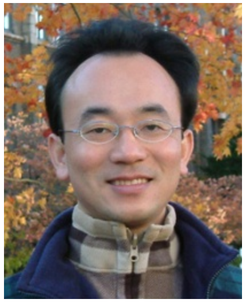
Tamkang University
淡江大學

Social Computing and Big Data Analytics
社群運算與大數據分析

Tamkang University

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

Source: http://www.ibmbigdatahub.com/infographic/what-makes-data-scientist

Social Media

Source: http://hungrywolfmarketing.com/2013/09/09/what-are-your-social-marketing-goals/

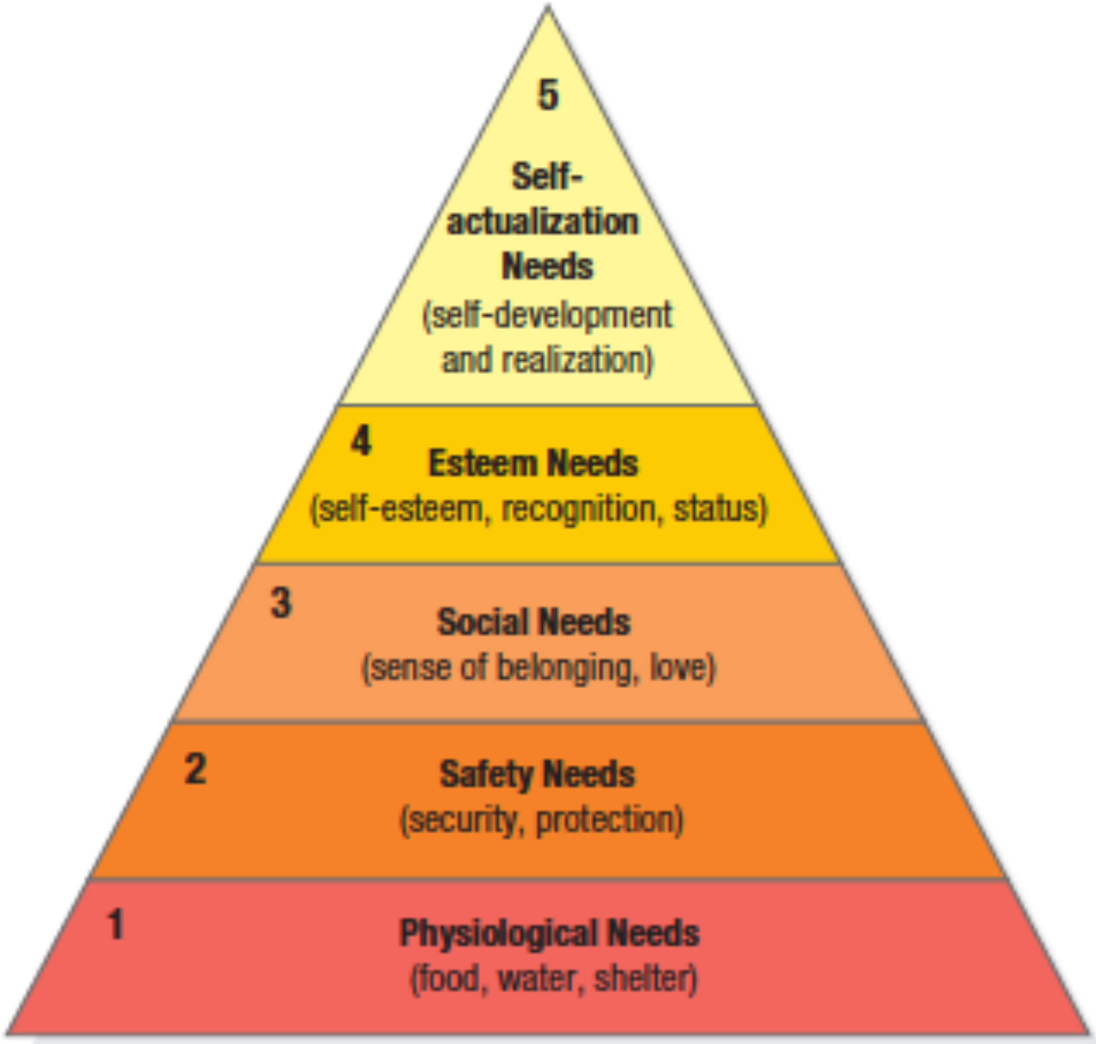
Emotions

Love	Anger
Joy	Sadness
Surprise	Fear

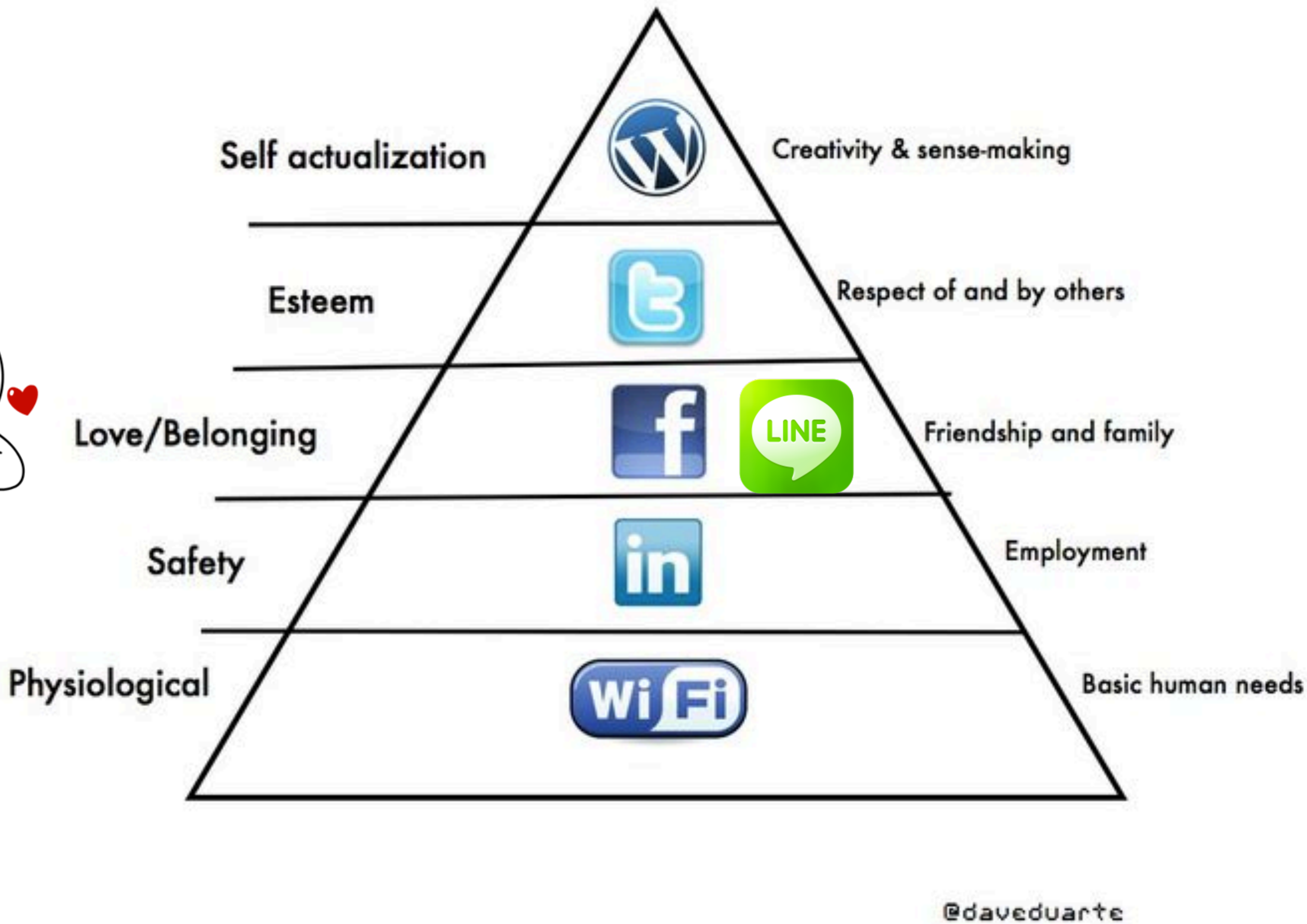
Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

