

Social Computing and Big Data Analytics

社群運算與大數據分析

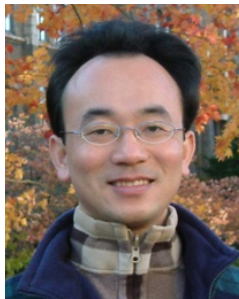
Sentiment Analysis on Social Media with Deep Learning

(深度學習社群媒體情感分析)

1042SCBDA11

MIS MBA (M2226) (8628)

Wed, 8,9, (15:10-17:00) (B309)



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2016-05-11



課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
1	2016/02/17	Course Orientation for Social Computing and Big Data Analytics (社群運算與大數據分析課程介紹)
2	2016/02/24	Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data (資料科學與大數據分析： 探索、分析、視覺化與呈現資料)
3	2016/03/02	Fundamental Big Data: MapReduce Paradigm, Hadoop and Spark Ecosystem (大數據基礎：MapReduce典範、 Hadoop與Spark生態系統)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
4	2016/03/09	Big Data Processing Platforms with SMACK: Spark, Mesos, Akka, Cassandra and Kafka (大數據處理平台SMACK : Spark, Mesos, Akka, Cassandra, Kafka)
5	2016/03/16	Big Data Analytics with Numpy in Python (Python Numpy 大數據分析)
6	2016/03/23	Finance Big Data Analytics with Pandas in Python (Python Pandas 財務大數據分析)
7	2016/03/30	Text Mining Techniques and Natural Language Processing (文字探勘分析技術與自然語言處理)
8	2016/04/06	Off-campus study (教學行政觀摩日)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
9	2016/04/13	Social Media Marketing Analytics (社群媒體行銷分析)
10	2016/04/20	期中報告 (Midterm Project Report)
11	2016/04/27	Deep Learning with Theano and Keras in Python (Python Theano 和 Keras 深度學習)
12	2016/05/04	Deep Learning with Google TensorFlow (Google TensorFlow 深度學習)
13	2016/05/11	Sentiment Analysis on Social Media with Deep Learning (深度學習社群媒體情感分析)

課程大綱 (Syllabus)

週次 (Week)	日期 (Date)	內容 (Subject/Topics)
14	2016/05/18	Social Network Analysis (社會網絡分析)
15	2016/05/25	Measurements of Social Network (社會網絡量測)
16	2016/06/01	Tools of Social Network Analysis (社會網絡分析工具)
17	2016/06/08	Final Project Presentation I (期末報告 I)
18	2016/06/15	Final Project Presentation II (期末報告 II)

Sentiment Analysis on Social Media with Deep Learning

Data Scientist

What makes a data scientist?

The big data phenomenon trained a bright spotlight on those who perform deep information analysis and can combine quantitative and statistical modeling expertise with business acumen and a talent for finding hidden patterns. Here's a closer look.

Data scientists rely on analytics, predictive models, statistical analysis and modeling, data mining, sentiment and what-if analysis, and more to do their jobs. Cleansing raw data and building models is detailed work, and the right tools make the process much more efficient.

The IBM® BigInsights™ Data Scientist module accelerates data science with advanced analytics to extract valuable insights from Hadoop. Stable machine learning algorithms are optimized for Hadoop. Text analytics extract insight from unstructured data with existing tooling so analytic applications don't have to be developed from scratch. Big R statistical analysis and distributed frames allow data scientists to use the entire Hadoop cluster, not just a limited sample



Good data scientists select and address the business problems that have the most value to the organization. Armed with data and analytical results, they must present their informed conclusions and recommendations to technical and nontechnical stakeholders.

The BigInsights Analyst module lets data scientists use their existing skills to find data across the organization and visualize it without extra coding. IBM BigSheets is a spreadsheet-style data manipulation and visualization tool that gives business users direct access to data through a recognizable interface. IBM-designed Big SQL offers HDFS caching and high availability benefits as well as query optimization—without forcing data scientists to learn a new skill set.

