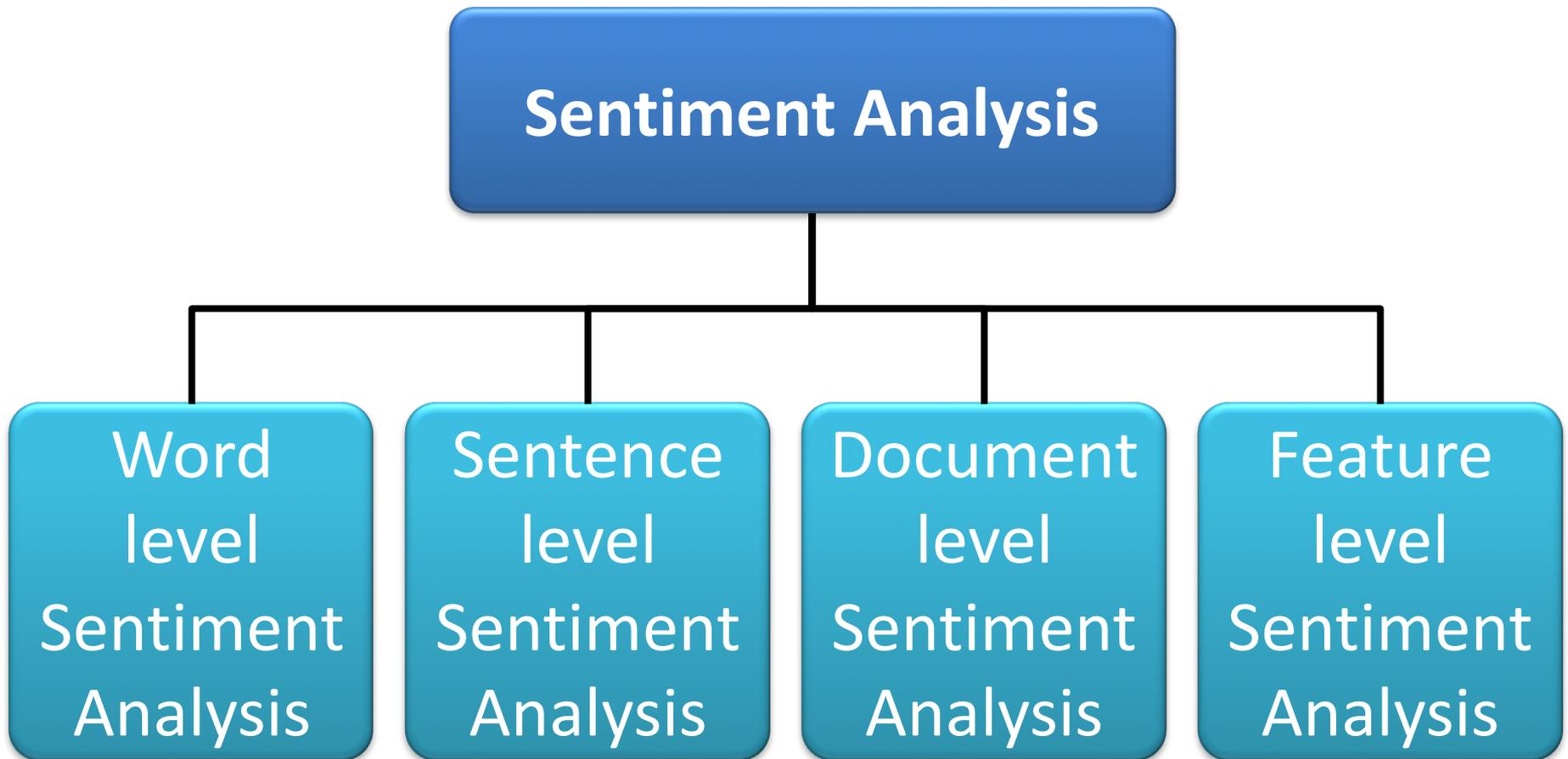
Sentiment Analysis

vs.