Maslow's Hierarchy of Needs



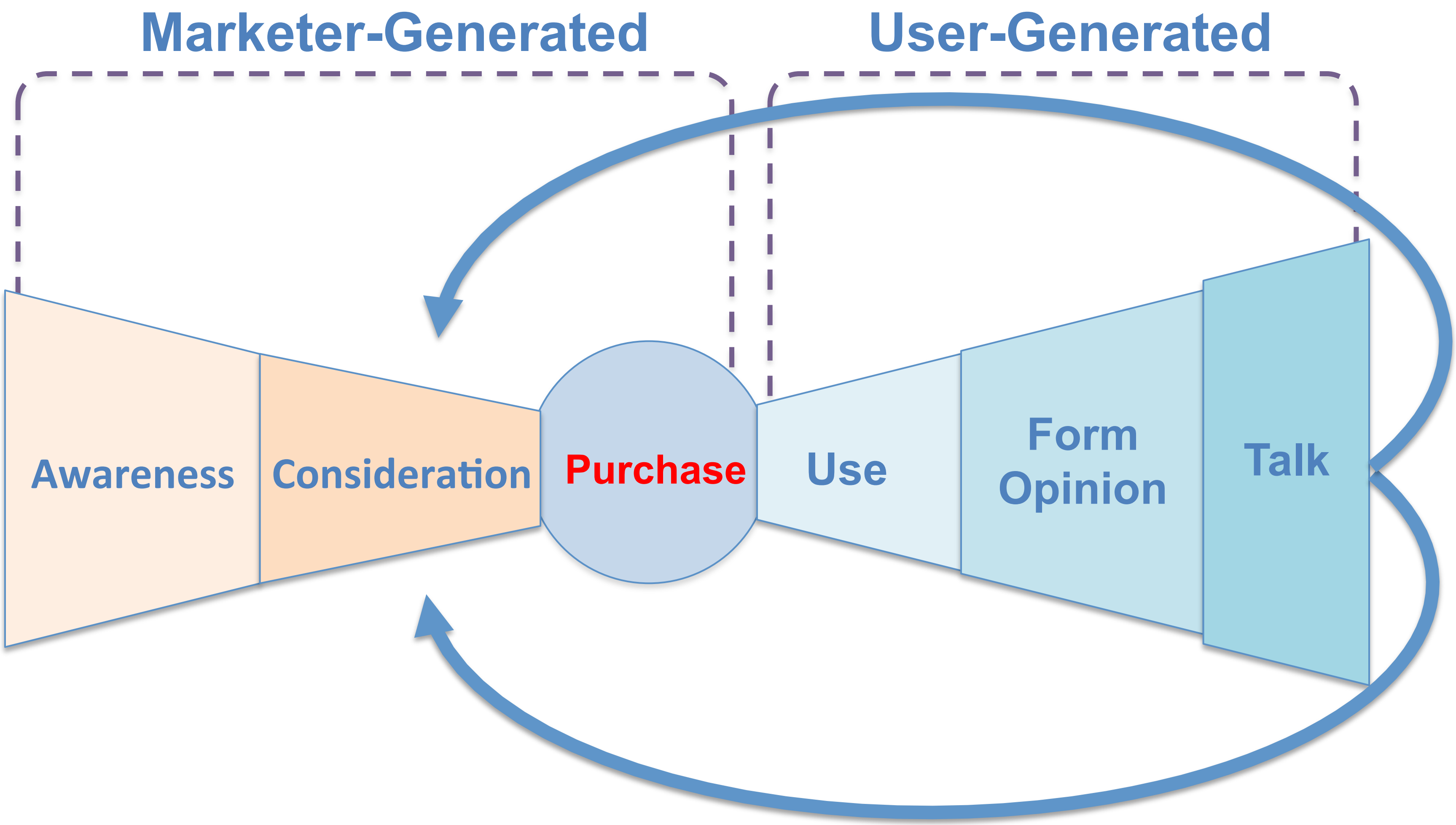
Source: Philip Kotler & Kevin Lane Keller, Marketing Management, 14th ed., Pearson, 2012

Social Media Hierarchy of Needs



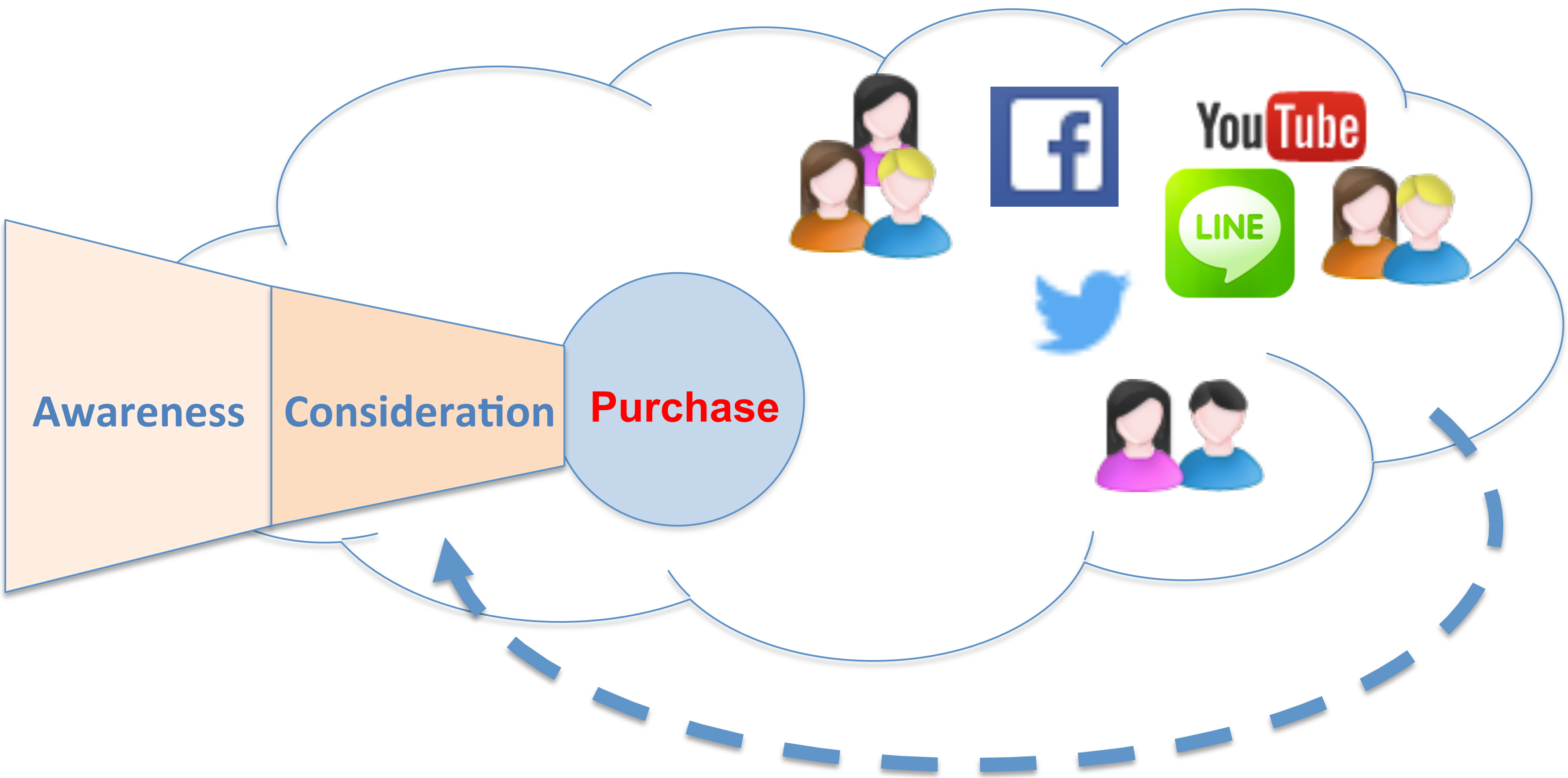
Source: http://www.pinterest.com/pin/186477859309035585/

The Social Feedback Cycle
Consumer Behavior on Social Media



Source: Evans et al. (2010), Social Media Marketing: The Next Generation of Business Engagement

The New Customer Influence Path



Source: Evans et al. (2010), Social Media Marketing: The Next Generation of Business Engagement

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. … "

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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. … "