Social Media



Emotions



Love

Anger

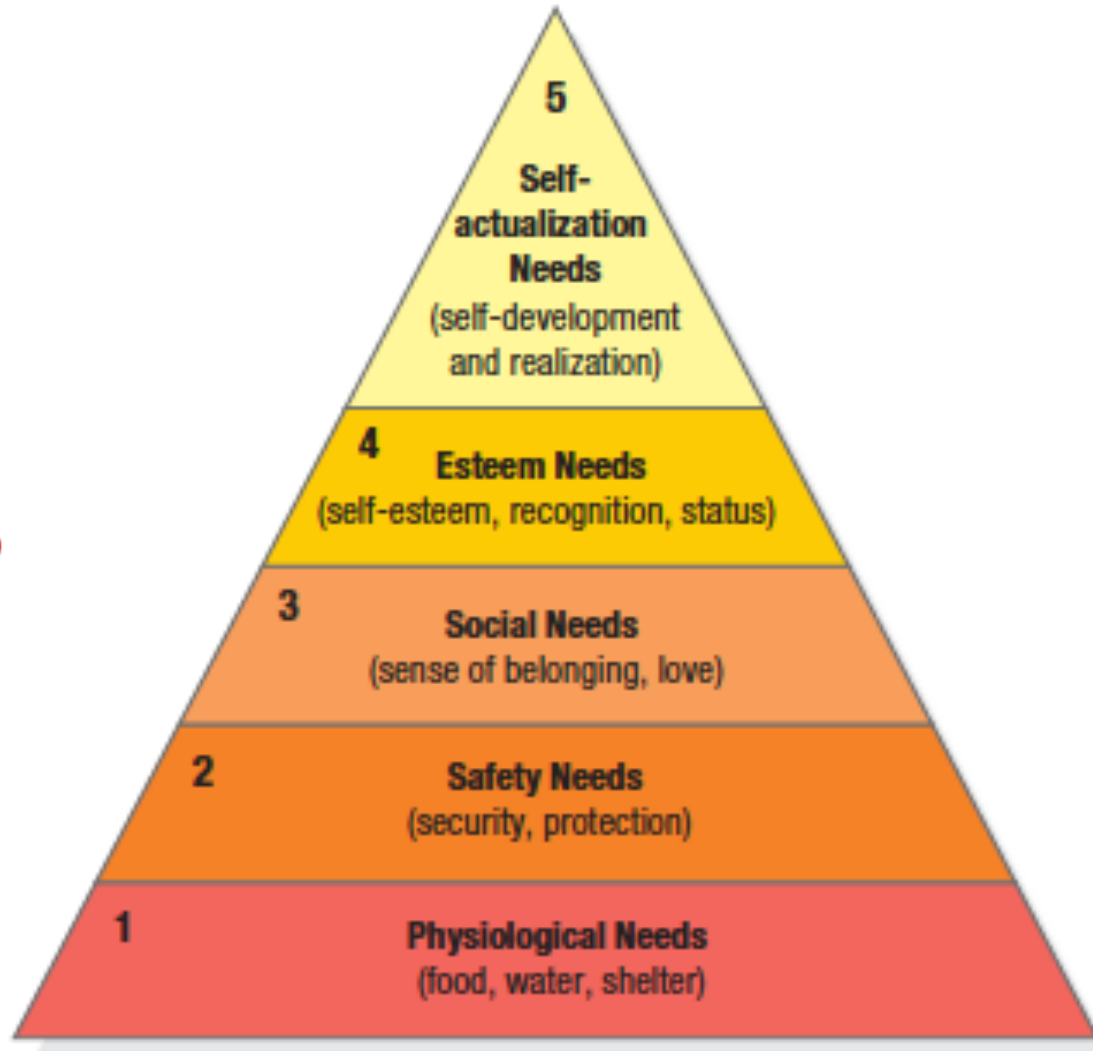
Joy

Sadness

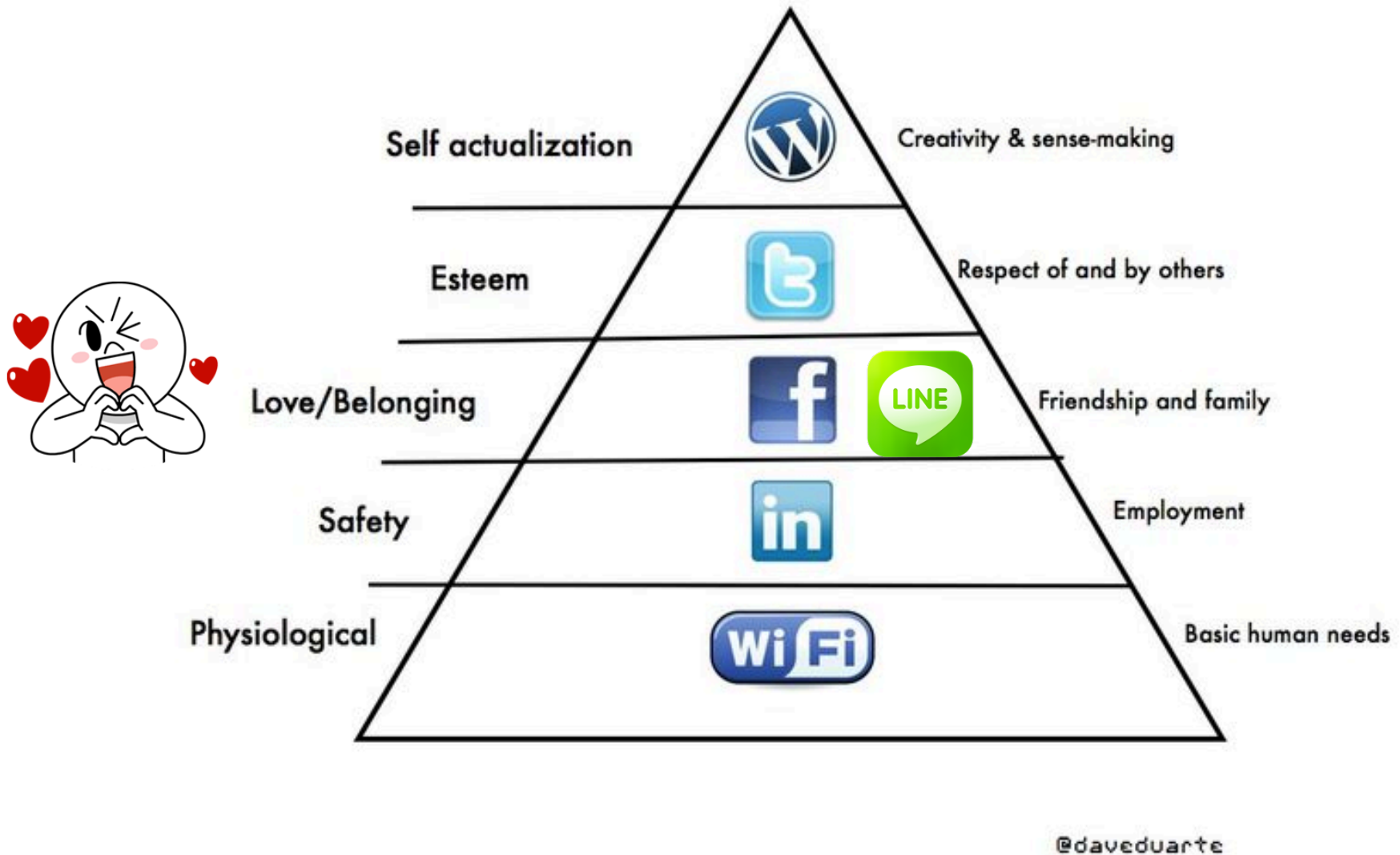
Surprise

Fear

Maslow's Hierarchy of Needs

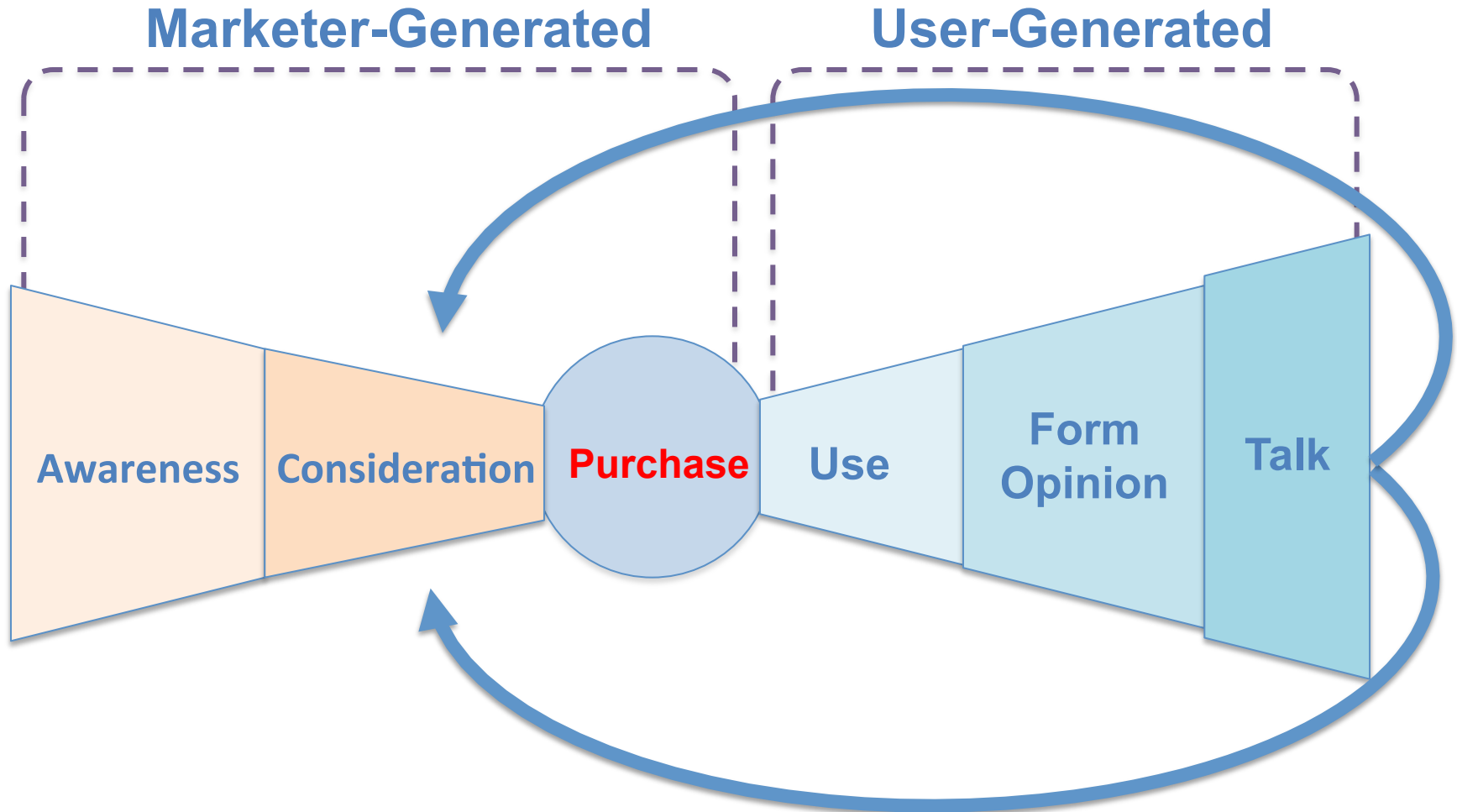


Social Media Hierarchy of Needs

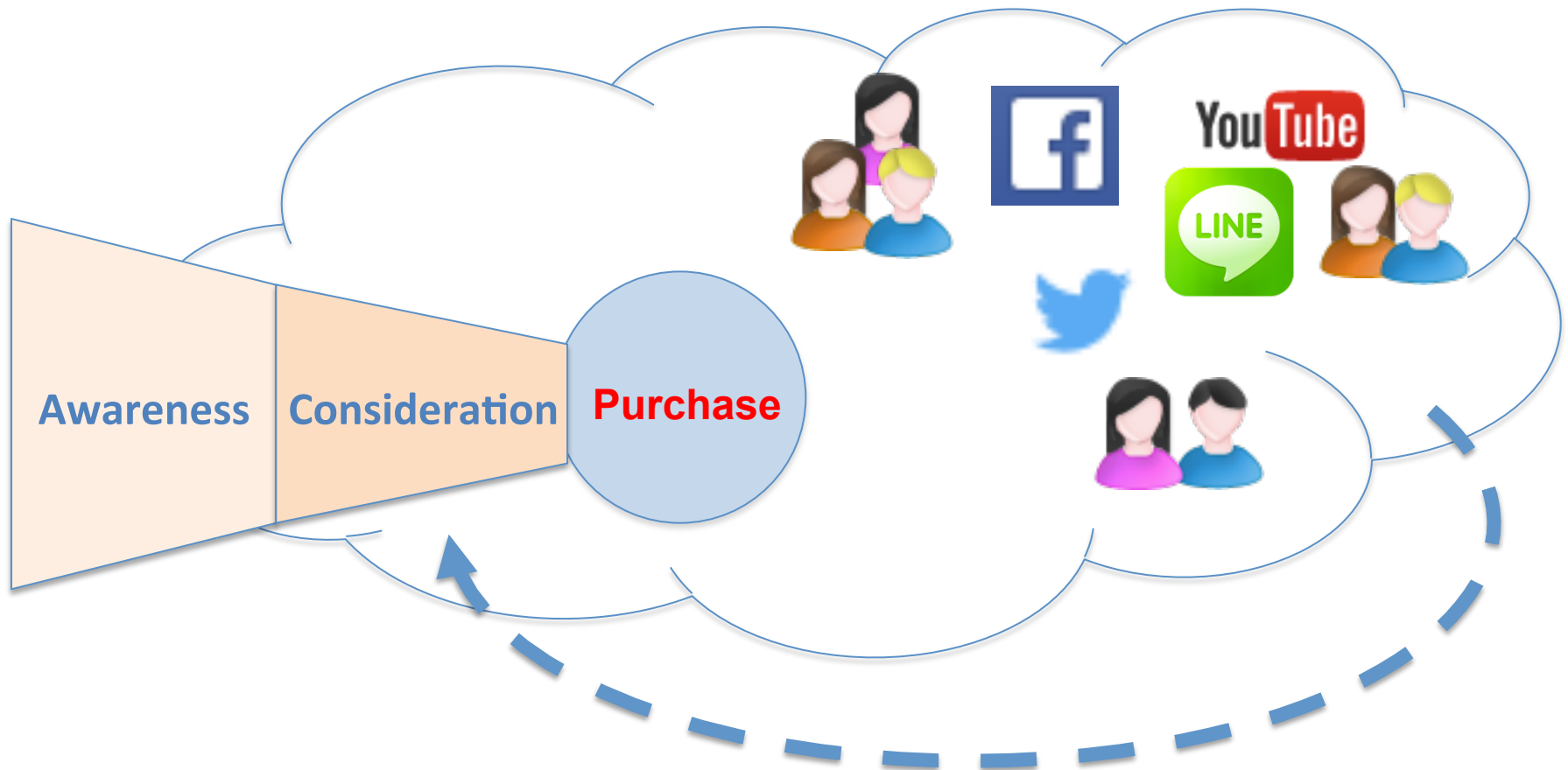


The Social Feedback Cycle

Consumer Behavior on Social Media



The New Customer Influence Path





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. ...”



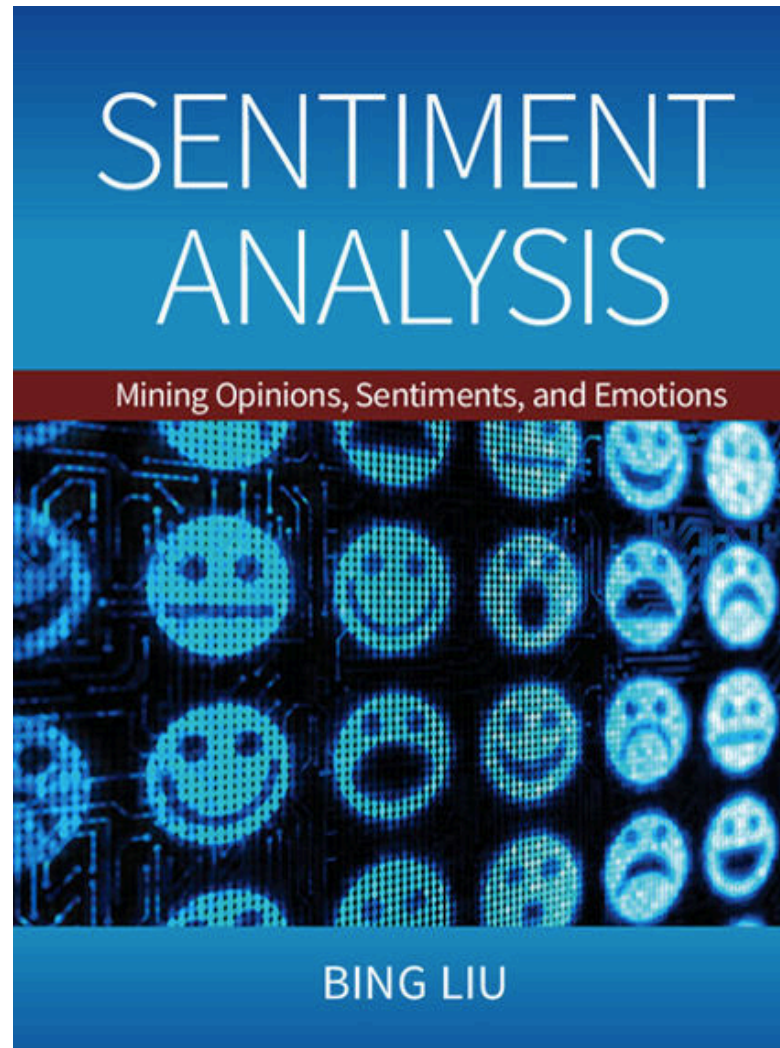
**+Positive
Opinion**



**-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*

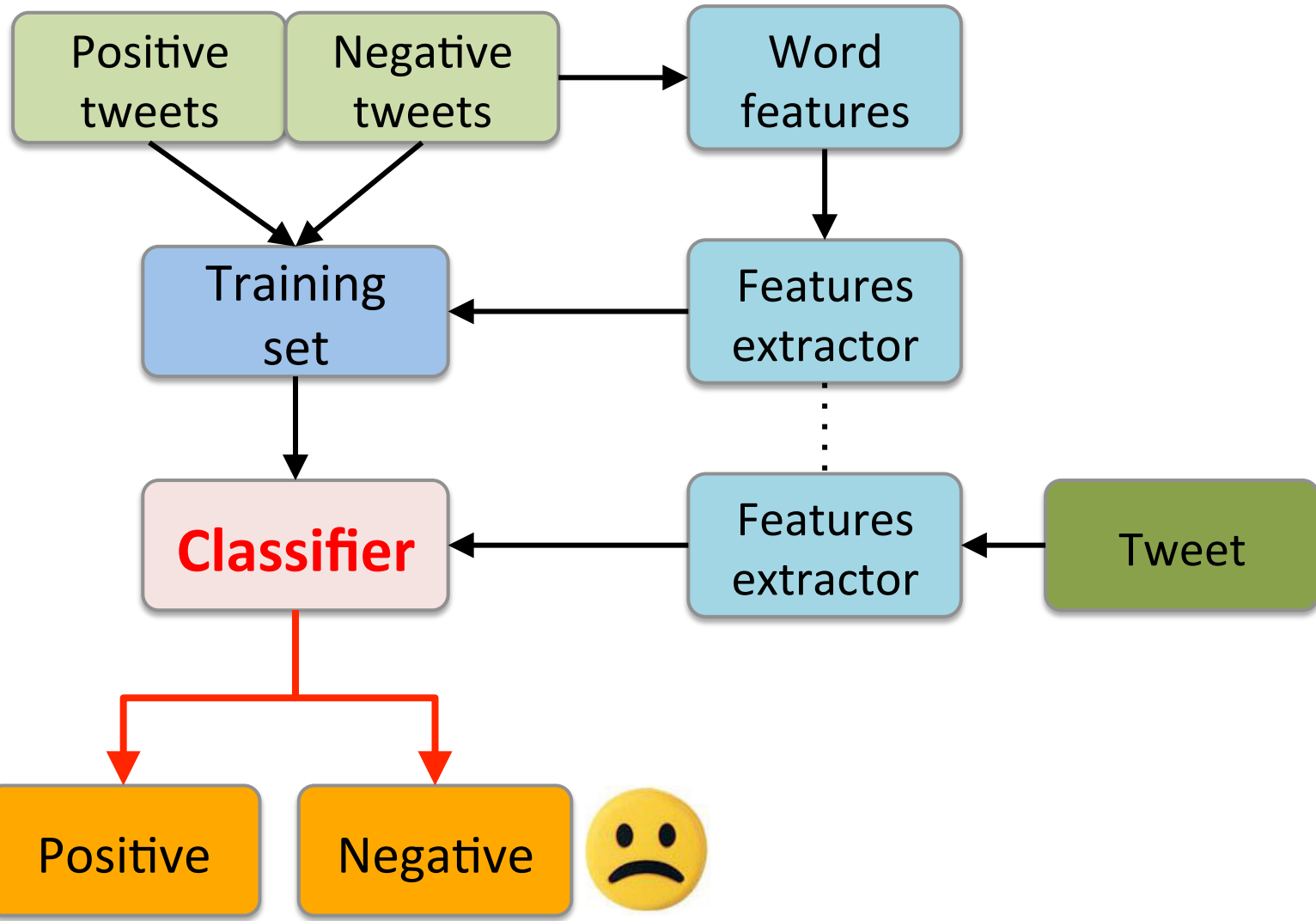
Opinion words in Sentiment classification