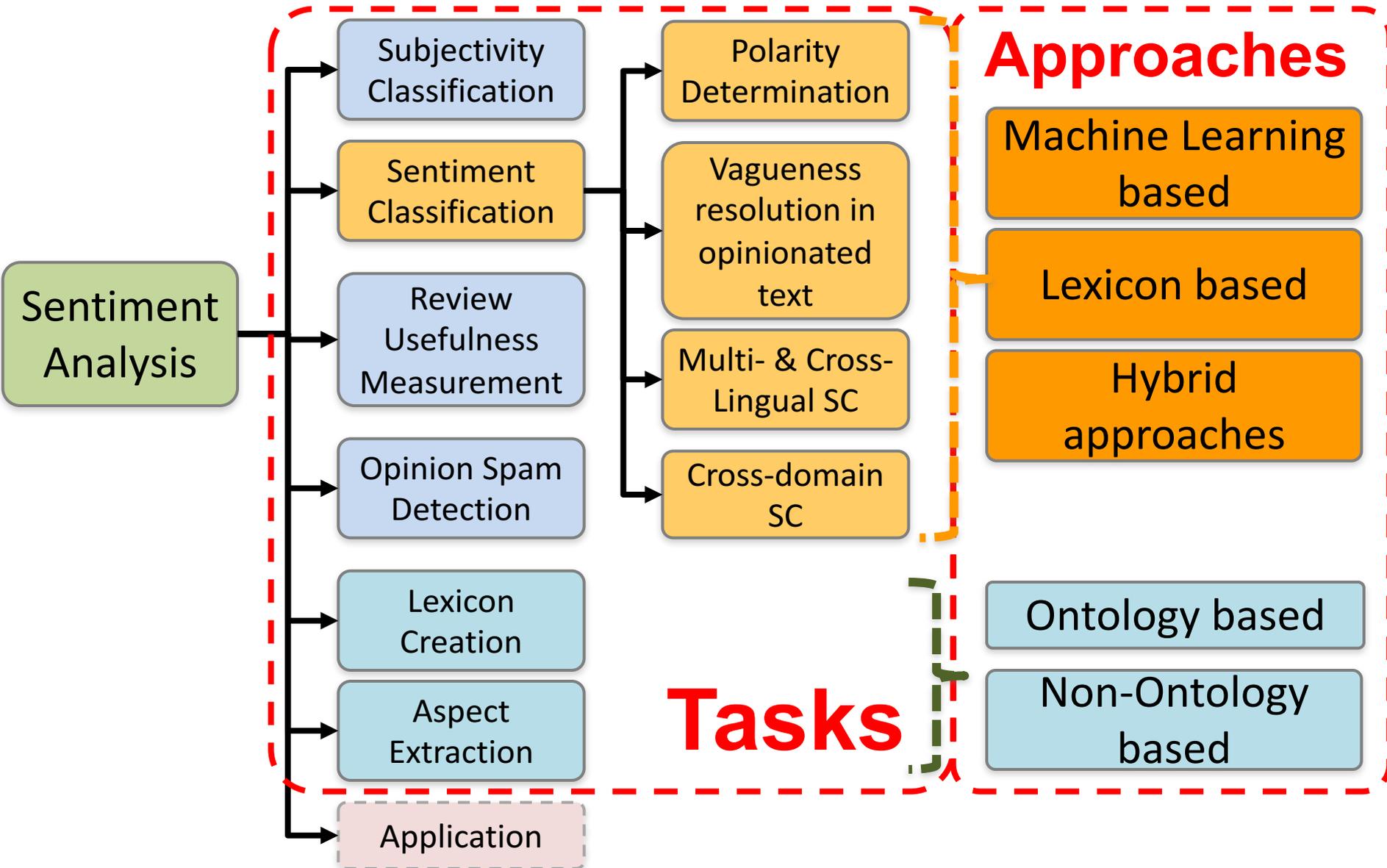
Subjectivity Analysis

Sentiment Analysis	Subjectivity Analysis
Positive	Subjective
Negative	
Neutral	Objective