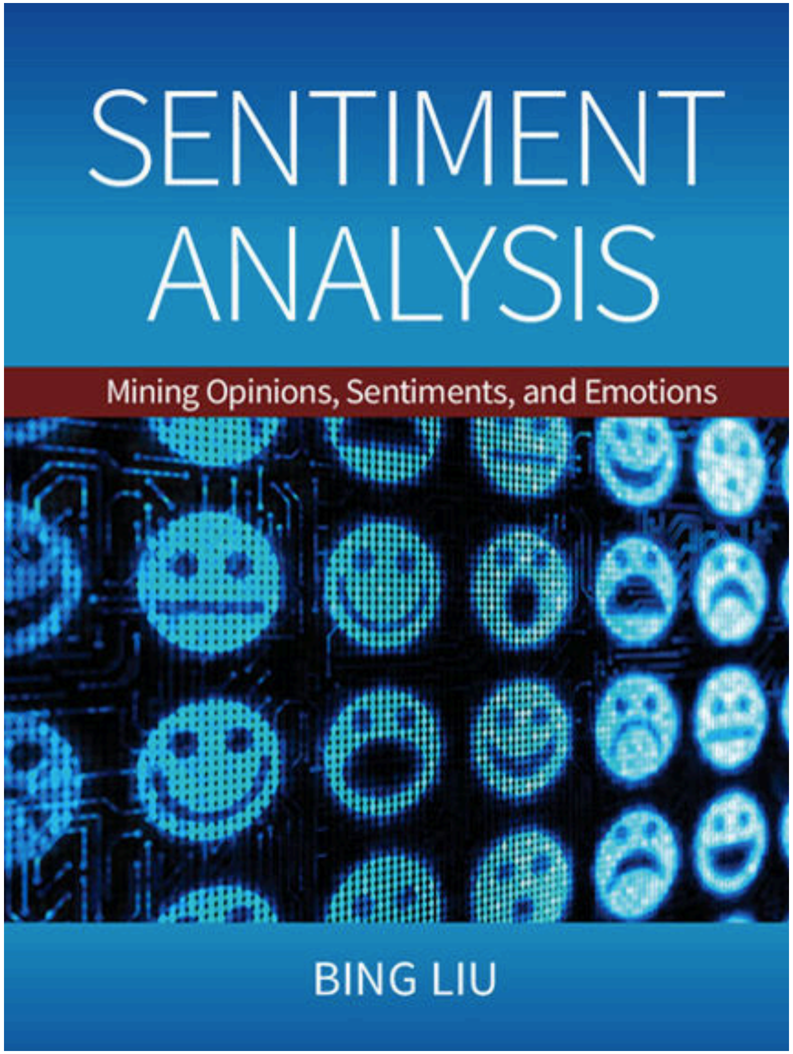
+Positive Opinion

-Negative Opinion

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Architectures of Sentiment Analytics

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



http://www.amazon.com/Sentiment-Analysis-Opinions-Sentiments-Emotions/dp/1107017890

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

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

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 policitians’ 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.

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

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

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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."

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

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

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Terminologies

- Entity: object
- Aspect: feature, attribute, facet
- Opinion holder: opinion source

- Topic: entity, aspect

- Product features, political issues

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

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.

Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Classification Based on Supervised Learning

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

Source: Bing Liu (2011) , “Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data,” Springer, 2nd Edition,

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*

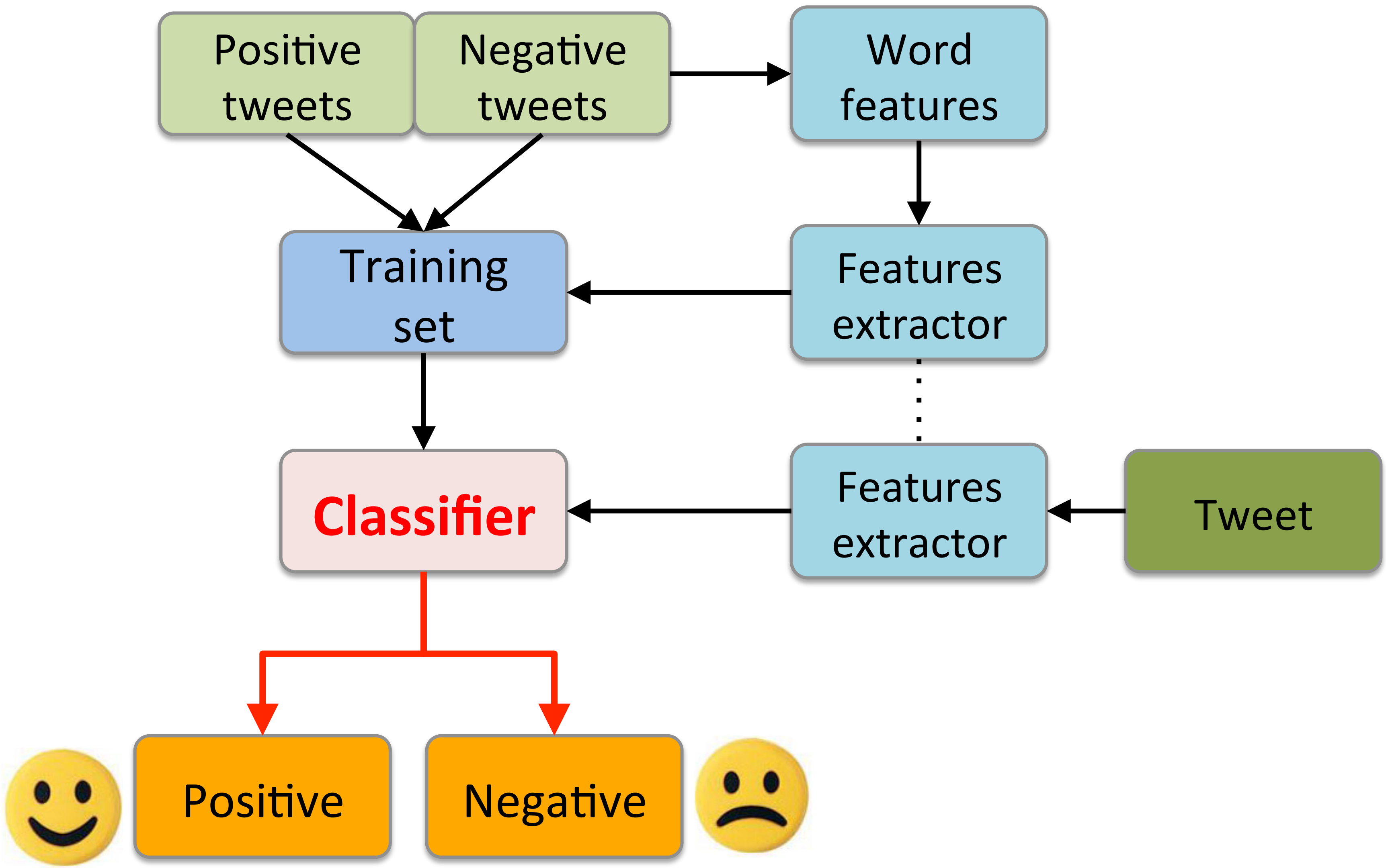
Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