- 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*

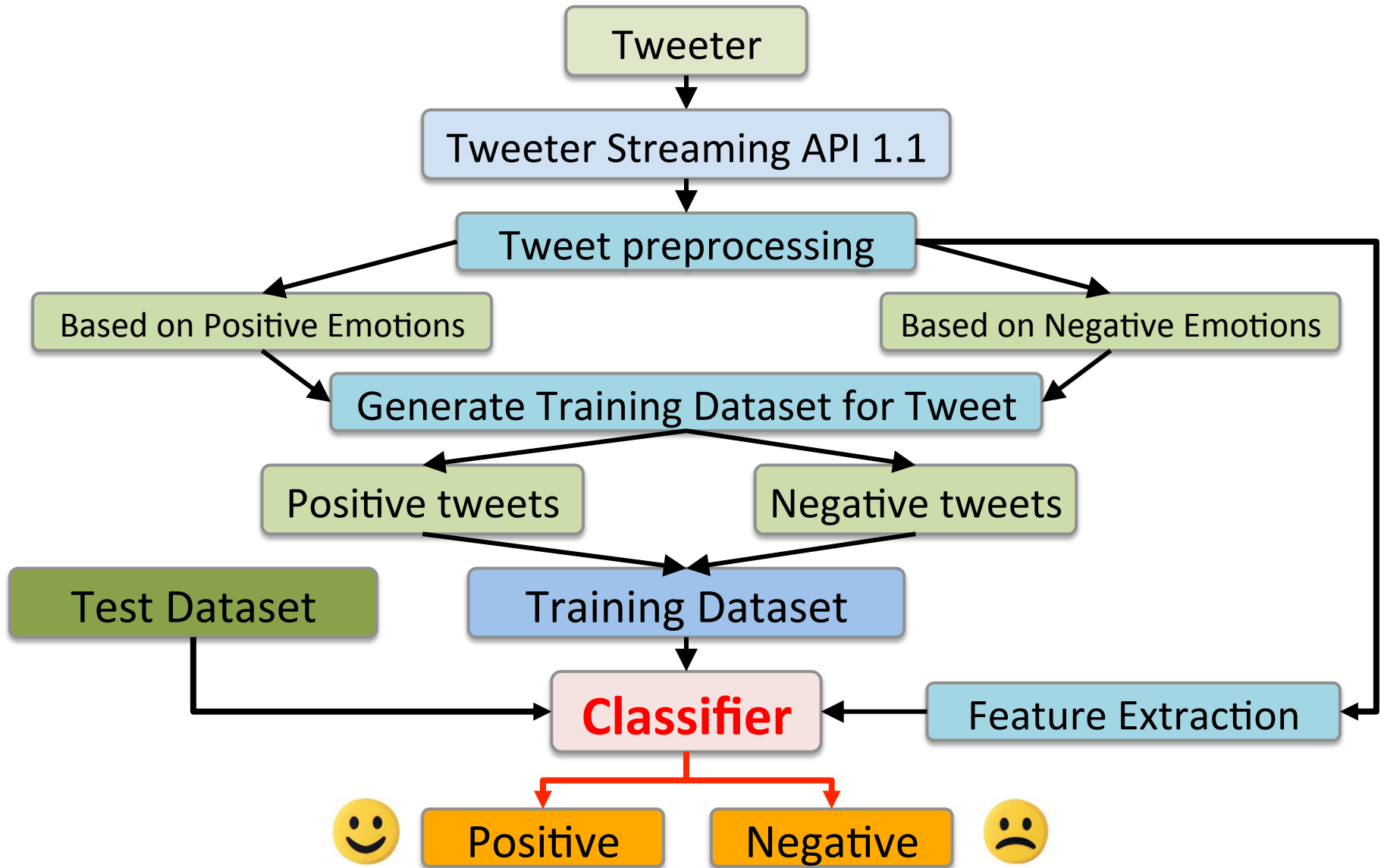
Features in Opinion Mining

- *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*

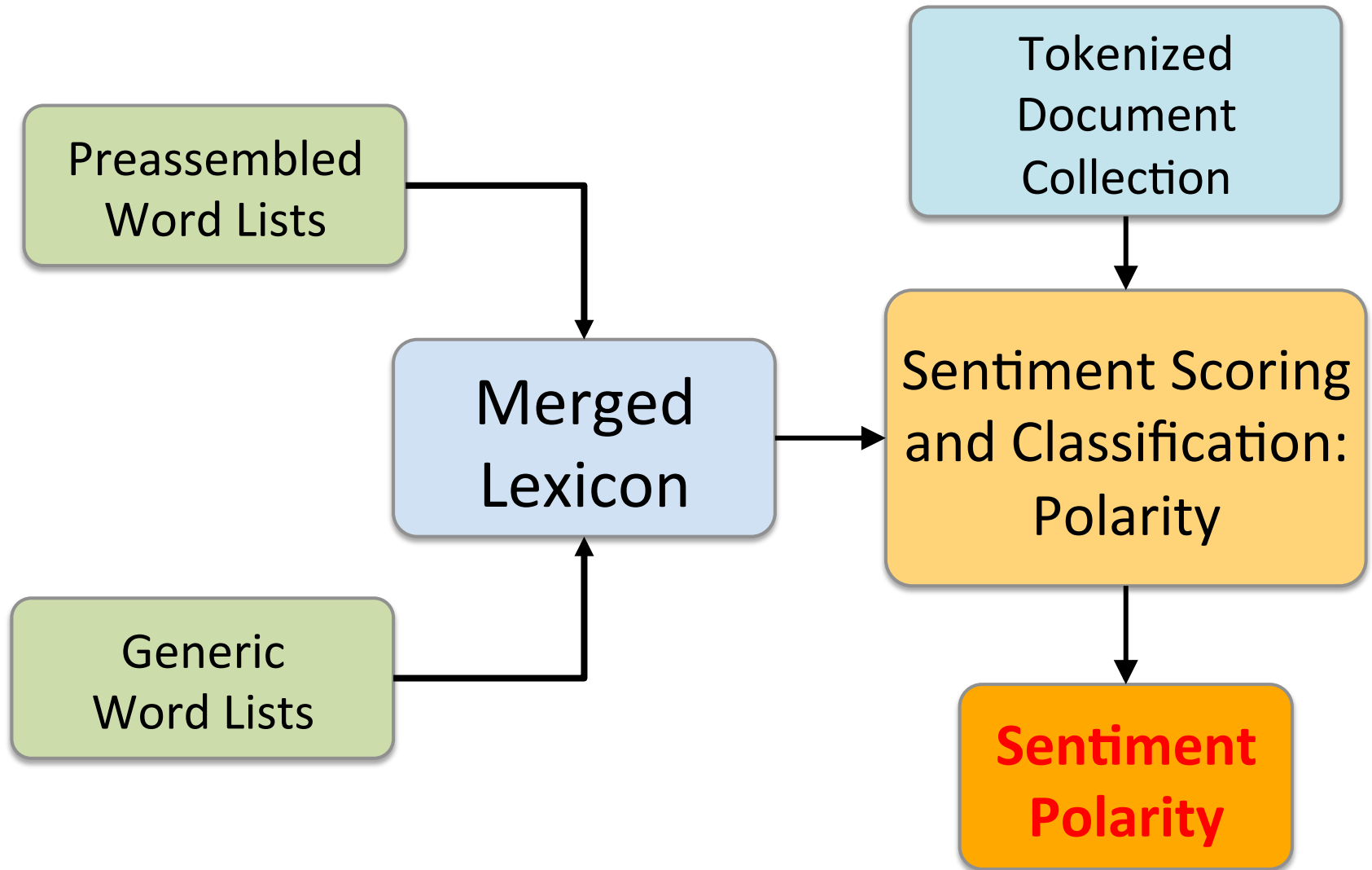
Sentiment Analysis Architecture



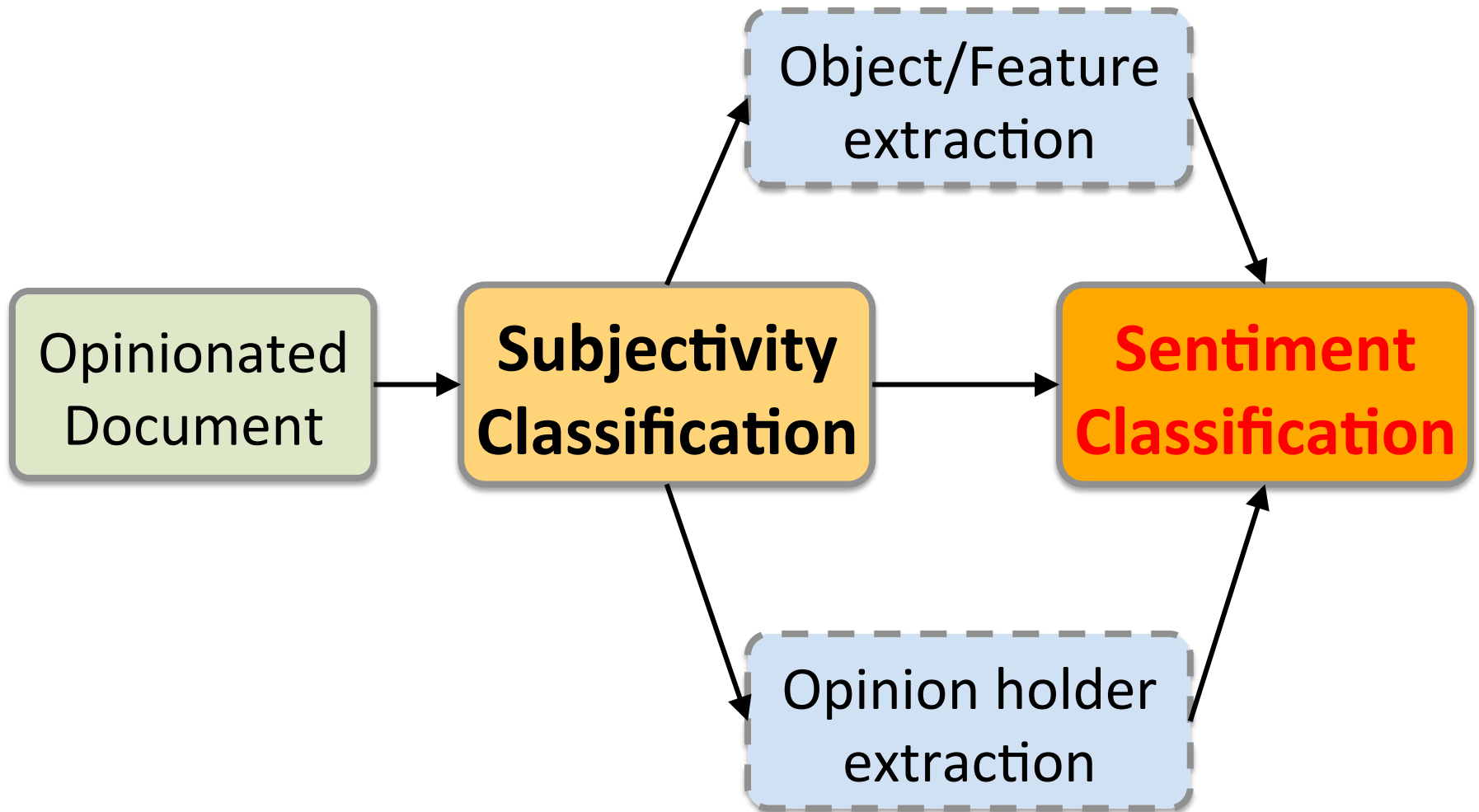
Sentiment Classification Based on Emoticons