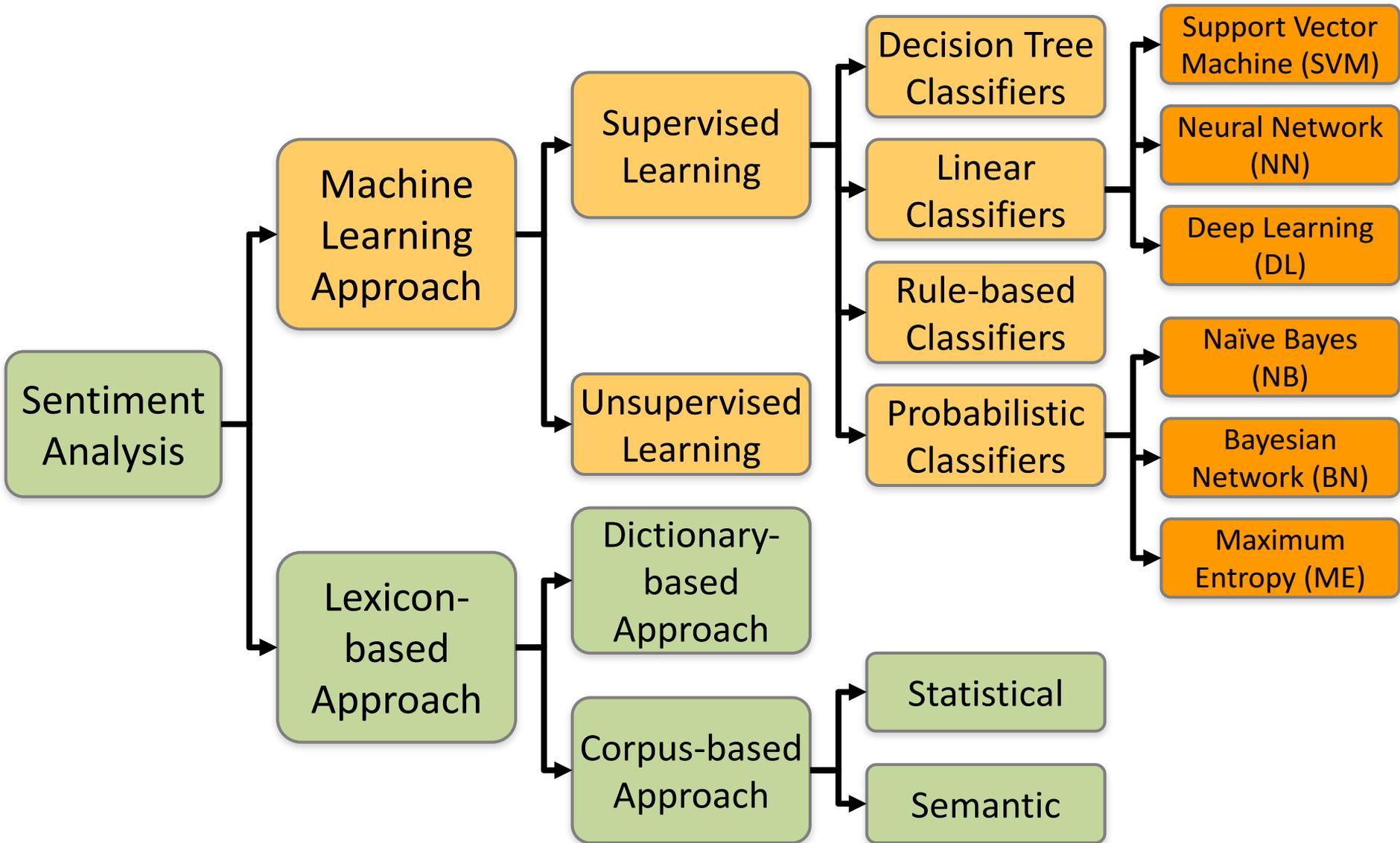
Levels of Sentiment Analysis



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

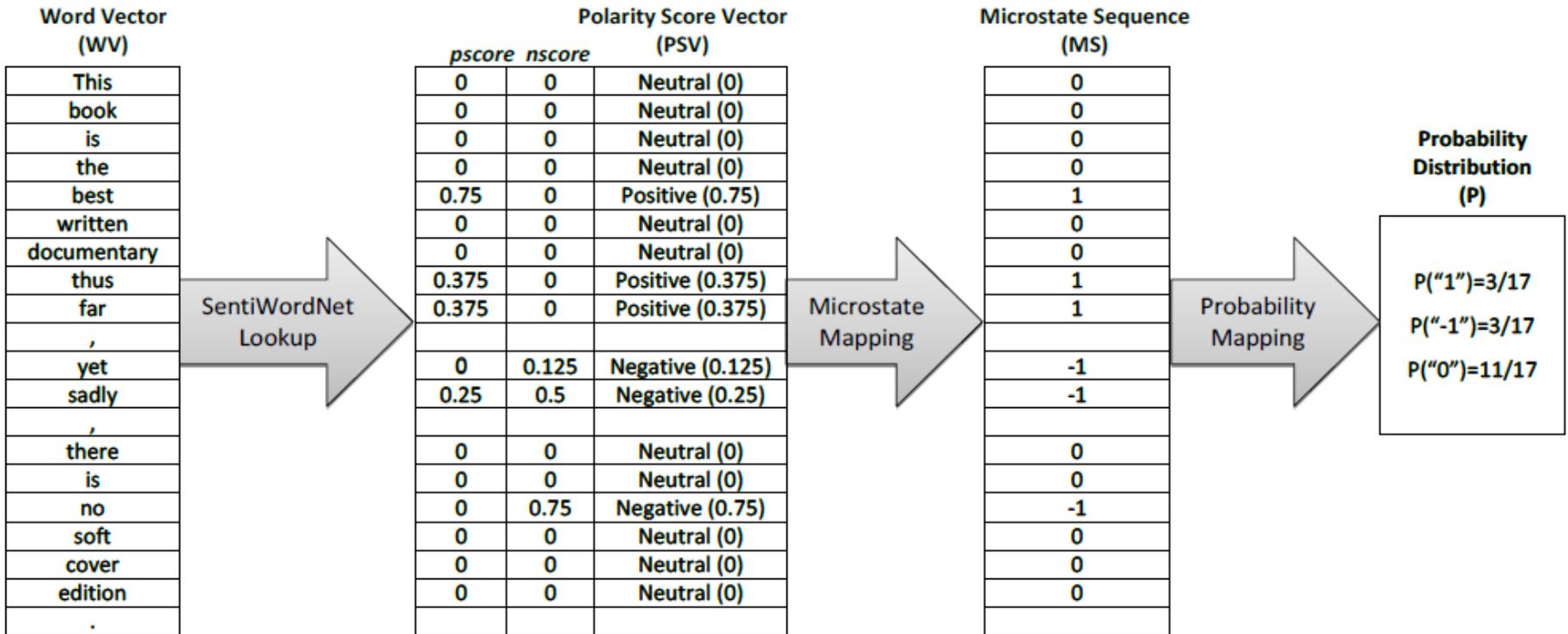
(Both = Subjectivity and Polarity; ML= Machine Learning; Lexicon/Rule= Lexicon enhanced by linguistic rules)

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	VCN
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
.	.	.

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

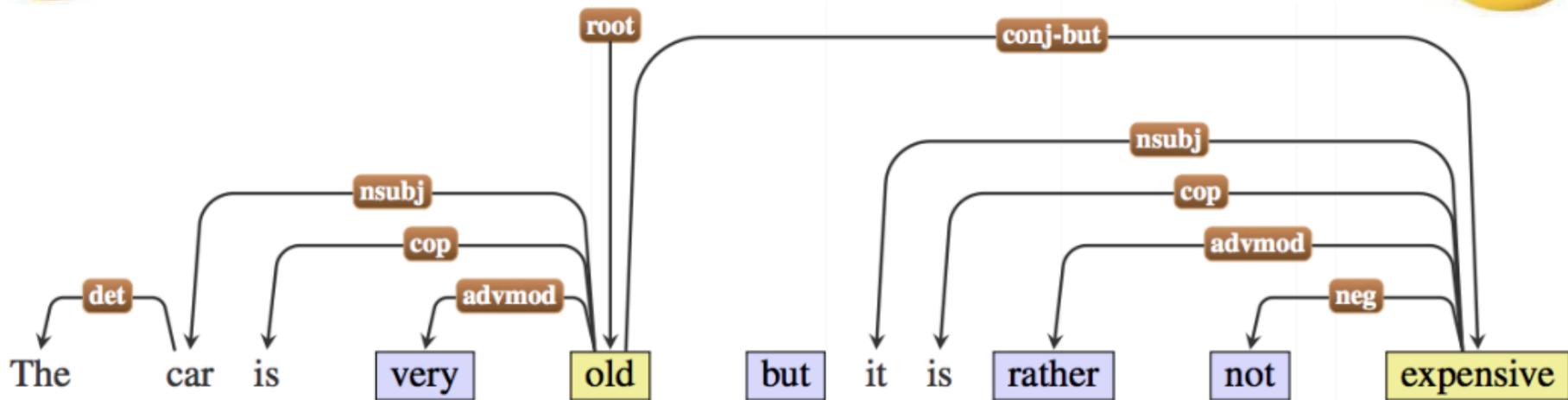


The car is very old but it is rather not expensive.