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*

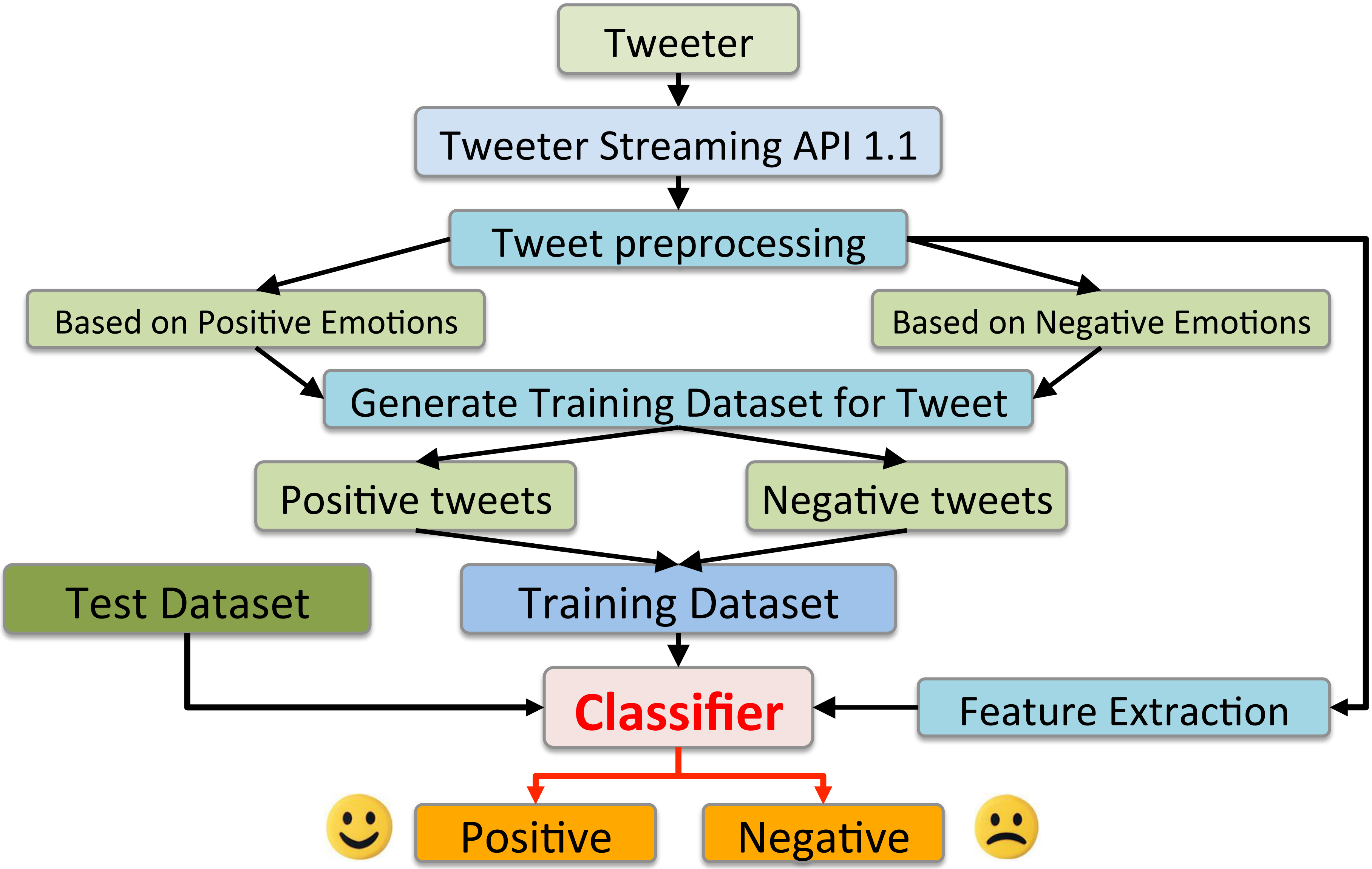
Source: Bing Liu (2011) , "Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data," Springer, 2nd Edition,

Sentiment Analysis Architecture



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

Sentiment Classification Based on Emoticons



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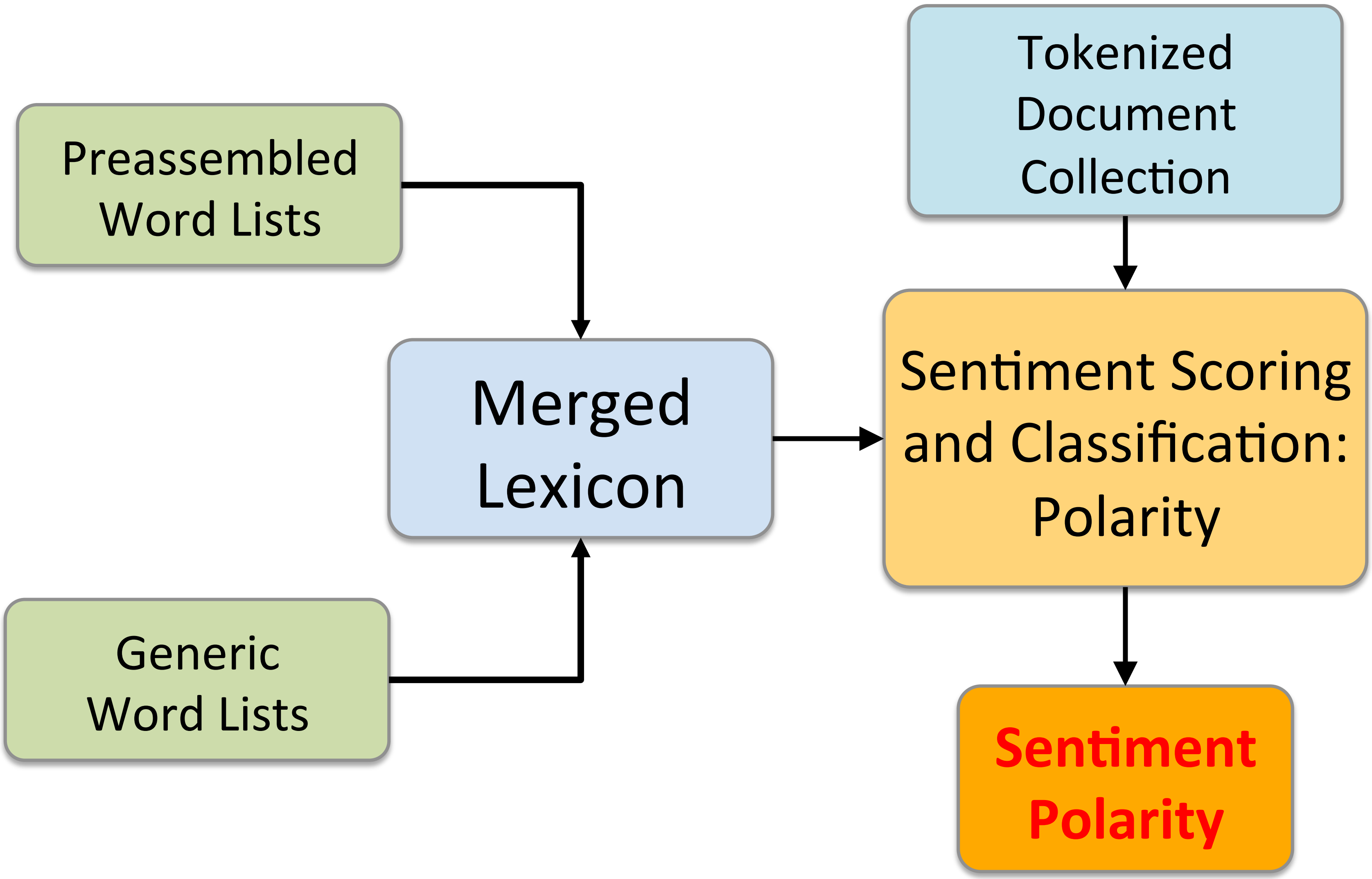
Lexicon-Based Model



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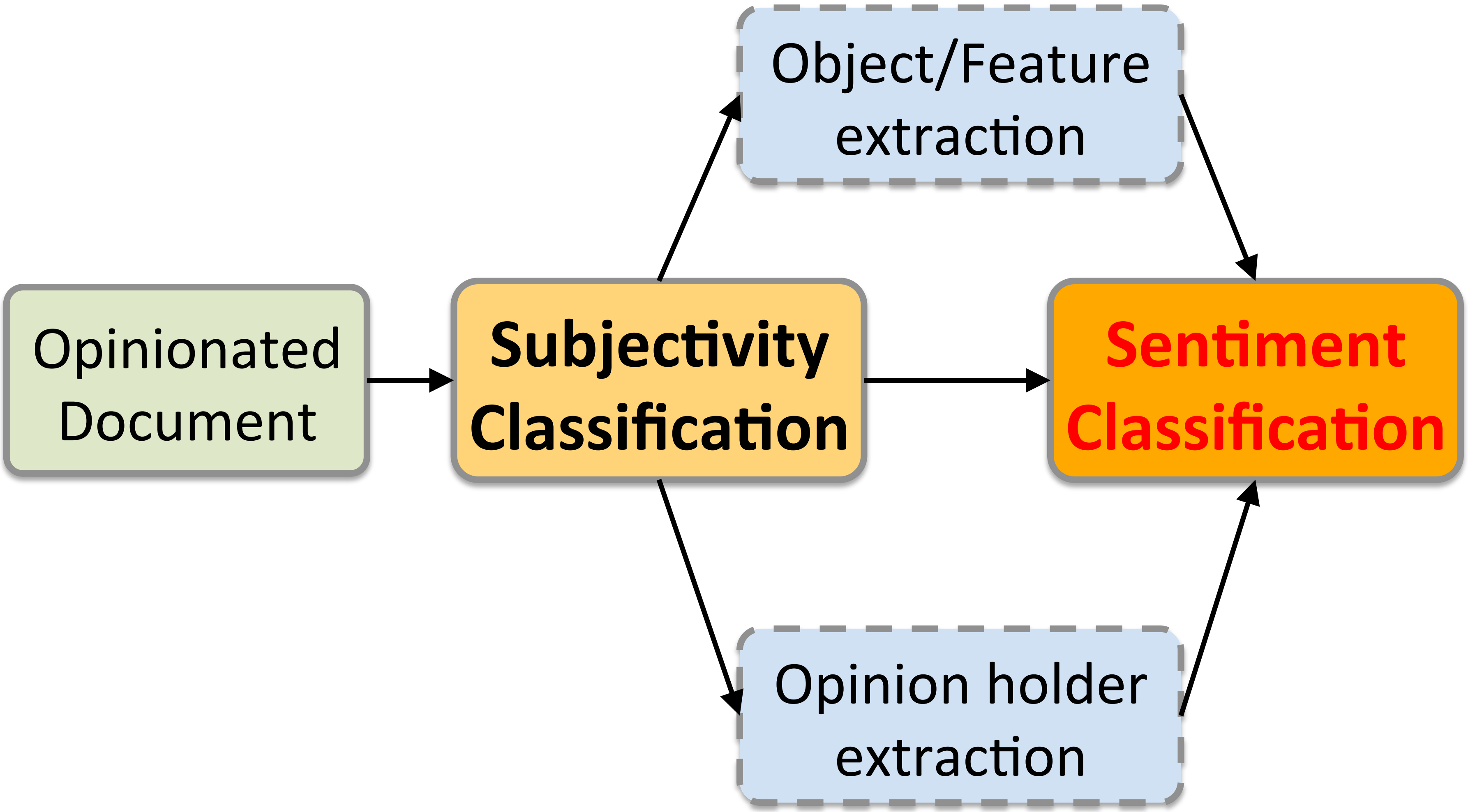
Sentiment Analysis Tasks