Lexicon-Based Model



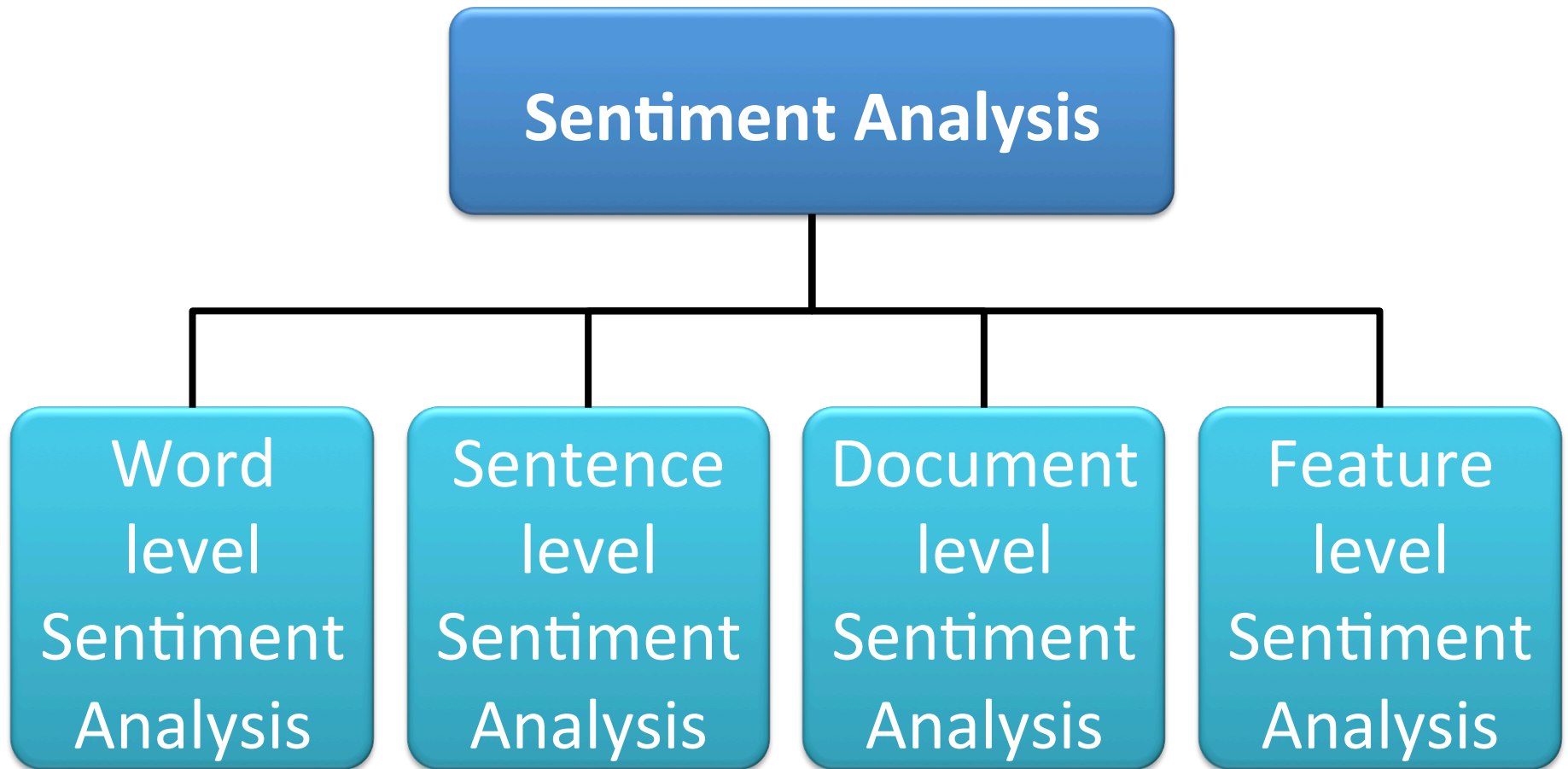
Sentiment Analysis Tasks



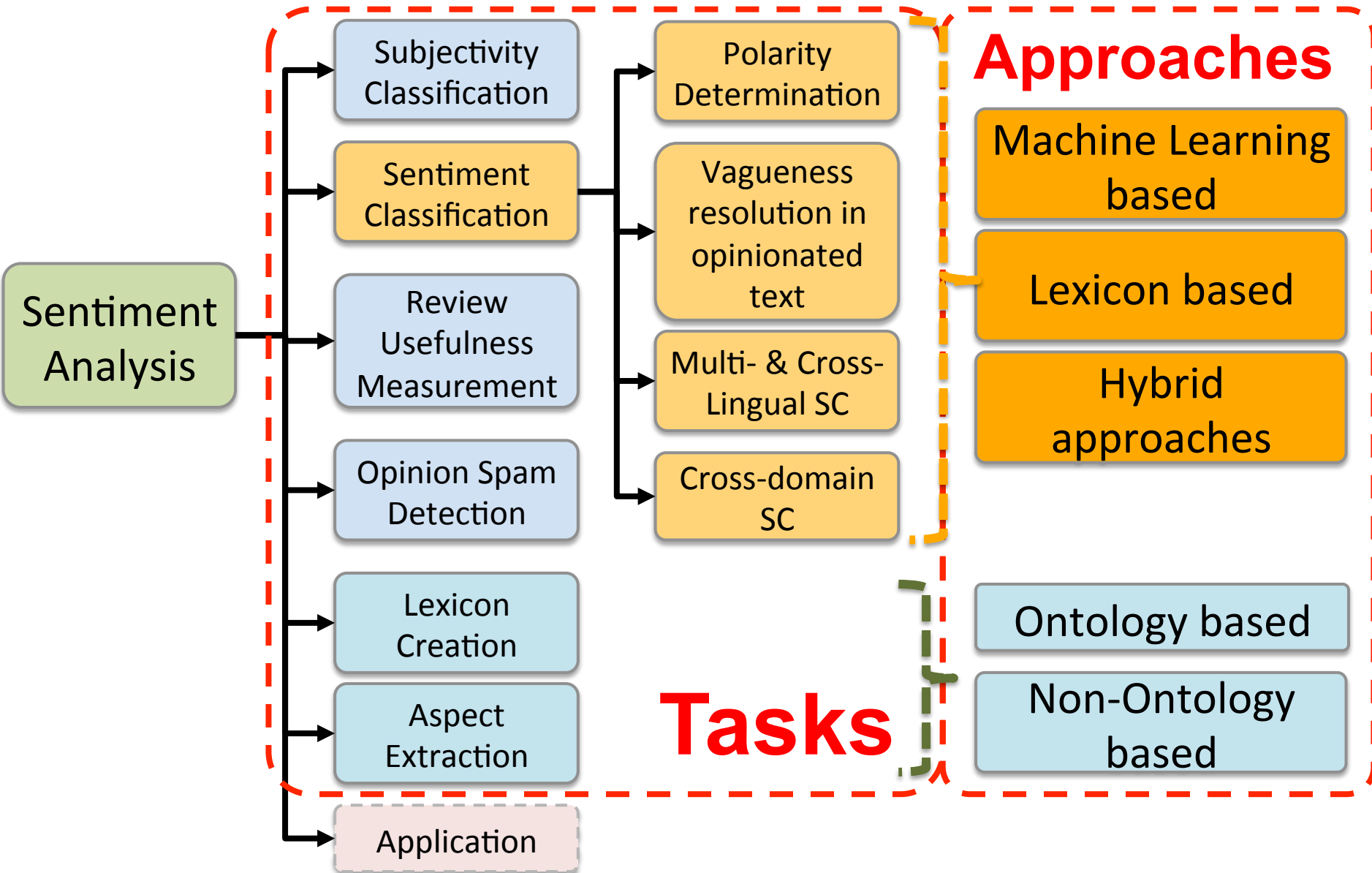
Sentiment Analysis vs. Subjectivity Analysis

Sentiment Analysis	Subjectivity Analysis
Positive	Subjective
Negative	
Neutral	Objective

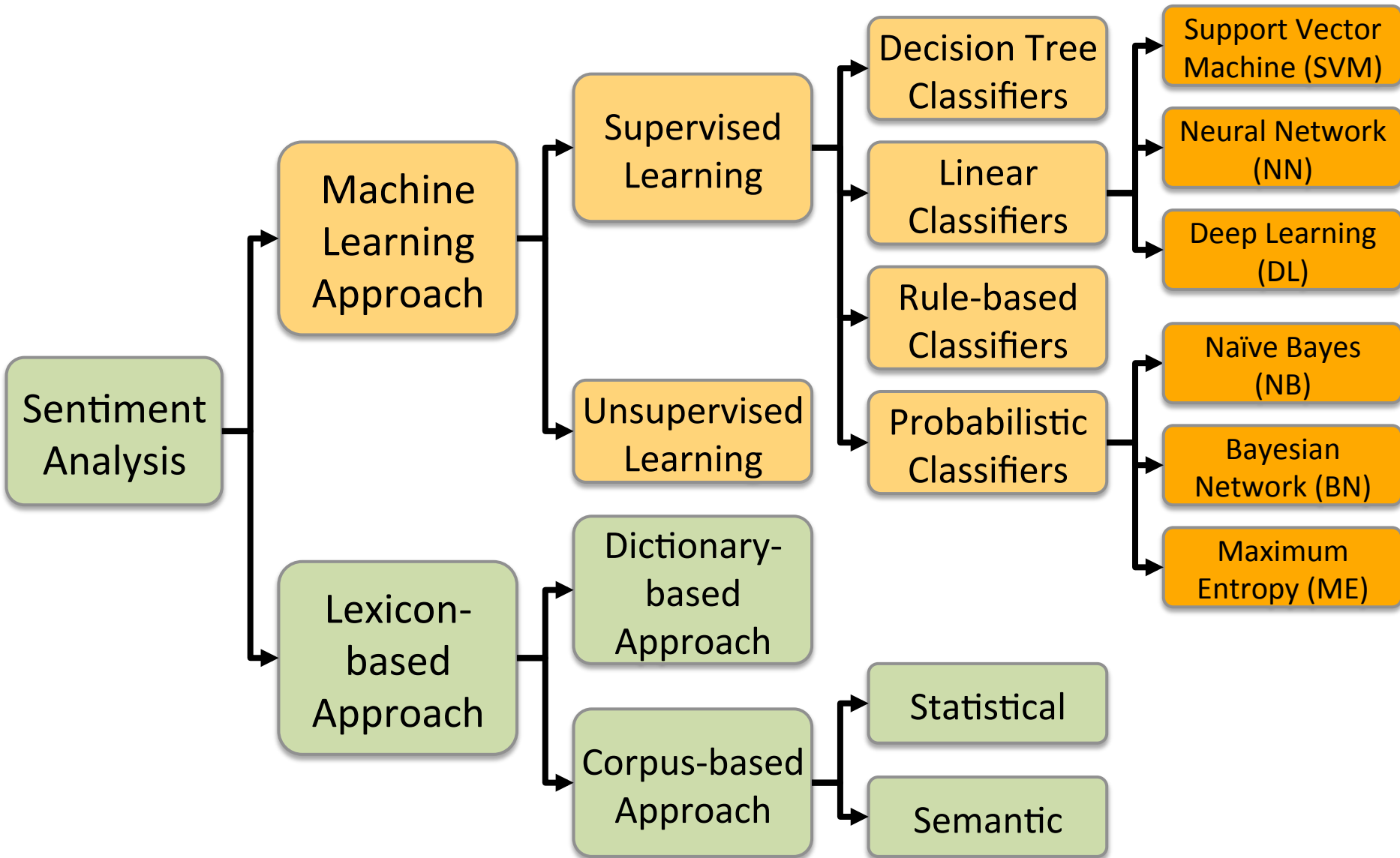
Levels of Sentiment Analysis



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
Airoidi, 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,"

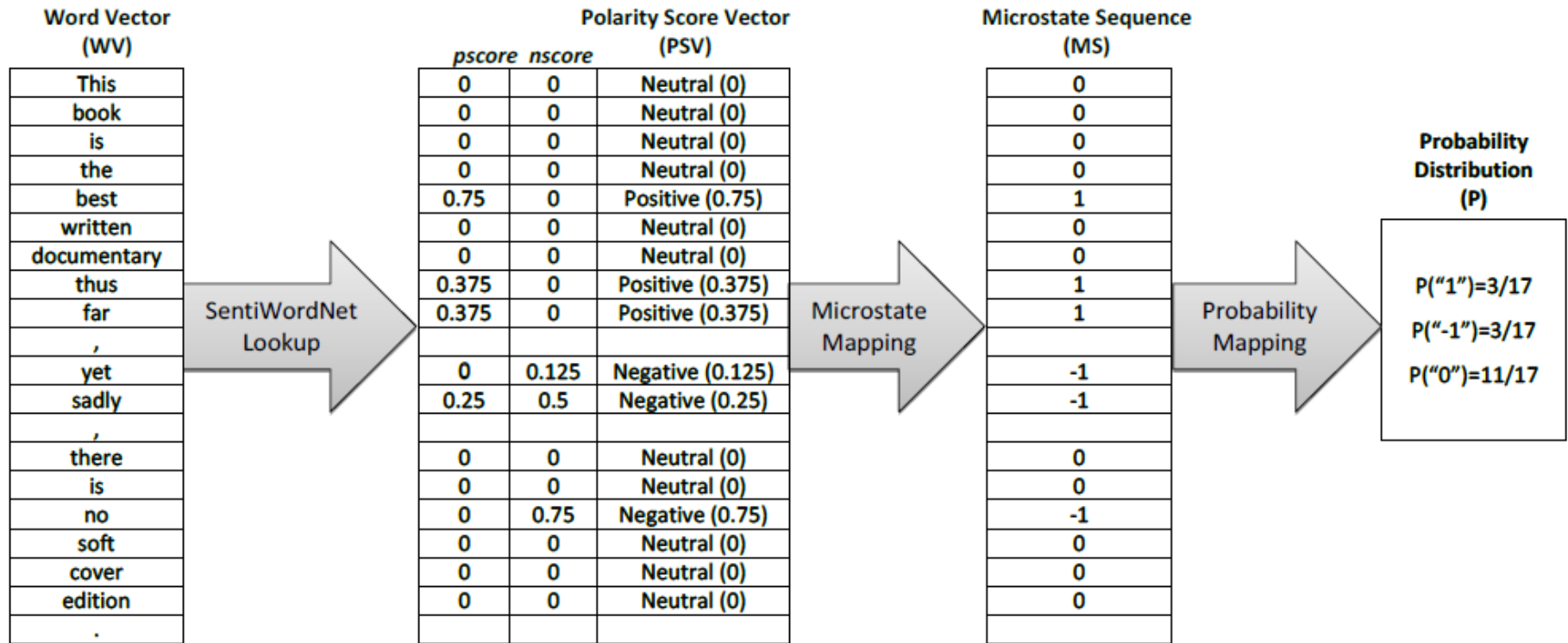
ACM Trans. Manage. Inf. Syst. (3:1) 2012, pp 1-23.,

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
.	.	.

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"	

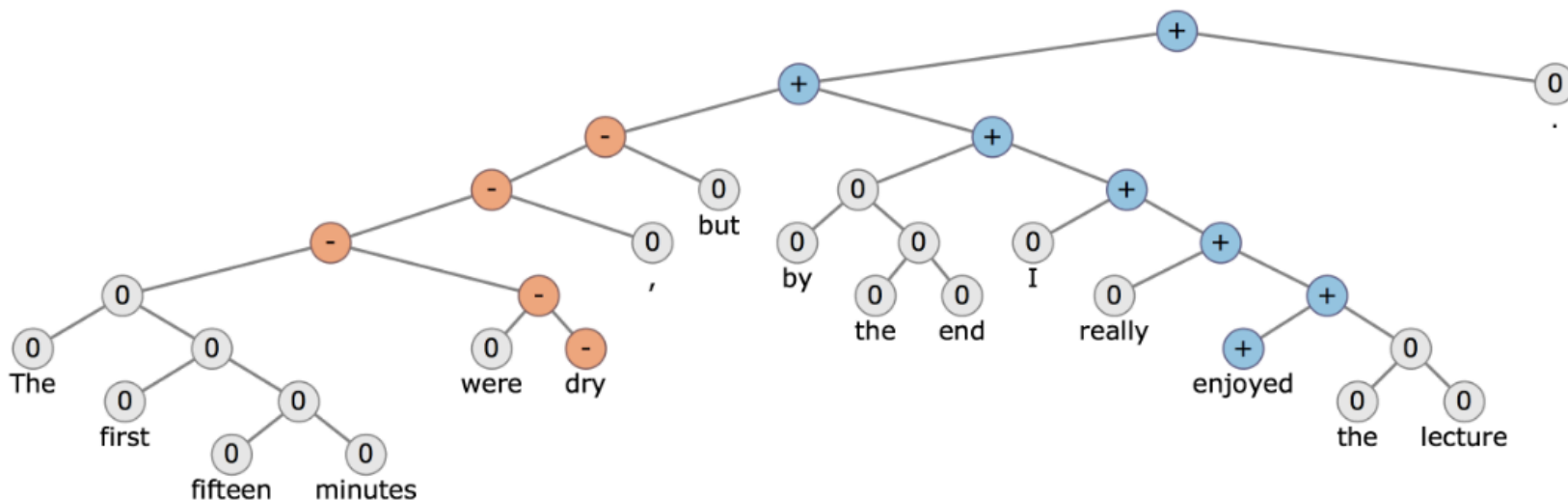
Evaluation of Text Mining and Sentiment Analysis

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

CS224d: Deep Learning for Natural Language Processing



CS224d: Deep Learning for Natural Language Processing



Course Description

Natural language processing (NLP) is one of the most important technologies of the information age. Understanding complex language utterances is also a crucial part of artificial intelligence. Applications of NLP are everywhere because people communicate most everything in language: web search, advertisement, emails, customer service, language translation, radiology reports, etc. There are a large variety of underlying tasks and machine learning models powering NLP applications. Recently, deep learning approaches

<http://cs224d.stanford.edu/>

Deeply Moving: Deep Learning for Sentiment Analysis



Sentiment Analysis

[Information](#)[Live Demo](#)[Sentiment Treebank](#)[Help the Model](#)[Source Code](#)

Deeply Moving: Deep Learning for Sentiment Analysis

This website provides a [live demo](#) for predicting the sentiment of movie reviews. Most sentiment prediction systems work just by looking at words in isolation, giving positive points for positive words and negative points for negative words and then summing up these points. That way, the order of words is ignored and important information is lost. In contrast, our new deep learning model actually builds up a representation of whole sentences based on the sentence structure. It computes the sentiment based on how words compose the meaning of longer phrases. This way, the model is not as easily fooled as previous models. For example, our model learned that *funny* and *witty* are positive but the following sentence is still negative overall:

This movie was actually neither that funny, nor super witty.