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

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

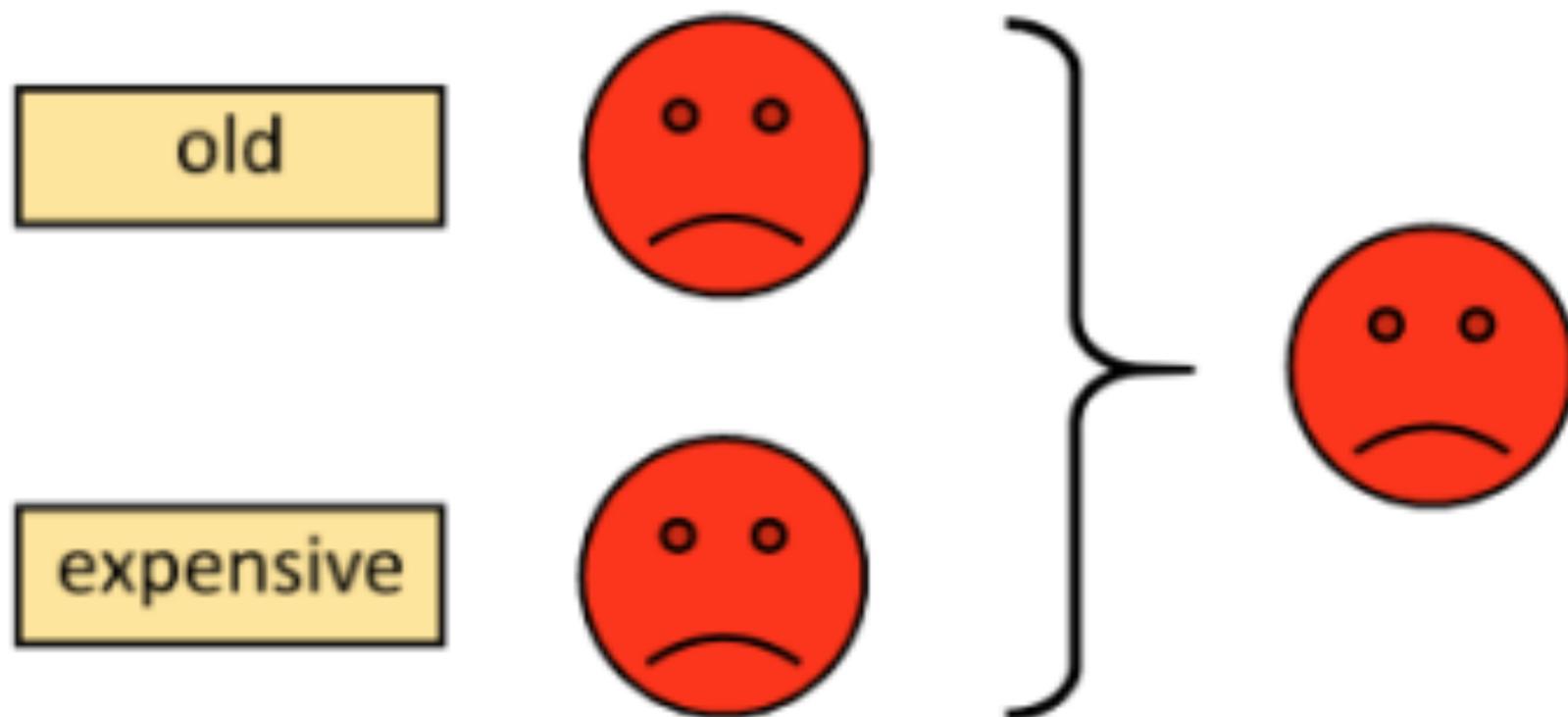
Polarity Detection with SenticNet



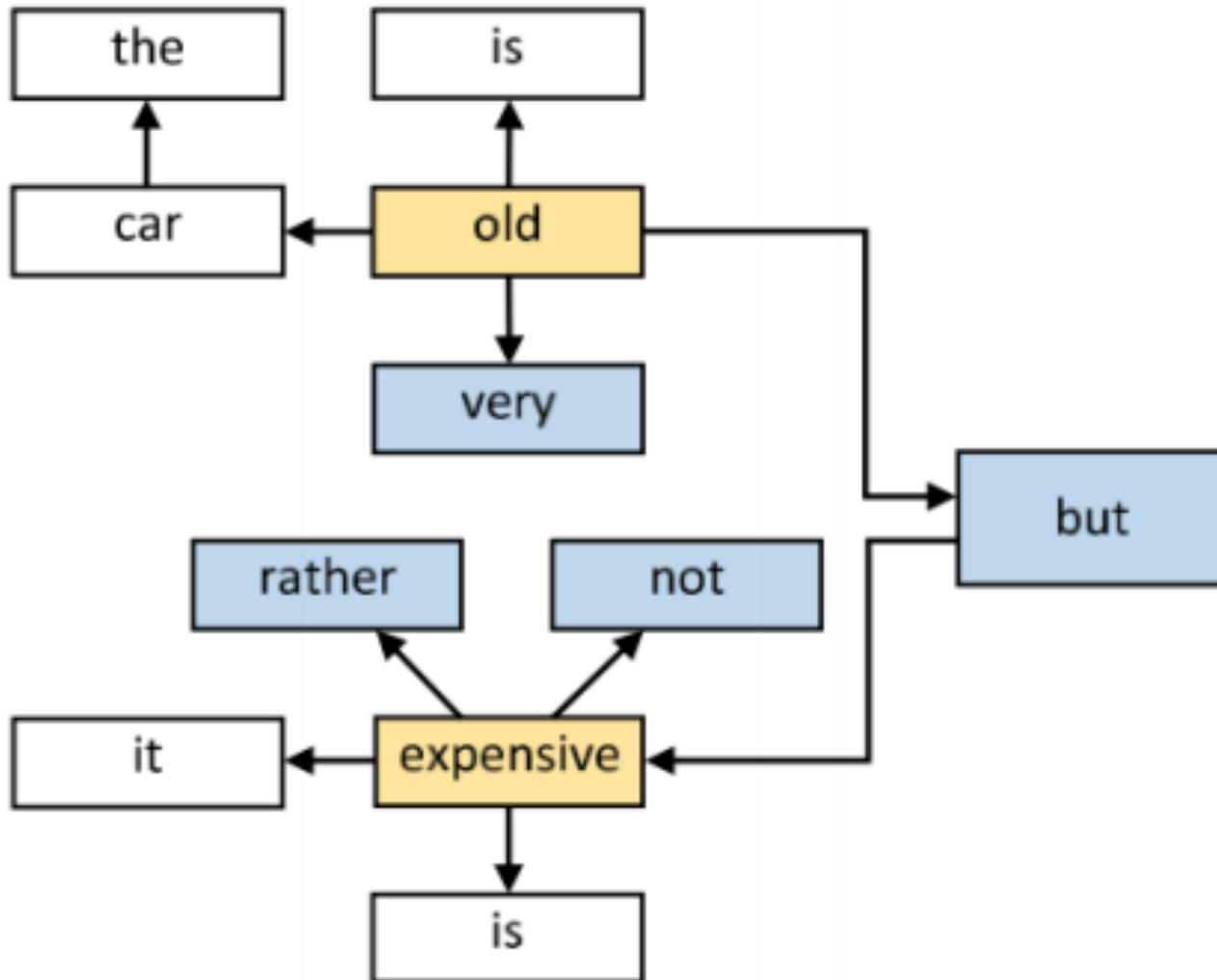
The car is very **old** but it is rather not **expensive**.

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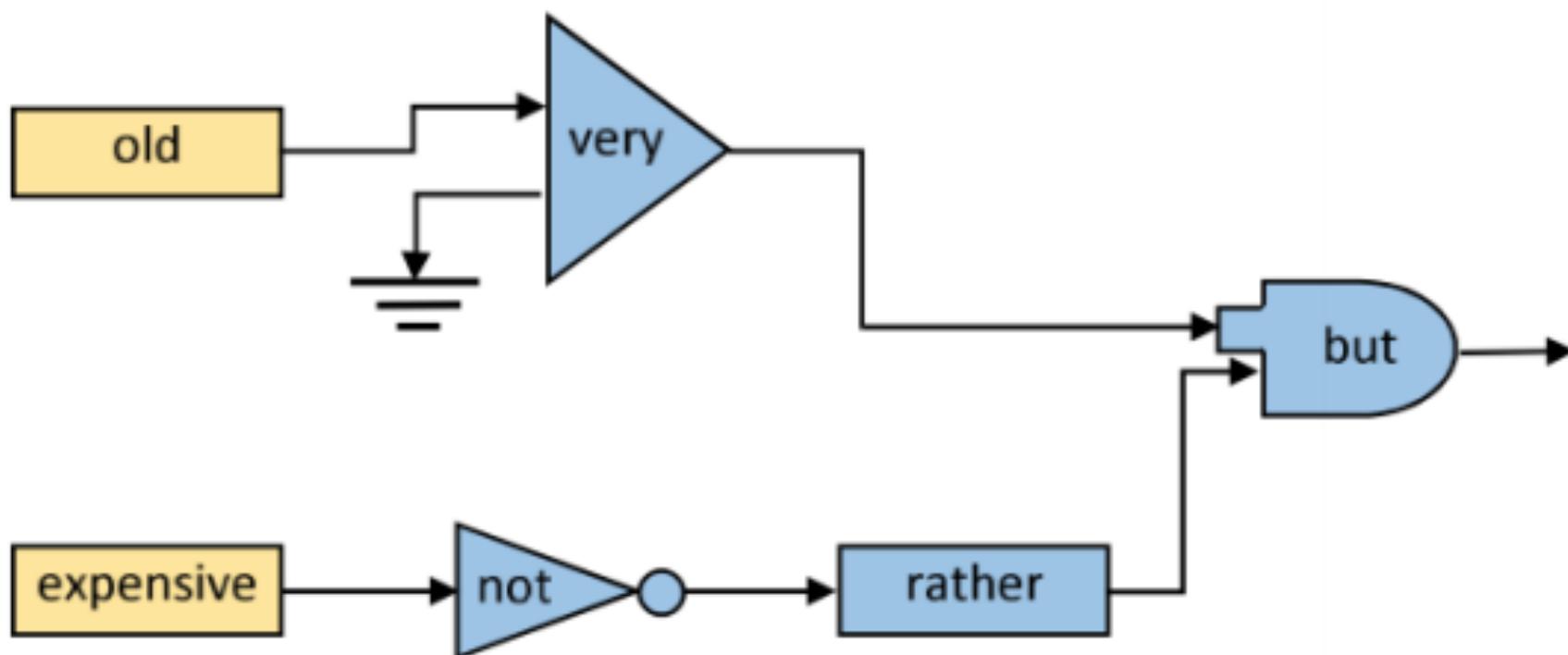
Polarity Detection with SenticNet