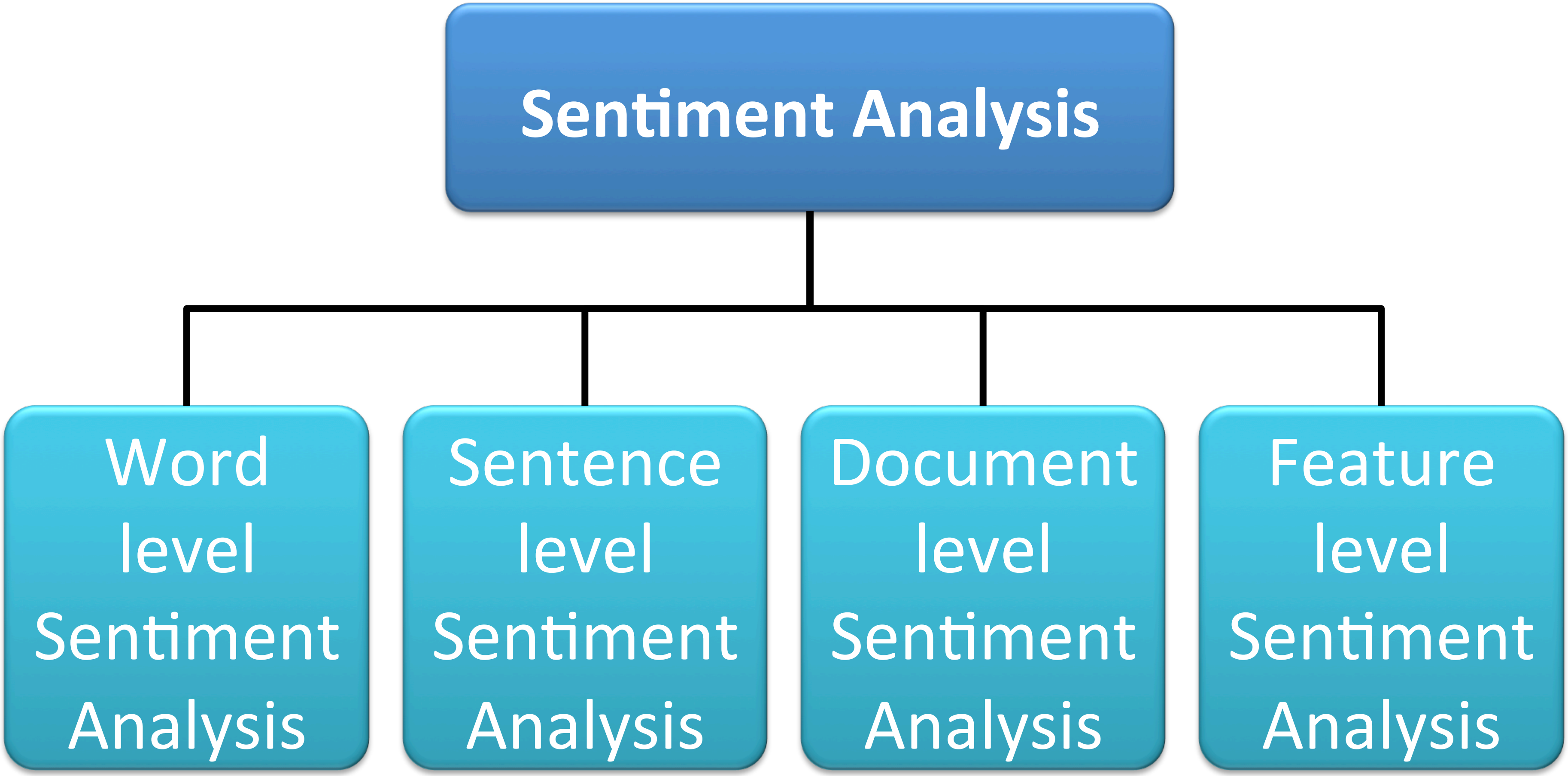


Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

Sentiment Analysis
vs.
Subjectivity Analysis

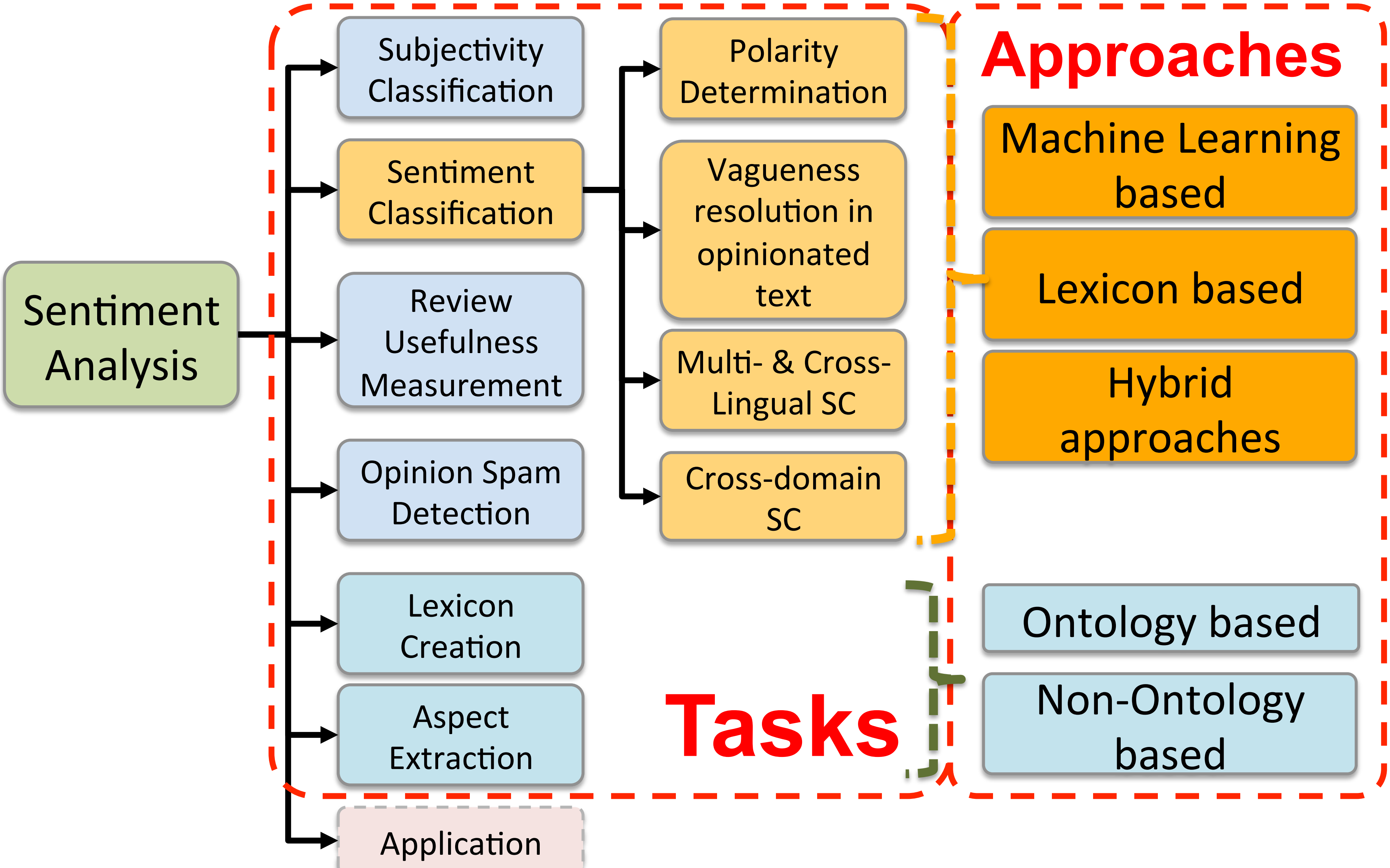
Sentiment Analysis	Subjectivity Analysis
Positive Negative	Subjective
Neutral	Objective