The underlying technology of this demo is based on a new type of *Recursive Neural Network* that builds on top of grammatical structures. You can also browse the [Stanford Sentiment Treebank](#), the dataset on which this model was trained. The model and dataset are described in an upcoming [EMNLP paper](#). Of course, no model is perfect. You can help the model learn even more by [labeling sentences](#) we think would help the model or those you try in the live demo.

Paper Title and Abstract

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Paper: [Download pdf](#)

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

Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank

Conference on Empirical Methods in Natural Language Processing (EMNLP 2013)

Dataset Downloads:

Main zip file with readme (6mb)
Dataset raw counts (5mb)
Train, Dev, Test Splits in PTB Tree Format

Code: [Download Page](#)

Press: [Stanford Press Release](#)

Dataset visualization and web design by Jason Chuang. Live demo by Jean Wu, Richard Socher, Rukmani Ravisundaram and Tayyab Tariq.

<http://nlp.stanford.edu/sentiment/>

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**

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{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-

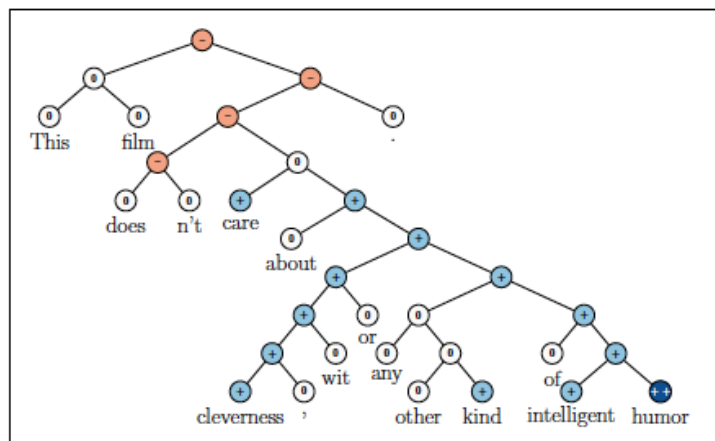
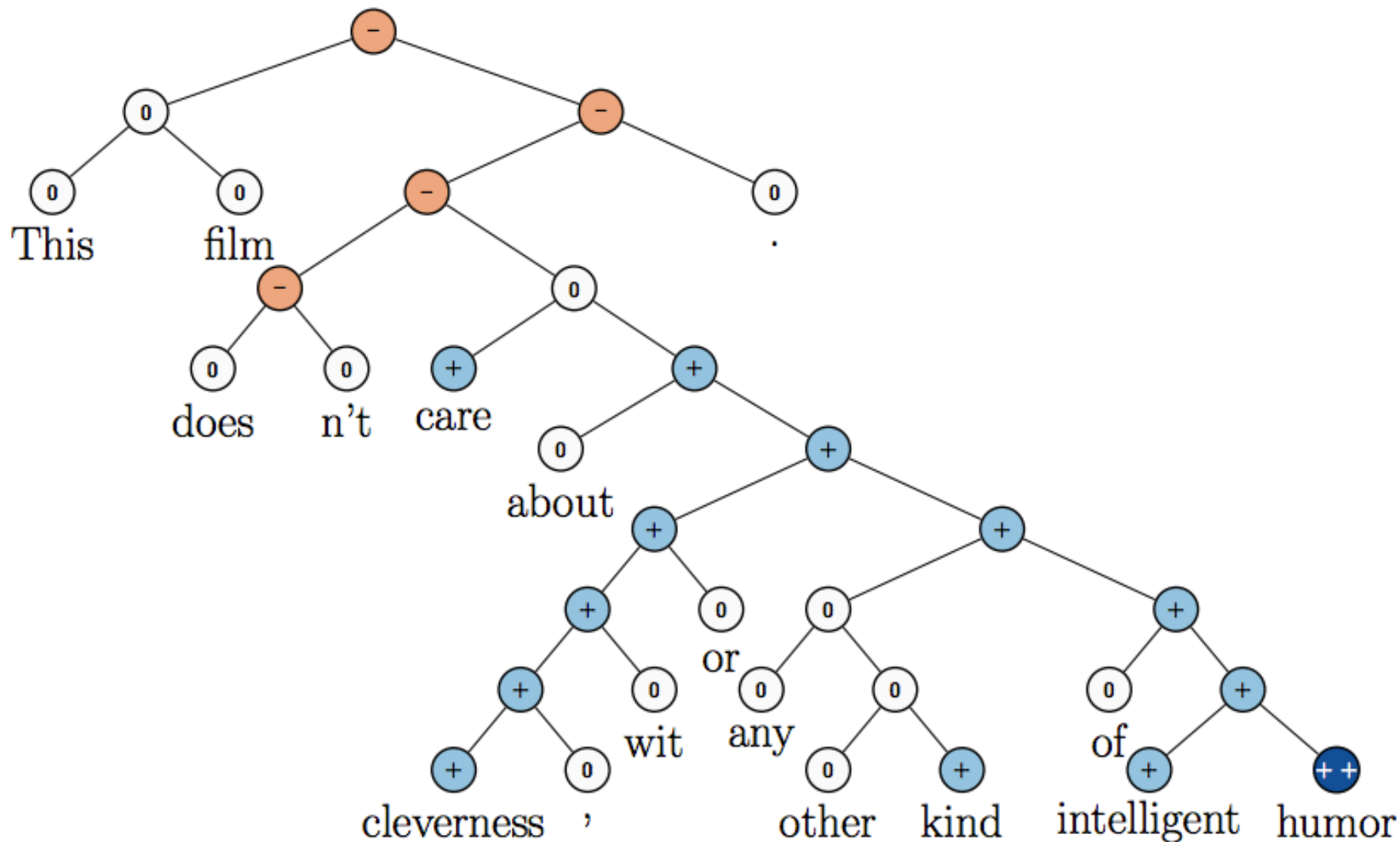


Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (--, -, 0, +, ++), at every node of a parse tree and capturing the negation and its scope in this sentence.

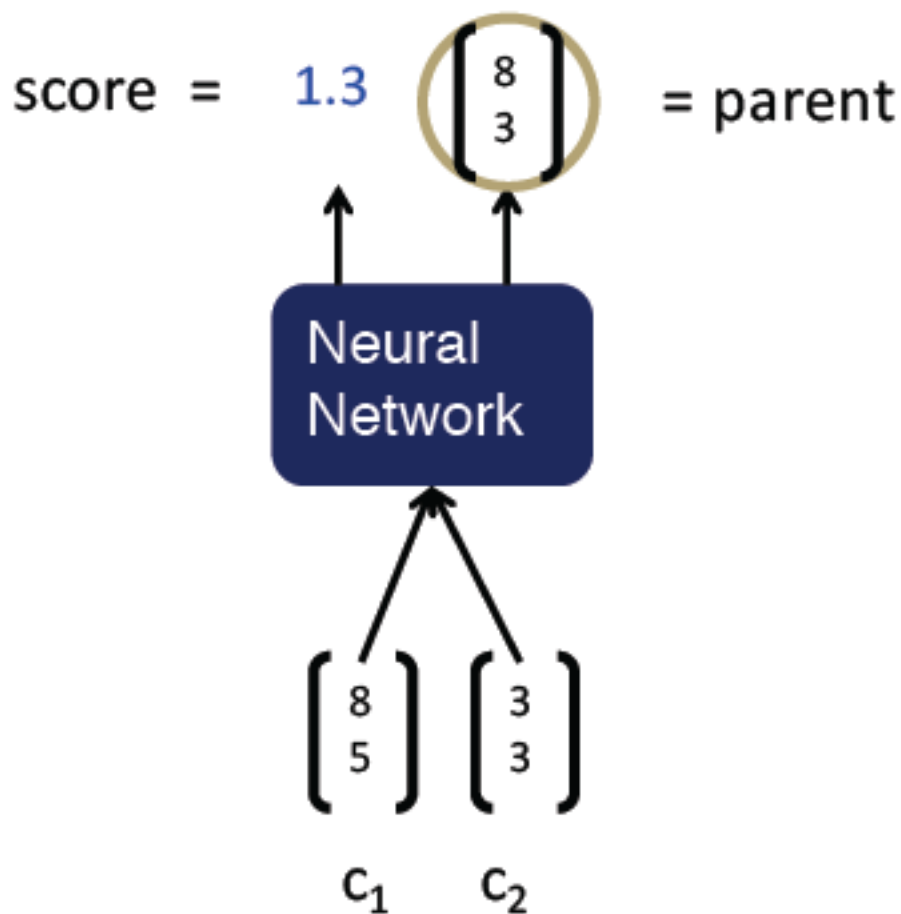
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Tensor Network (RNTN)



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

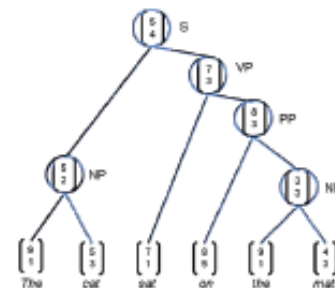
Recursive Neural Network Definition



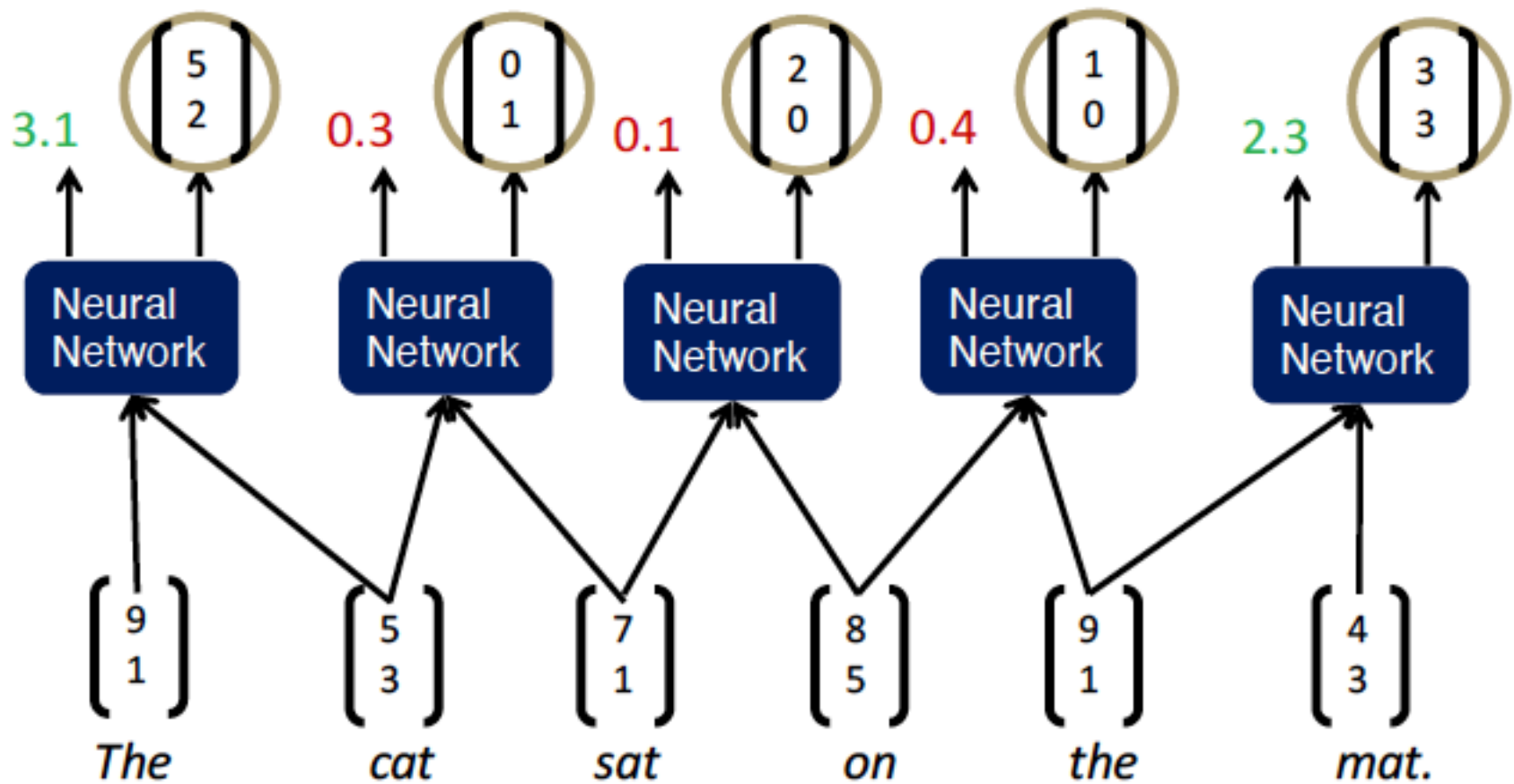
$$\text{score} = U^T p$$

$$p = \tanh\left(W \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right),$$