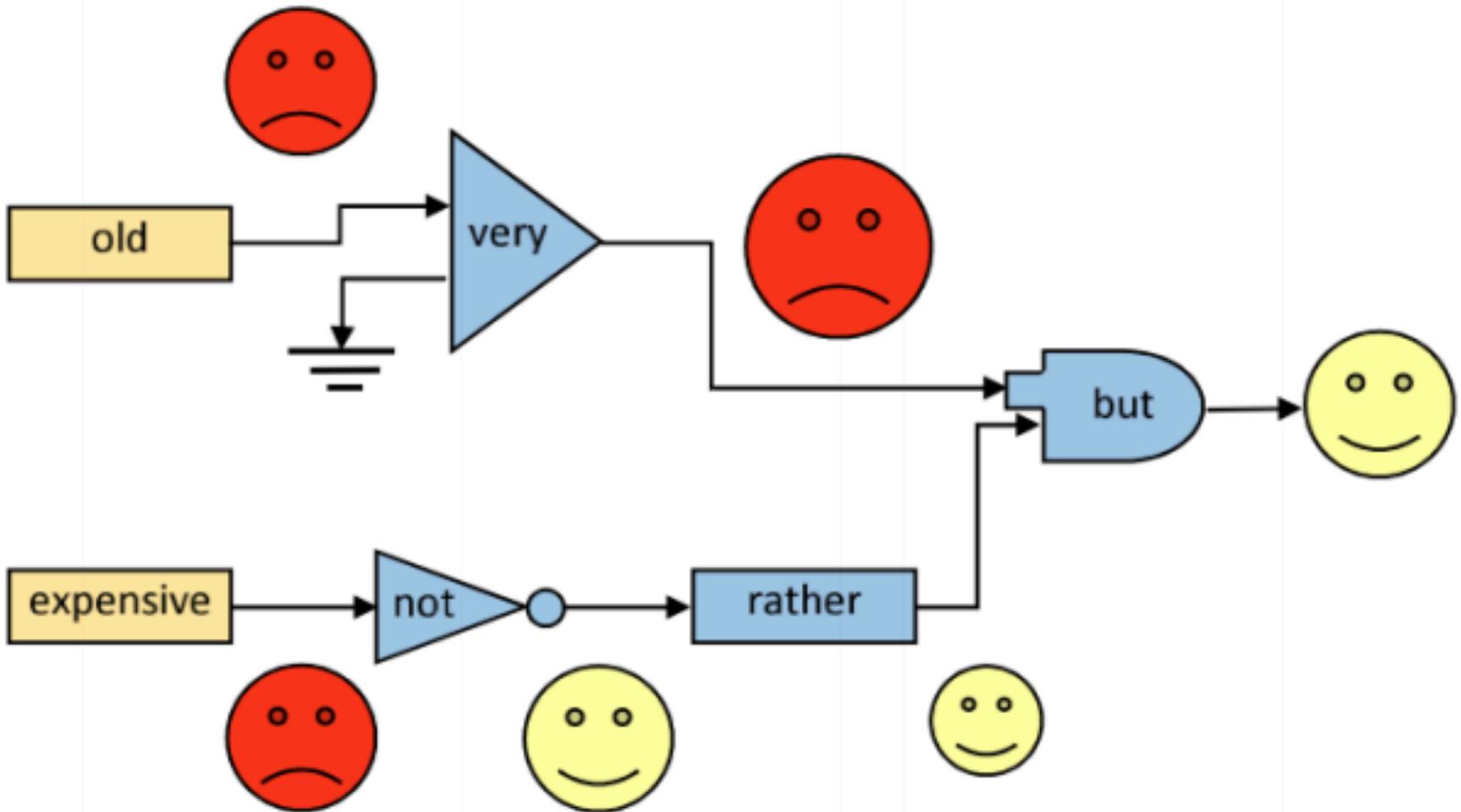
Polarity Detection with SenticNet



Polarity Detection with SenticNet



Polarity Detection with SenticNet



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-

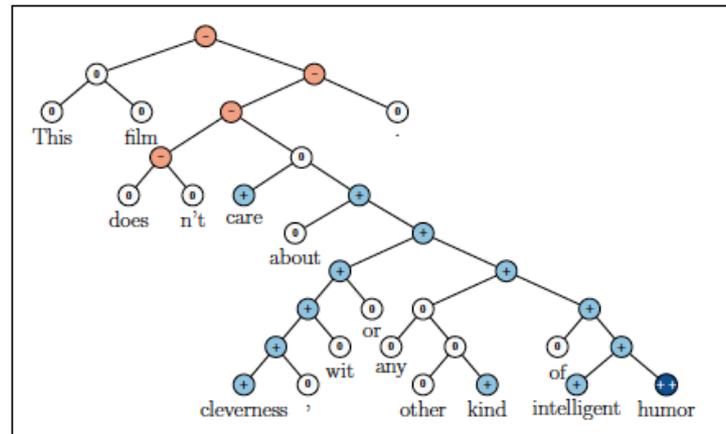