Levels of Sentiment Analysis



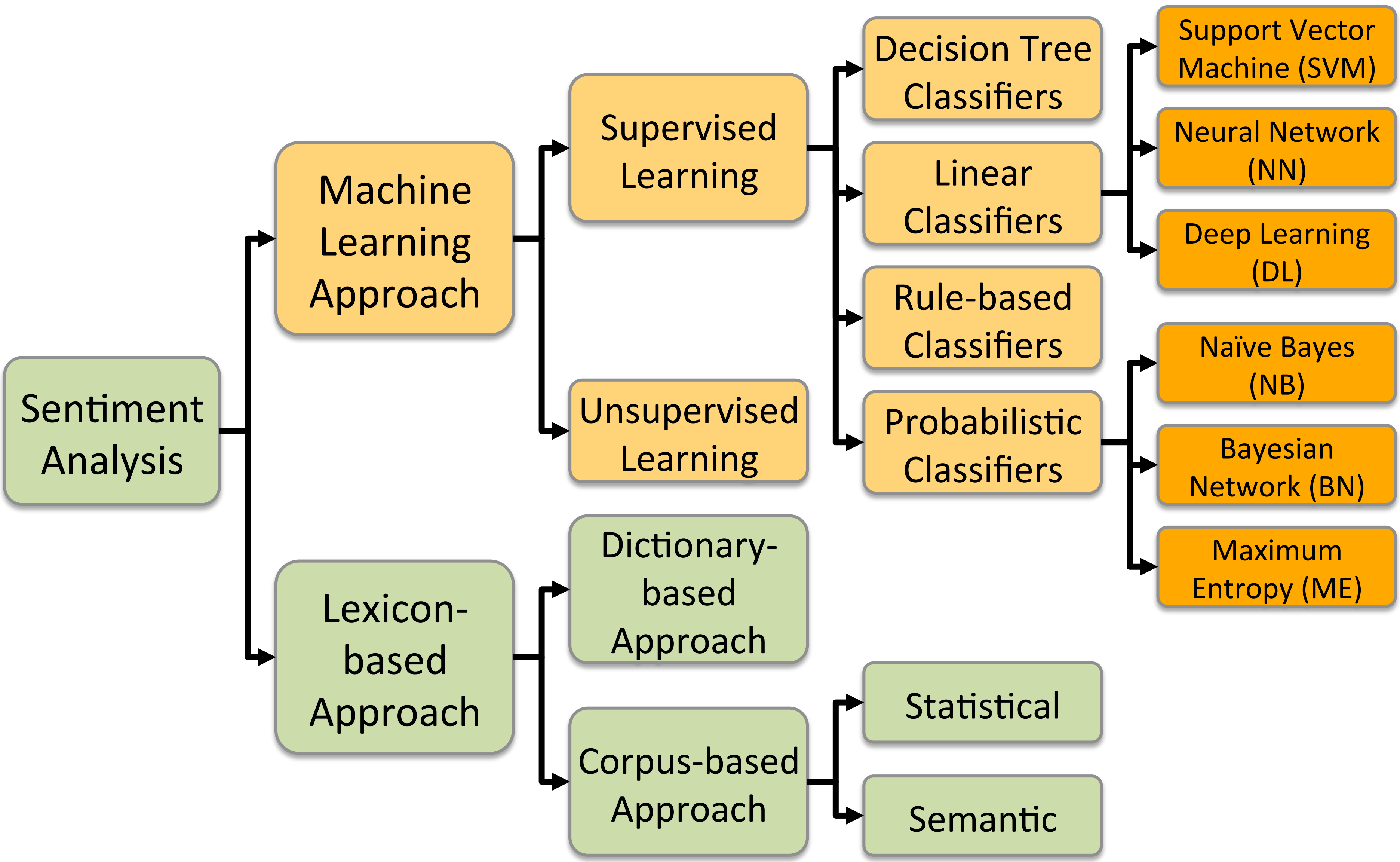
Vishal Kharde and Sheetal Sonawane (2016), "Sentiment Analysis of Twitter Data: A Survey of Techniques," International Journal of Computer Applications, Vol 139, No. 11, 2016. pp.5-15

Sentiment Analysis



Source: 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.

Sentiment Classification Techniques



Source: 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.

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.”

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.,

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

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

Word Vector (WV)	pscore	nscore	Polarity Score Vector (PSV)	Microstate Sequence (MS)
This	0	0	Neutral (0)	0
book	0	0	Neutral (0)	0
is	0	0	Neutral (0)	0
the	0	0	Neutral (0)	0
best	0.75	0	Positive (0.75)	1
written	0	0	Neutral (0)	0
documentary	0	0	Neutral (0)	0
thus	0.375	0	Positive (0.375)	1
far	0.375	0	Positive (0.375)	1
,				
yet	0	0.125	Negative (0.125)	-1
sadly	0.25	0.5	Negative (0.25)	-1
,				
there	0	0	Neutral (0)	0
is	0	0	Neutral (0)	0
no	0	0.75	Negative (0.75)	-1
soft	0	0	Neutral (0)	0
cover	0	0	Neutral (0)	0
edition	0	0	Neutral (0)	0
.				

SentiWordNet Lookup → Microstate Mapping → Probability Mapping

Probability Distribution (P)

P("1")=3/17

P("-1")=3/17

P("0")=11/17

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.,

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“

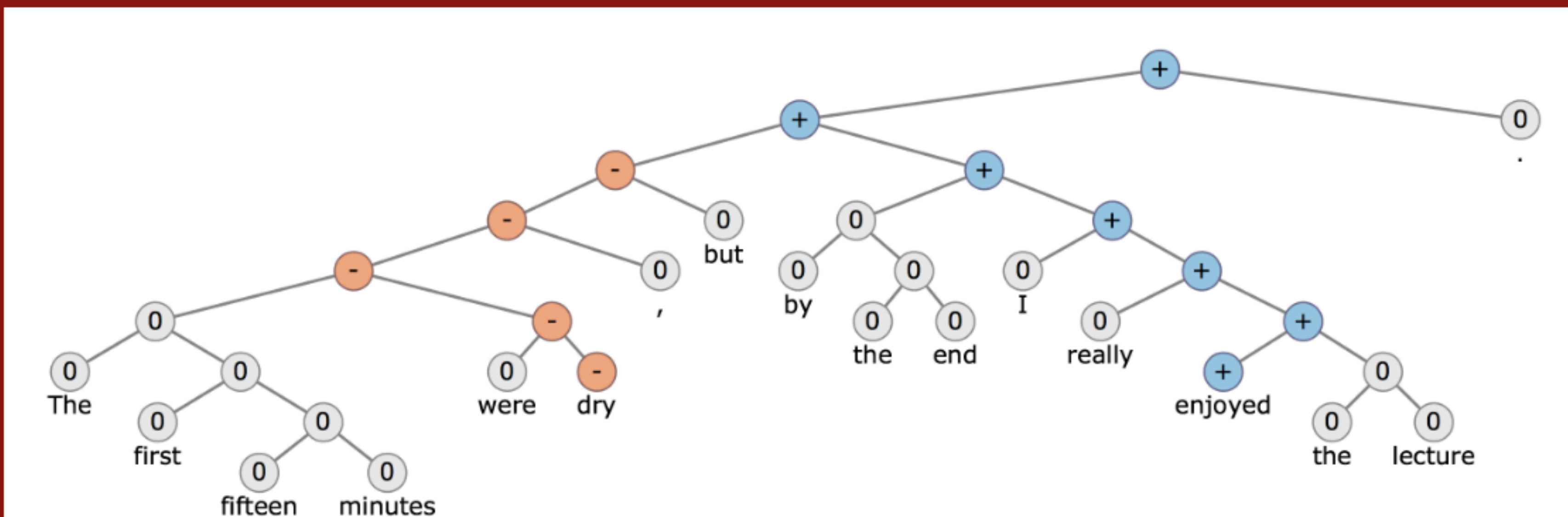
r 00404501 0 0.25 sadly#2 with sadness; in a sad manner; "`She died last night,' he said sadly"