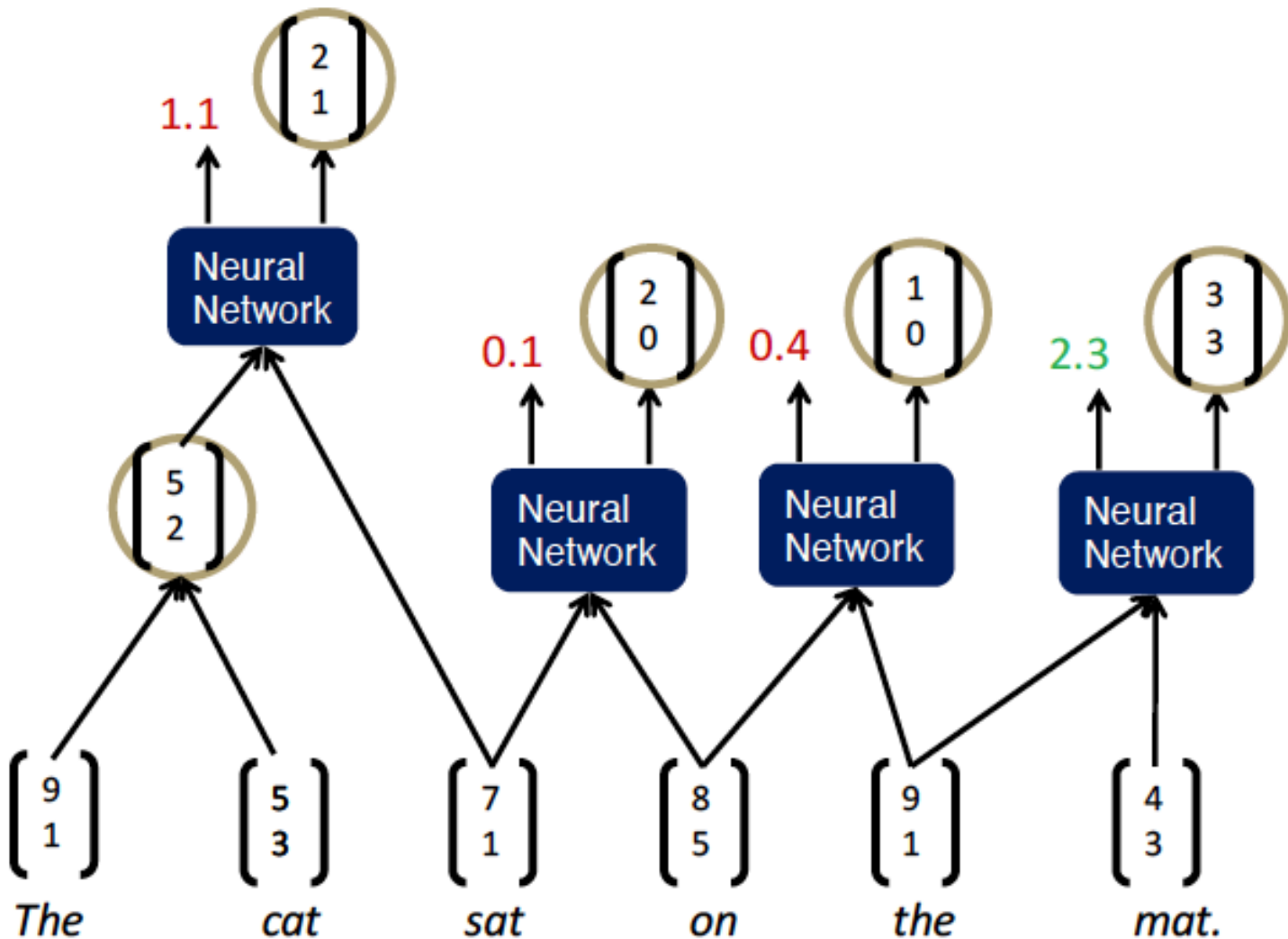
Same W parameters at all nodes of the tree