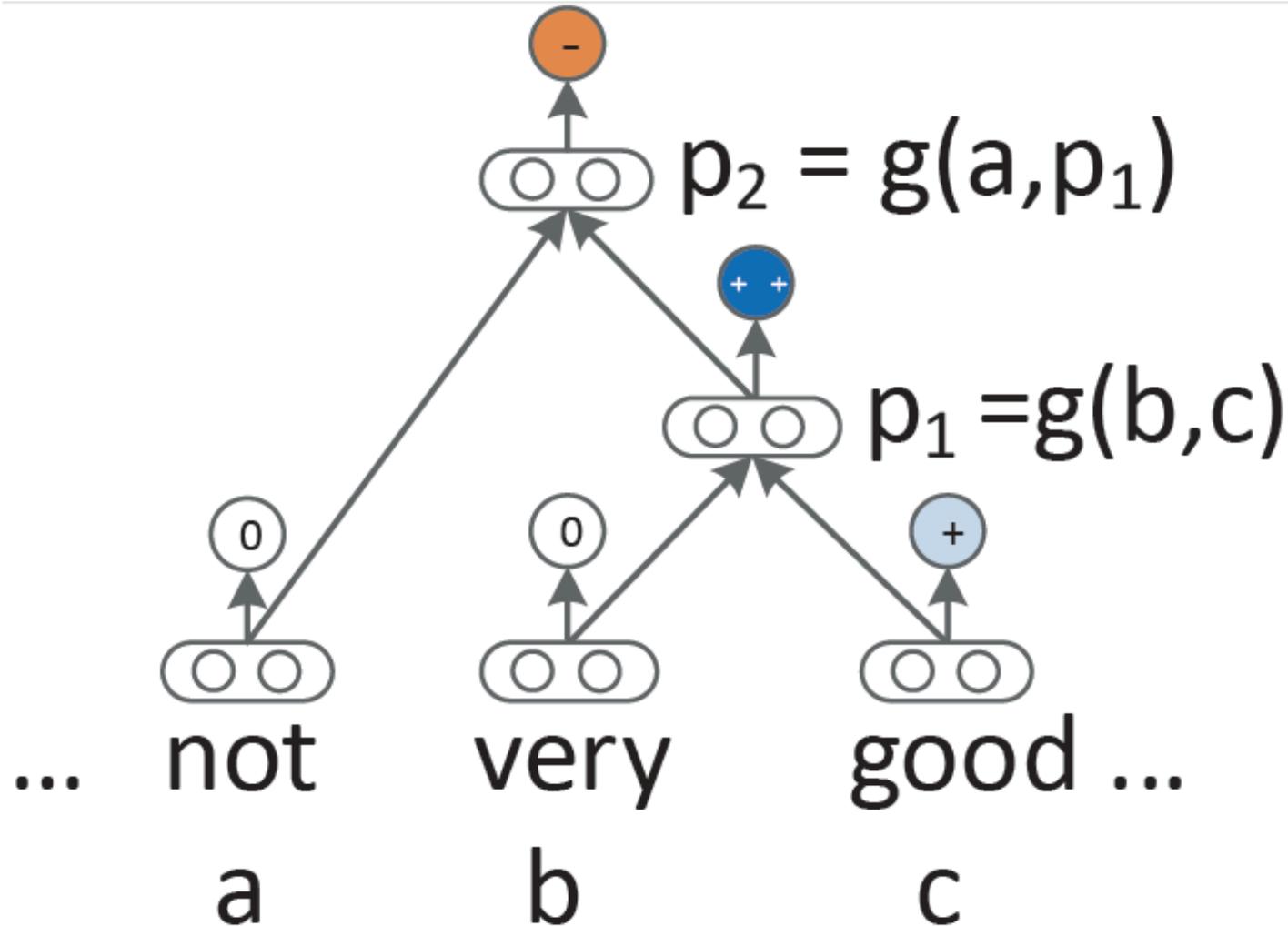
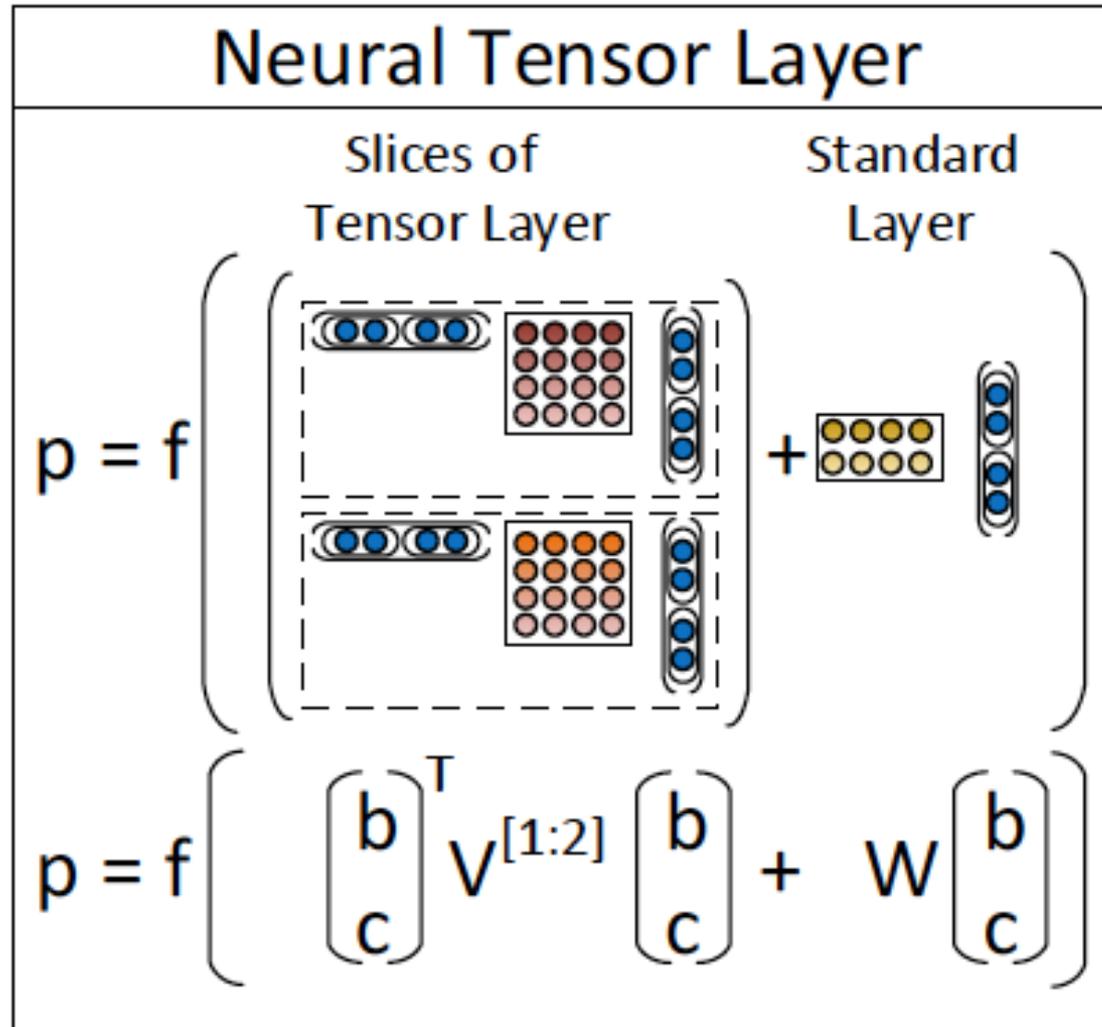


Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (--, -, 0, +, ++), at every node of a parse tree and capturing the negation and its scope in this sentence.