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 constrast, 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
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-

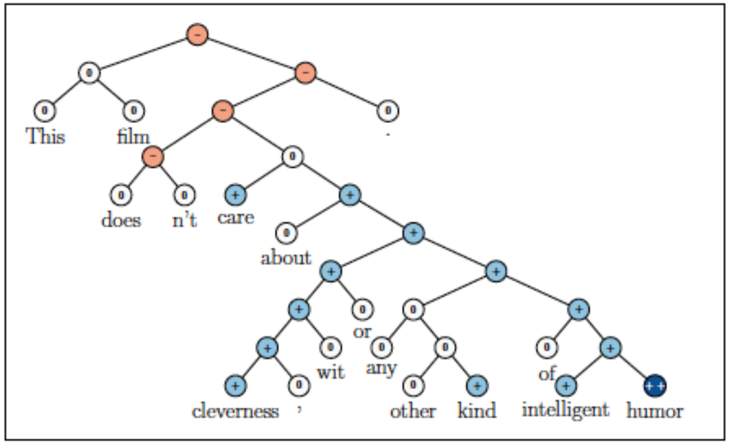
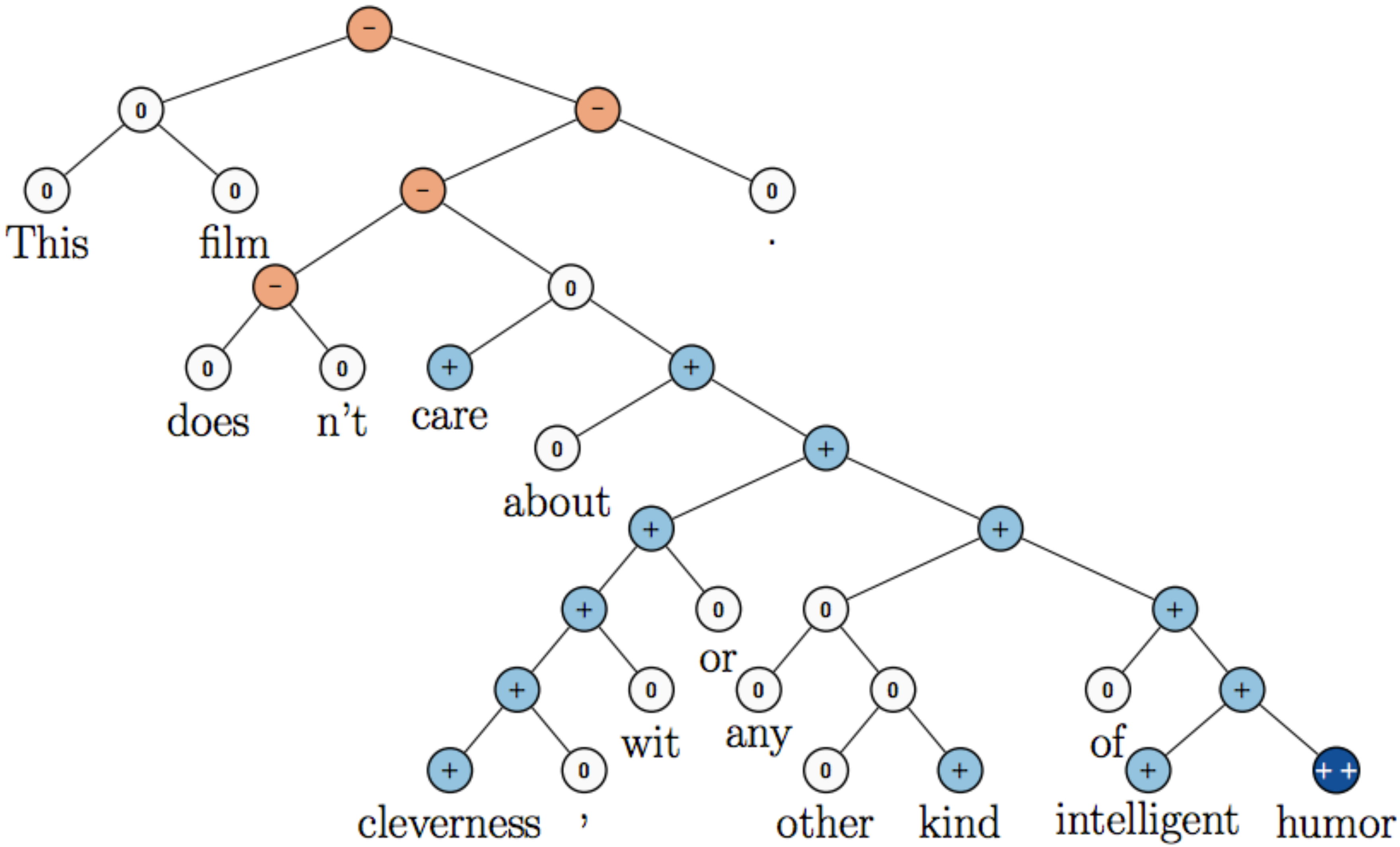


Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (– –, –, 0, +, + +), at every node of a parse tree and capturing the negation and its scope in this sentence.

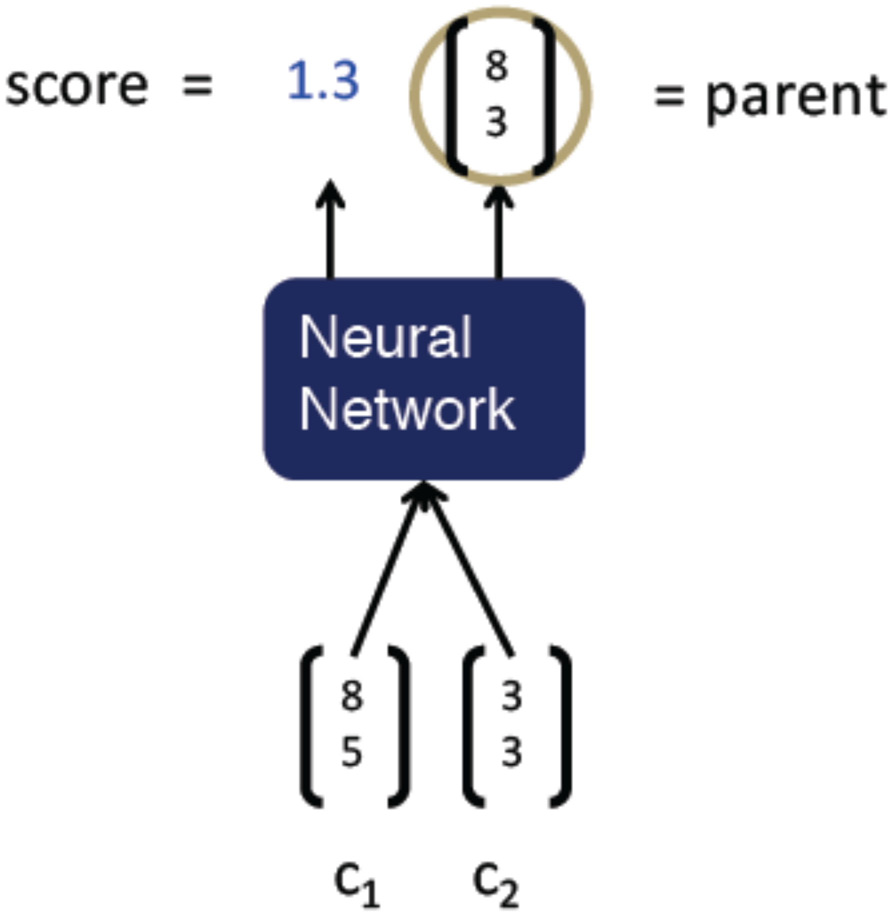
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