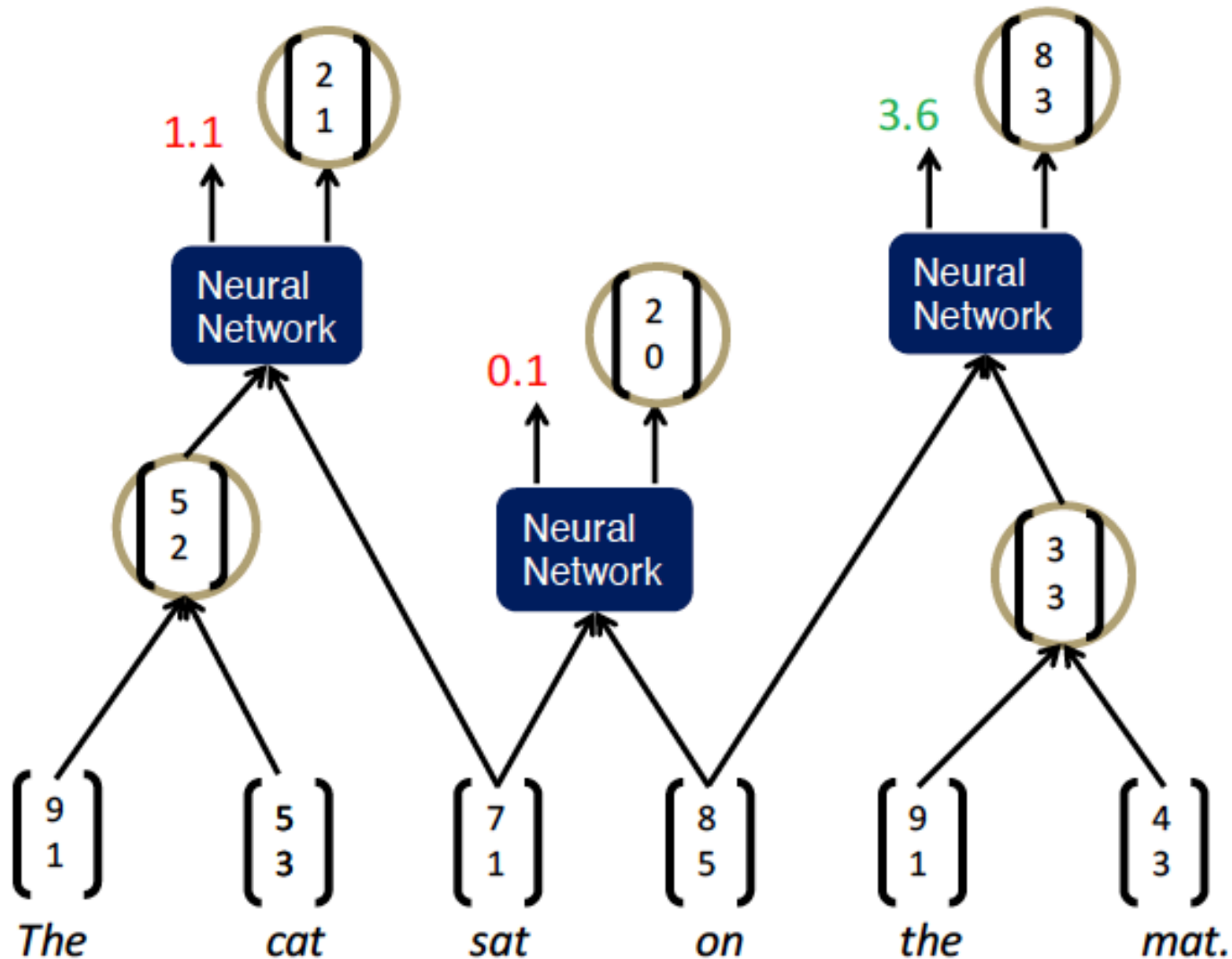
Parsing a sentence with an RNN



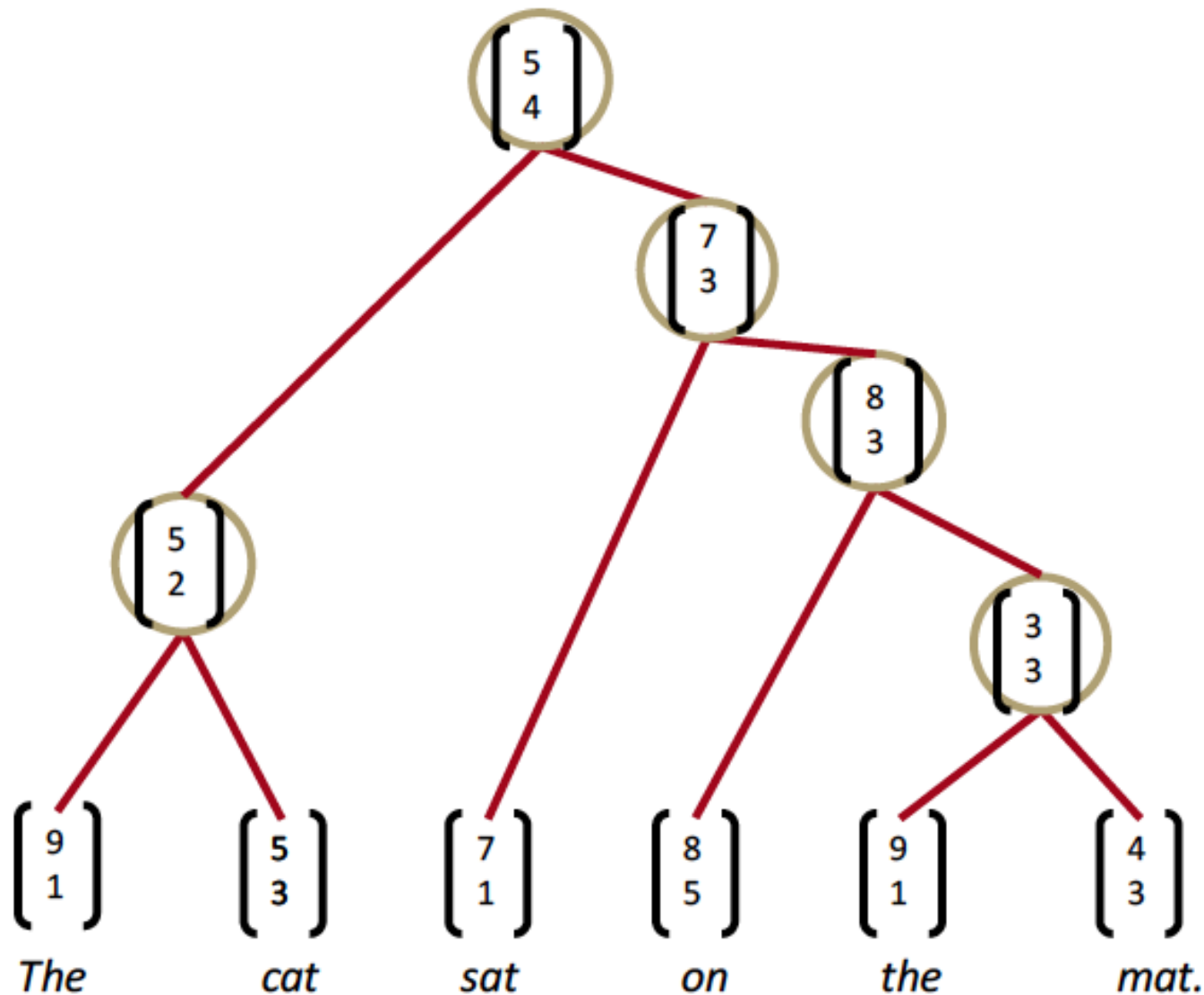
Parsing a sentence with an RNN



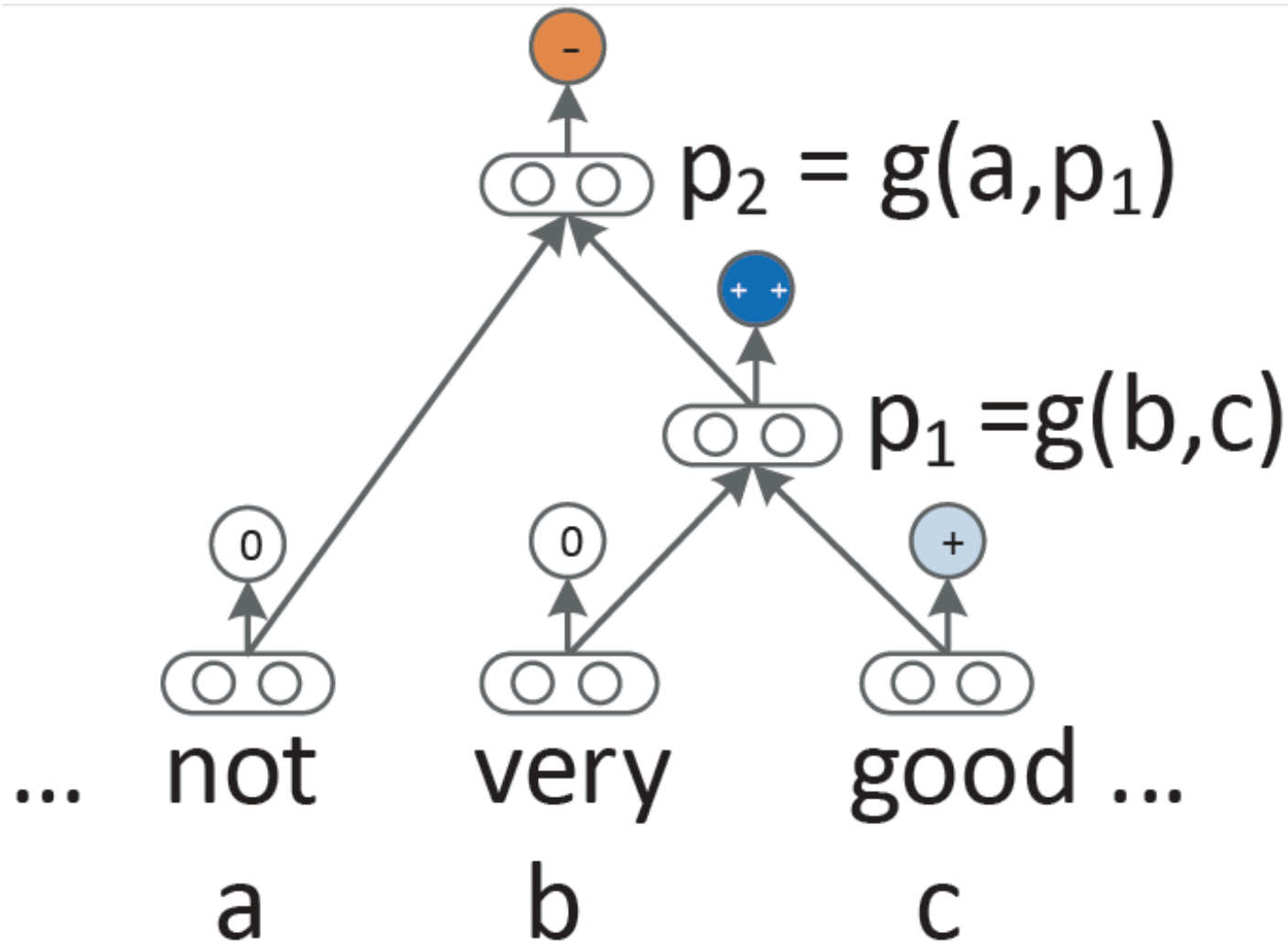
Parsing a sentence with an RNN



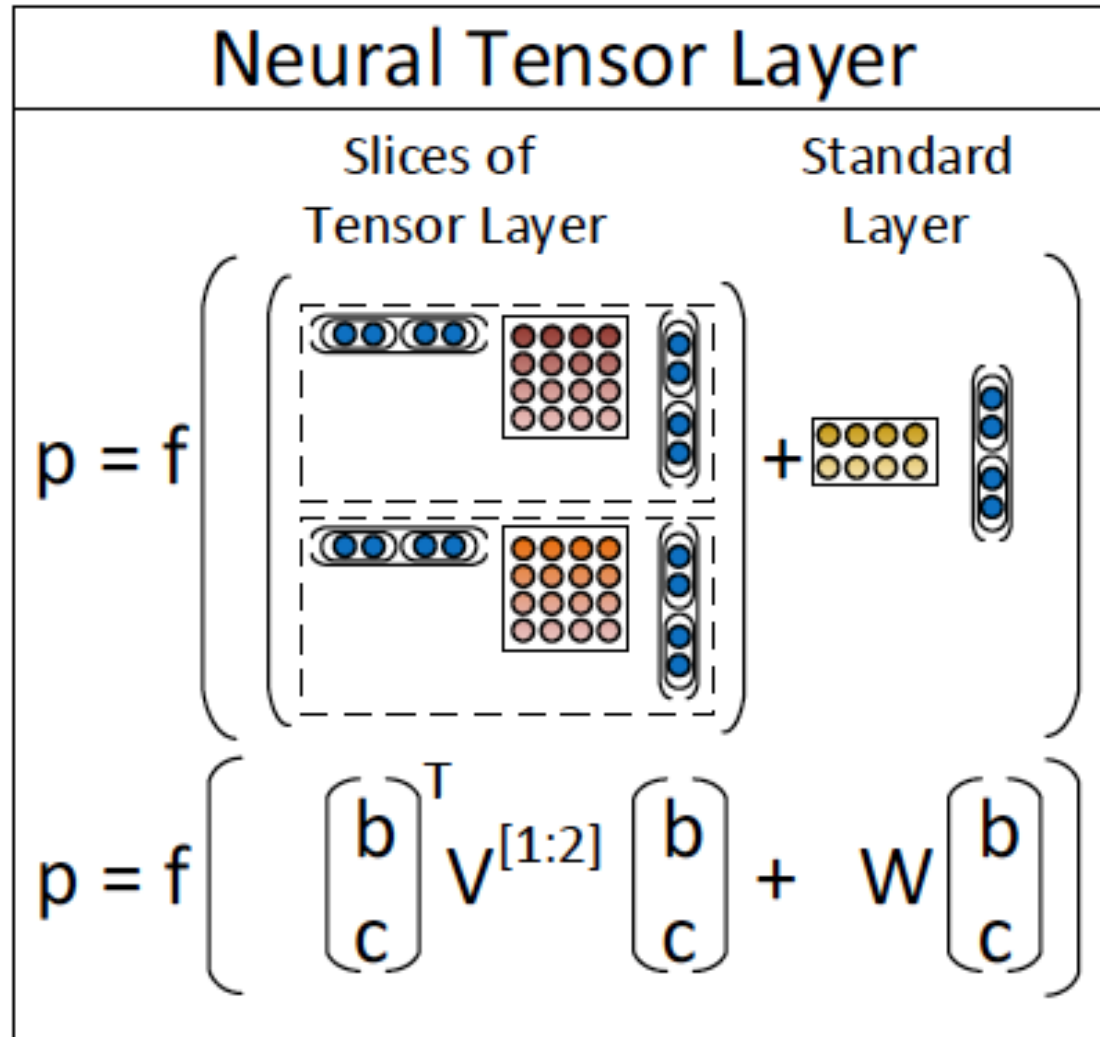
Parsing a sentence with an RNN



Recursive Neural Network (RNN) models for sentiment



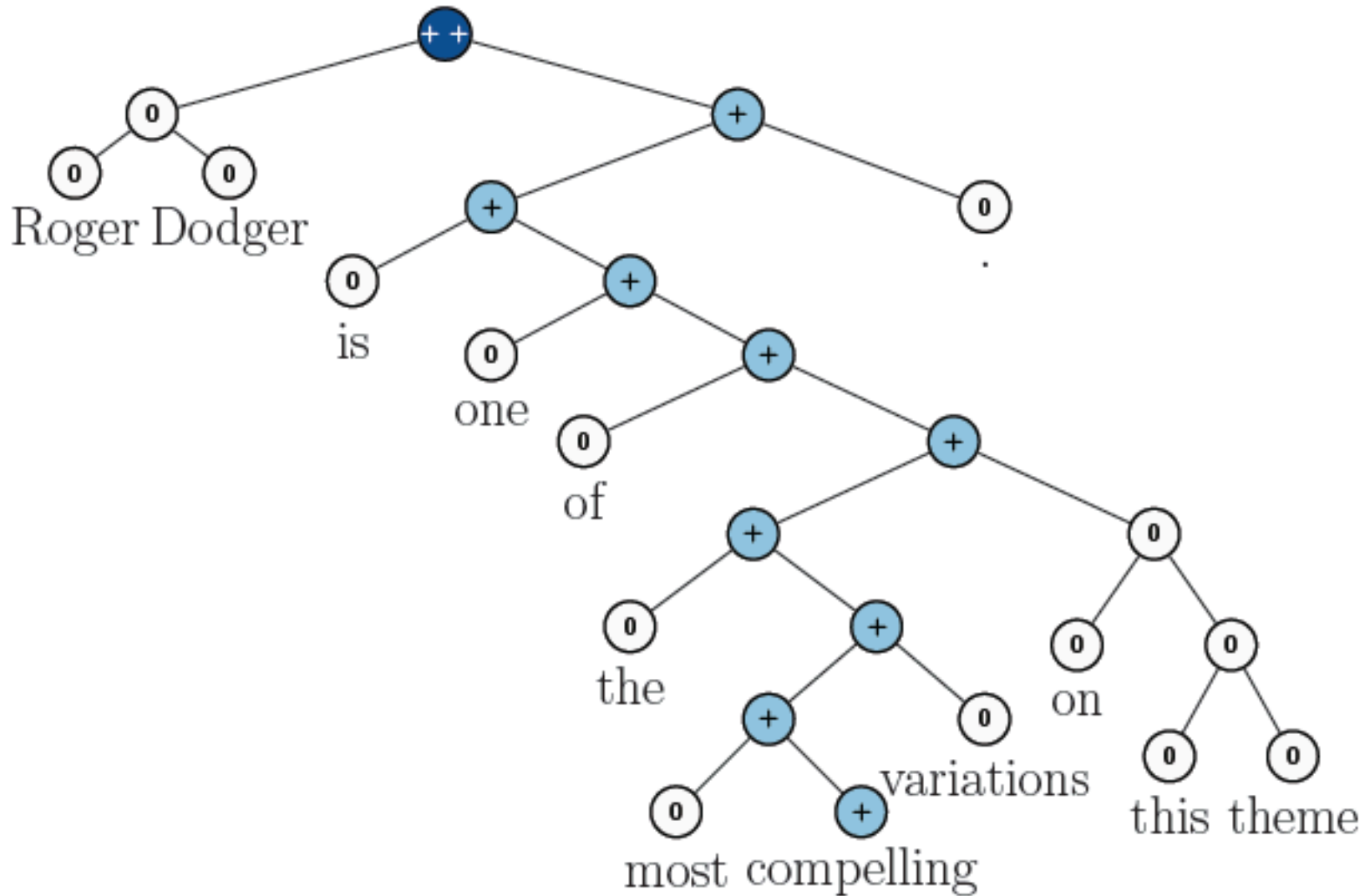
Recursive Neural Tensor Network (RNTN)