Recursive Neural Network (RNN) models for sentiment



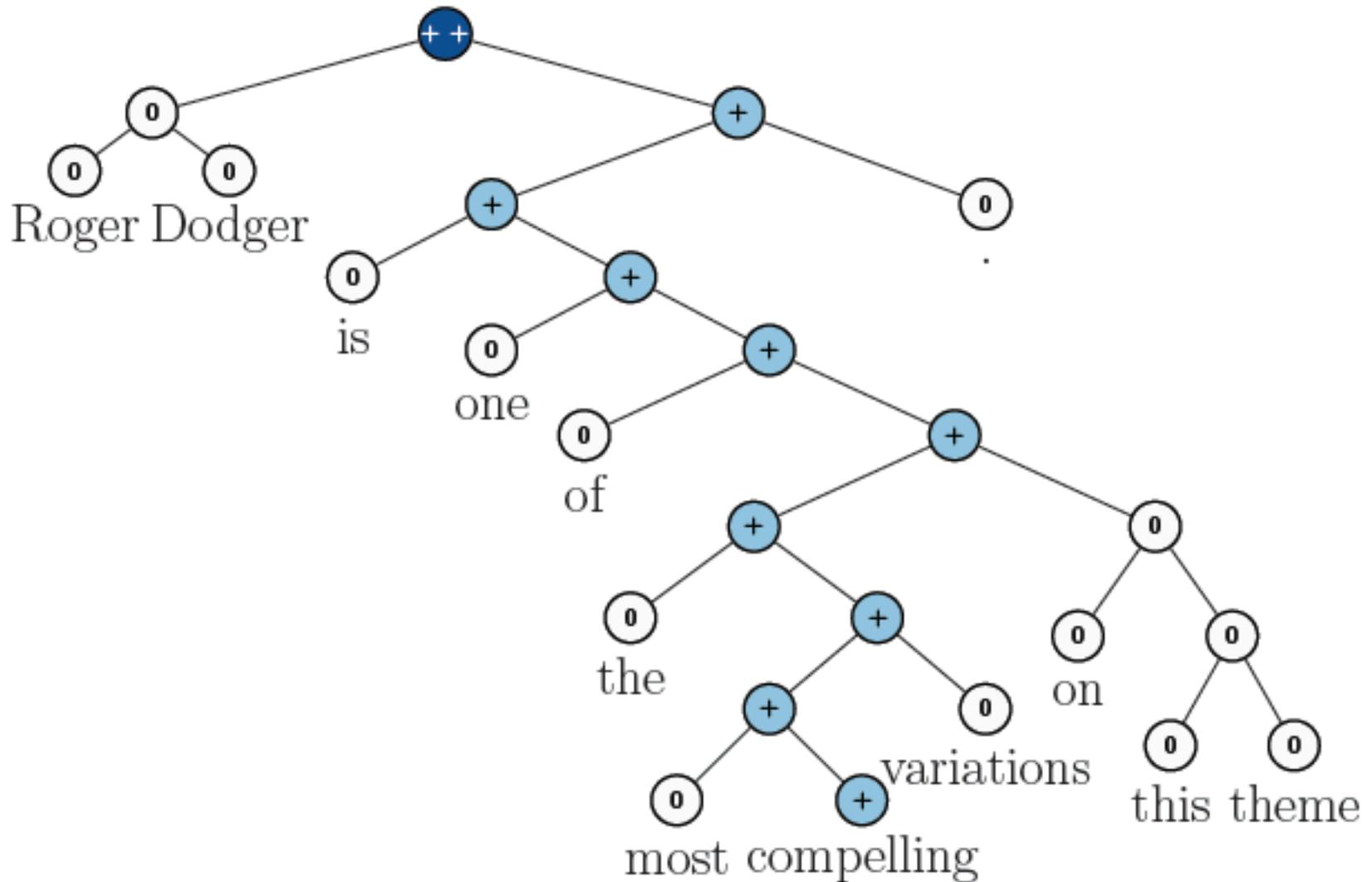
Recursive Neural Tensor Network (RNTN)