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

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

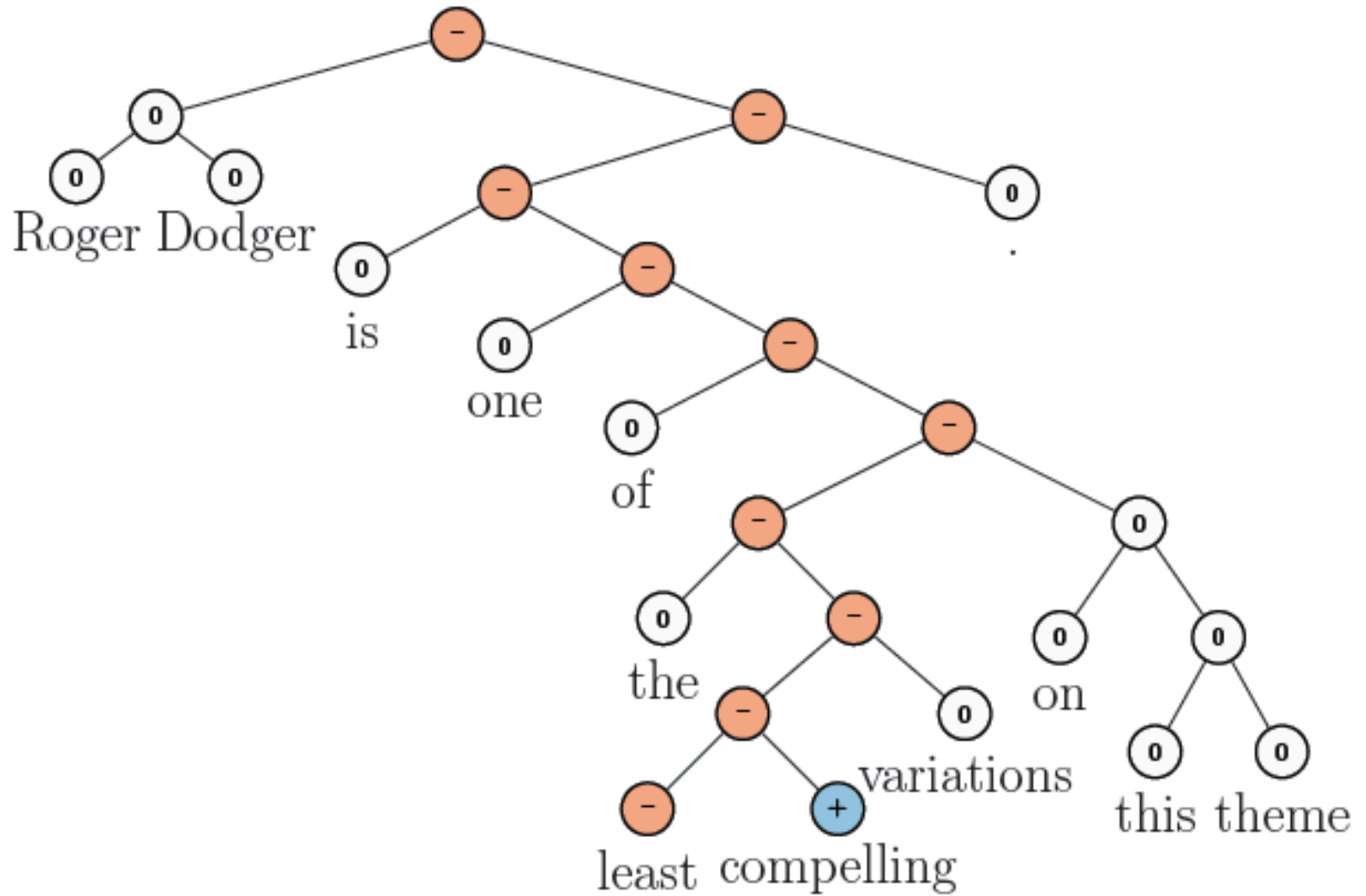
RNTN for Sentiment Analysis



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

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

RNTN for Sentiment Analysis



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

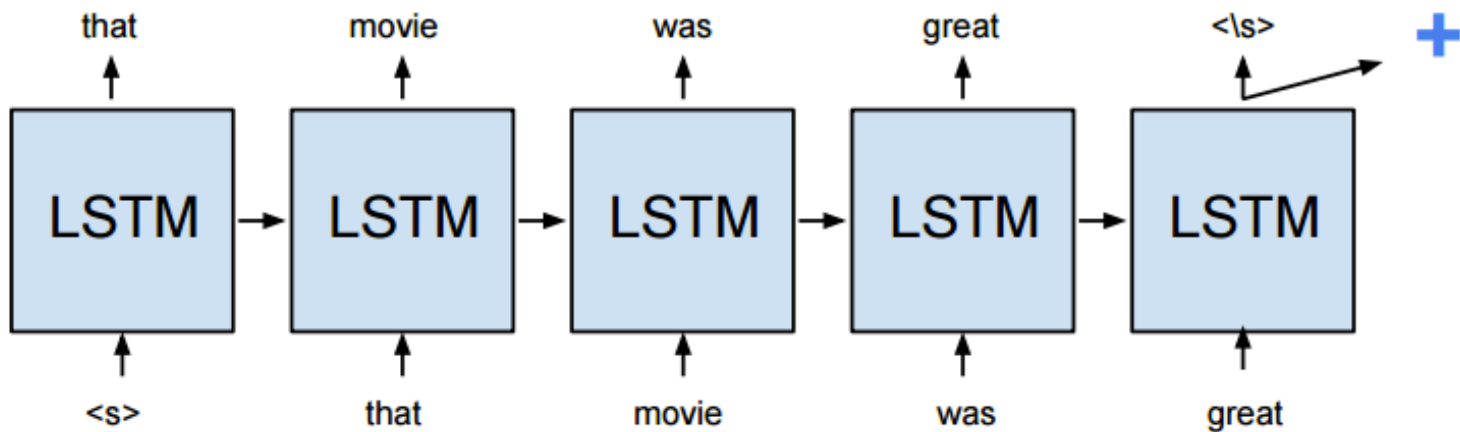
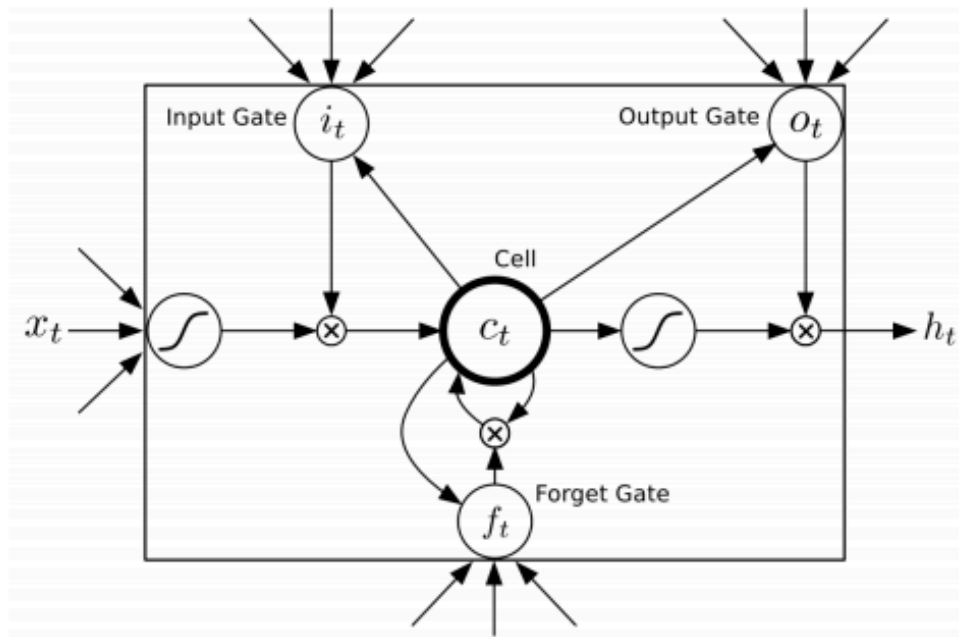
**Accuracy for fine grained (5-class)
and binary predictions
at the sentence level (root) and for all nodes**

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

Long Short-Term Memory (LSTM)



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,N TCIR,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's a navigation bar with the Attensity logo, a language selector set to 'English', and links for Contact, Resources, Support, Blog, and a search bar. Below this is a secondary navigation bar with links for Products, Solutions, Services, Customers, and Partners.

The main headline reads: "Your real-time window into the social web." Below this is a quote from Yahoo! stating: "Teaming with a leading analytics provider like Attensity offers Yahoo! a great opportunity to deliver the key news and analysis that matter." - Yahoo! A green 'Learn More' button is positioned below the quote.

On the left side, there's a vertical menu with the following items: Social Analytics, Social Response, Customer Analytics, Industry Solutions, and Why Attensity.

The right side of the main content area features several charts and graphs, including a bar chart titled "Comparison of Feedback Over Different Time Periods" showing metrics like Neg. Coverage, Neg. Price, Neg. Experience, and Neg. Cost Service. There are also two circular gauges labeled "NPS Index" and a pie chart labeled "Proportion of Feedback".

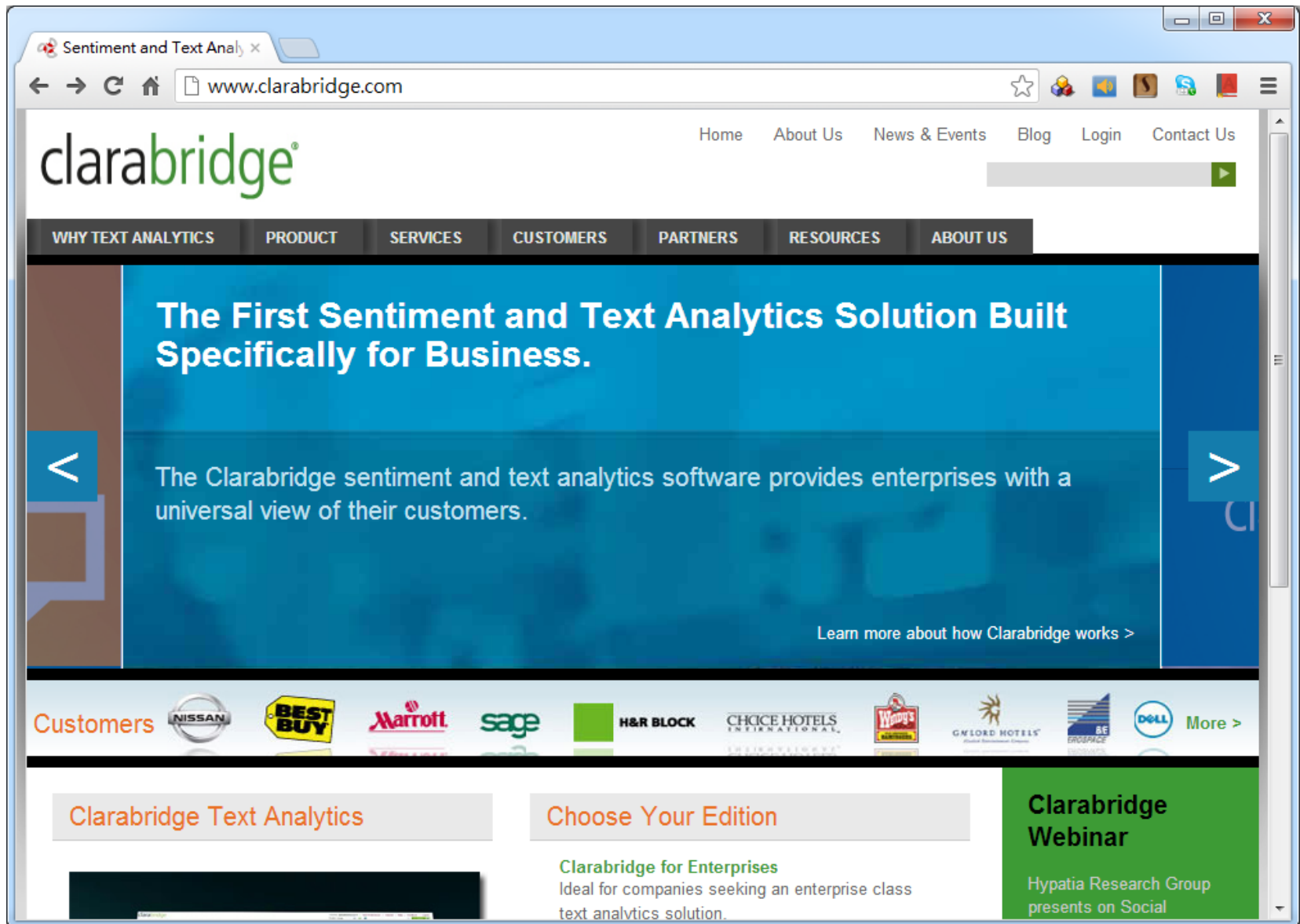
Below the main content area, there are several sections: "Attensity for Marketing" and "Attensity for Customer Service" (both with sub-sections for IT and effectiveness of social marketing strategies), "Success Story" featuring JetBlue Airways with a "DOWNLOAD NOW" button, "About Attensity" (describing it as the leading provider of social analytics and engagement solutions), and "Watch Video" (Command Center Video).

The footer contains the URL www.attensity.com/home/#fragment-1 and a "jence." logo.

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

Clarabridge: Sentiment and Text Analytics Software

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



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

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

Social Media Monitoring x

www.radian6.com

Country 1 888 672 3426 About Radian6 Contact CUSTOMER LOGIN Search GO

salesforce **radian6**

How We Help What We Sell See Demo Free Resources Training & Support

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](#)

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

radian6 Community

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

Social Media Monitoring x

← → ↻ ⬆ ⌚ www.sas.com/software/customer-intelligence/social-media-analytics/ ☆ 📱 📧 📄 📅 🔍

 **THE POWER TO KNOW.**

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NEWS EVENTS CONSULTING CAREERS RESOURCE CENTER

SEARCH

Home Products & Solutions Customer Success Partners Company Support & Training

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




Questions?

📞 Phone

📄 Contact Form



White Paper



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

Download Now

SAS® Social Media Analytics

[» Overview](#)

RESOURCES

[» Fact Sheet \(PDF\)](#)

[» Solution Brief \(PDF\)](#)

[» White Papers](#)

What do tweeples think ab x

www.tweetfeel.com/index.php#iPhone4s

FAQ | Contact Us

tweetfeel

|| 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.


[Read our FAQ](#) [Legal Stuff](#) [100% Guarantee](#) [Share](#)

Follow us Email us [Brought to you by conversation](#) [Powered by twitter](#)

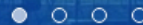
eLand

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



關於意藍 產品與雲端服務 ▾ 新聞與活動 聯絡資訊 

< 巨量搜尋。語意分析。社群大數據 >



OpView社群口碑資料庫

OpView

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



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社群大數據

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<http://www.i-buzz.com.tw/>



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產業數據

時事議題

社群研究

解決方案

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

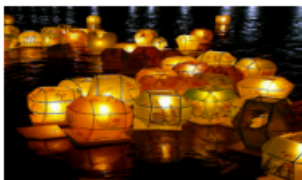


母親節好禮大比拼 聽聽網友怎麼說

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

 **SponsoredReviews.com**
Bloggers Earn Cash, Advertisers Build Buzz!

[Members Login](#)

Sales Toll-Free (877) 360-3683

[Home](#) [Sign-Up](#) [FAQs](#) [Our Blog](#) [Contact Us](#)

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.

[Free Sign Up](#) [Read More](#)

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.

[Free Sign Up](#) [Read More](#)

How it works:


 Advertiser  Blogger

PayPerPost : Blog Marke x

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.

[signup now](#)



bloggers

Make money blogging! PayPerPost lets you pick your advertisers, name your own price and negotiate your own deals. You can get paid to blog on virtually any subject. Sign up below!


[signup now](#)

see how it works



[click here and watch the video](#)

customer testimonial



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

-C. Litchfield

1 (877) 816 POST



Post Project

Find Freelancers

Browse Projects

Post Contest

Search for Freelancers, Projects...



Need someone to write and post positive reviews

f Like 0 f Send t Tweet 0 g +1 0 Share

Bids

10

Avg Bid (USD)

N/A

Project Budget (USD)

\$250 - \$750

Featured

Sealed

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 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



Follow

Project posted by:

dvel

★★★★★ 5.0 (1 Review)

VERIFIED

Your ad could

From \$100/week

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.
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Source: <http://www.cs.uic.edu/~liub/FBS/fake-reviews.html>

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http://nlp.stanford.edu/~socherr/EMNLP2013_RNTN.pdf
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