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

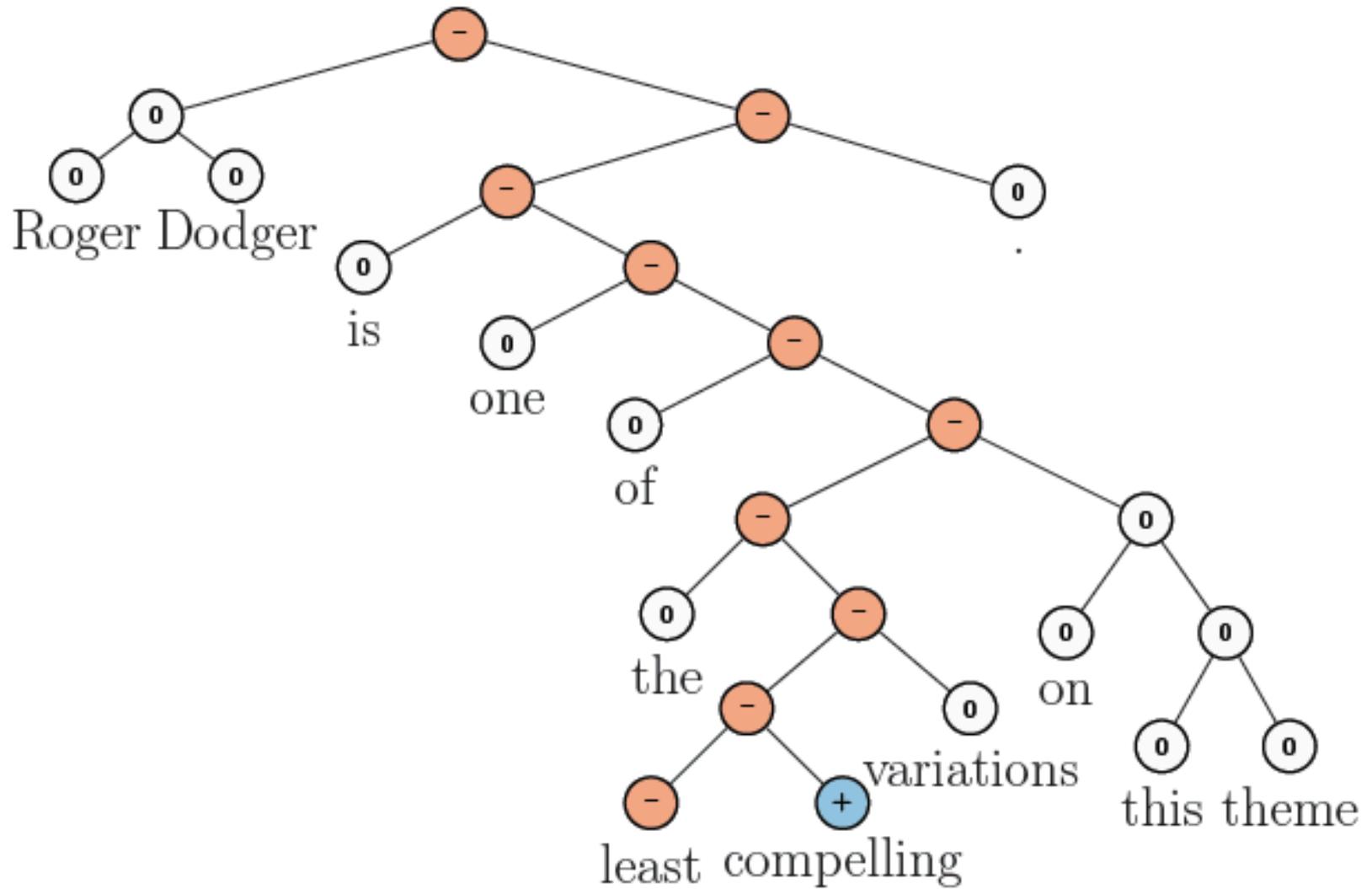
Roger Dodger is one of the **least
compelling variations on this
theme.**

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

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

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			Bollegala[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 website homepage. At the top, there is a navigation bar with the Attensity logo, a language selector set to 'English', and links for 'Contact', 'Resources', 'Support', and 'Blog'. A search bar is also present. Below the navigation, there are tabs for 'Products', 'Solutions', 'Services', 'Customers', and 'Partners'. The main content area features a large central headline: "Your real-time window into the social web." Below this headline is a quote from Yahoo! and a "Learn More" button. To the left of the headline is a vertical menu with categories: "Social Analytics", "Social Response", "Customer Analytics", "Industry Solutions", and "Why Attensity". To the right of the headline are several dashboard screenshots showing various analytics, including a bar chart titled "Comparison of Feedback Over Different Time Periods" and a "Twitter Accounts" section. At the bottom of the page, there are sections for "Attensity for Marketing", "Attensity for Customer Service", "Attensity for IT", "Success Story" (featuring JetBlue Airways), "About Attensity", and "Watch Video" (featuring a "Command Center Video").

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

Clarabridge: Sentiment and Text Analytics Software

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

The image shows a screenshot of a web browser displaying the Clarabridge website. The browser's address bar shows the URL www.clarabridge.com. The website features a navigation menu with links for Home, About Us, News & Events, Blog, Login, and Contact Us. Below the navigation is a main banner with the headline "The First Sentiment and Text Analytics Solution Built Specifically for Business." and a sub-headline "The Clarabridge sentiment and text analytics software provides enterprises with a universal view of their customers." A "Learn more about how Clarabridge works >" link is positioned at the bottom right of the banner. A "Customers" section below the banner displays logos for Nissan, Best Buy, Marriott, Sage, H&R Block, Choice Hotels International, Wendy's, Gwlord Hotels, BE Aerospace, and Dell, followed by a "More >" link. The footer contains three columns: "Clarabridge Text Analytics", "Choose Your Edition" (with a sub-section for "Clarabridge for Enterprises" described as "Ideal for companies seeking an enterprise class text analytics solution."), and "Clarabridge Webinar" (with the text "Hypatia Research Group presents on Social").

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

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

Social Media Monitoring x

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The Social Enterprise.
Get closer to your customer.
Learn how >

Have Us Contact You

Live Demo

Free Trial

Chat & find out more.

Offline. Leave us a message

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 >](#)

Newsletter Sign up and get the regular Radian6 goods. Enter email address GO

radian6 Community

Mashable named Radian6's Co-founder Chris Ramsey one of five masterminds redefining social media

JUST Get the Skinny

WEBINAR / June 7th at 2pm est

CASE STUDY

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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 - 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.

“ 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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Product Demo

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Contact Form

White Paper

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

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SAS® Social Media Analytics

[Overview](#)

RESOURCES

- [Fact Sheet \(PDF\)](#)
- [Solution Brief \(PDF\)](#)
- [White Papers](#)

The screenshot shows a web browser window with the URL www.tweetfeel.com/index.php#iPhone4s. The page features the 'tweetfeel' logo with a blue bird icon. A search bar contains the text 'iPhone4s' and a yellow 'Search' button. Below the search bar, it displays 'Try some Twitter trends: [Tomorrow is June](#) [H&M](#) [Defense of Marriage Act](#) [Diddy's](#) [Bloomberg](#) [UCLA](#) [ESPN](#)'. A sentiment analysis graphic shows a green smiley face with '40' below it, a red frowny face with '41' below it, and an equals sign followed by '51%'. A text block reads: '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.](#)' Below this are six tweet snippets, each with a small profile picture and text mentioning 'iPhone4s' and 'wtf'. The footer contains links for 'Read our FAQ', 'Legal Stuff', '100% Guarantee', and 'Share', along with social media icons for 'Follow us' and 'Email us', and logos for 'conversion' and 'Powered by twitter'.

eLand

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< 巨量搜尋。語意分析。社群大數據 >



 OpView社群口碑資料庫

OpView

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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



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](http://ir.dcs.gla.ac.uk/test%20collections/access%20to%20data.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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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.



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

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Bloggers
Earn Cash.



- 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.

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How it works:  Advertiser  Blogger

PayPerPost : Blog Marke x

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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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Need someone to write and post positive reviews

Like 0 Send Tweet 0 +1 0 Share

Bids	Avg Bid (USD)	Project Budget (USD)	CLOSED
10	N/A	\$250 - \$750	

Featured Sealed

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 too 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



Project posted by:
dvel
★★★★★ 5.0 (1 Review)
VERIFIED

Follow

Your ad could *From \$100/week*

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Summary

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

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