Recursive Neural Tensor Network (RNTN)



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

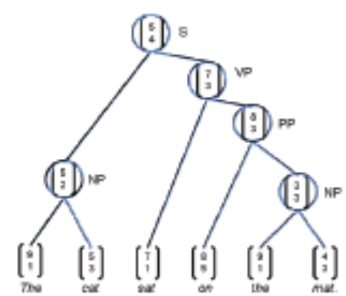
Recursive Neural Network Definition



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

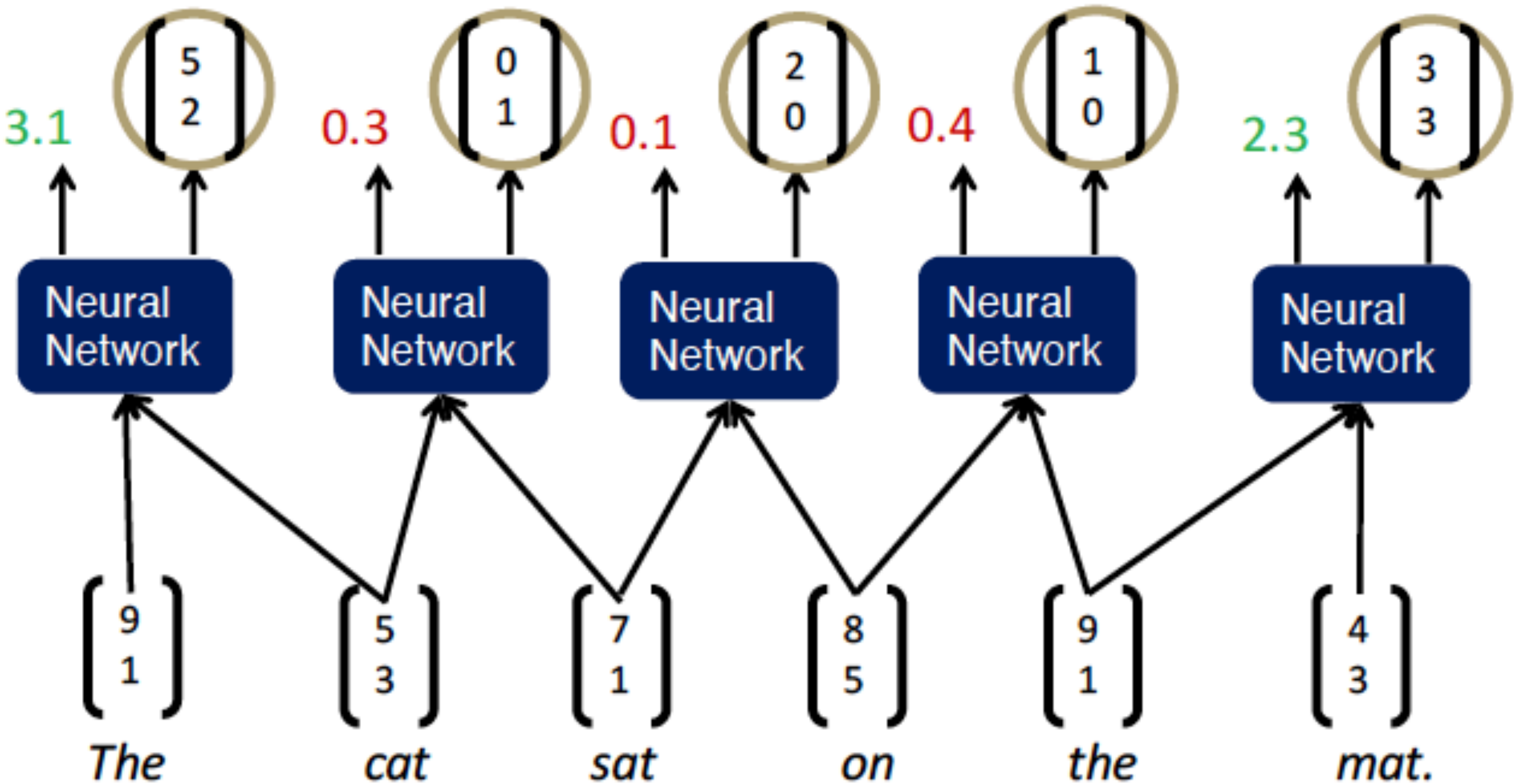
$$\boxed{p = \tanh\left(W\begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + b\right),}$$

Same *W* parameters at all nodes of the tree



Source: http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf

Parsing a sentence with an RNN



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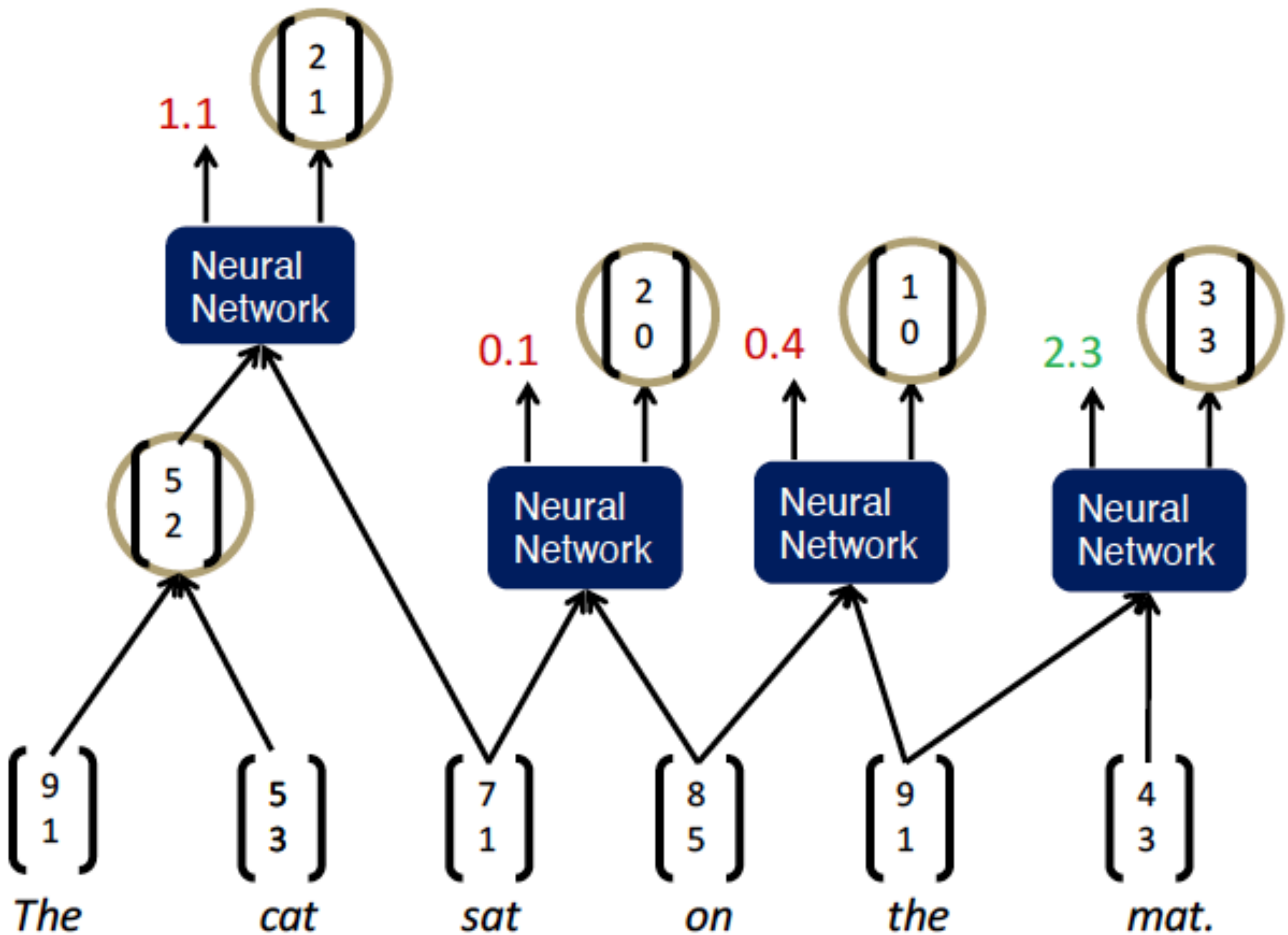
Parsing a sentence with an RNN



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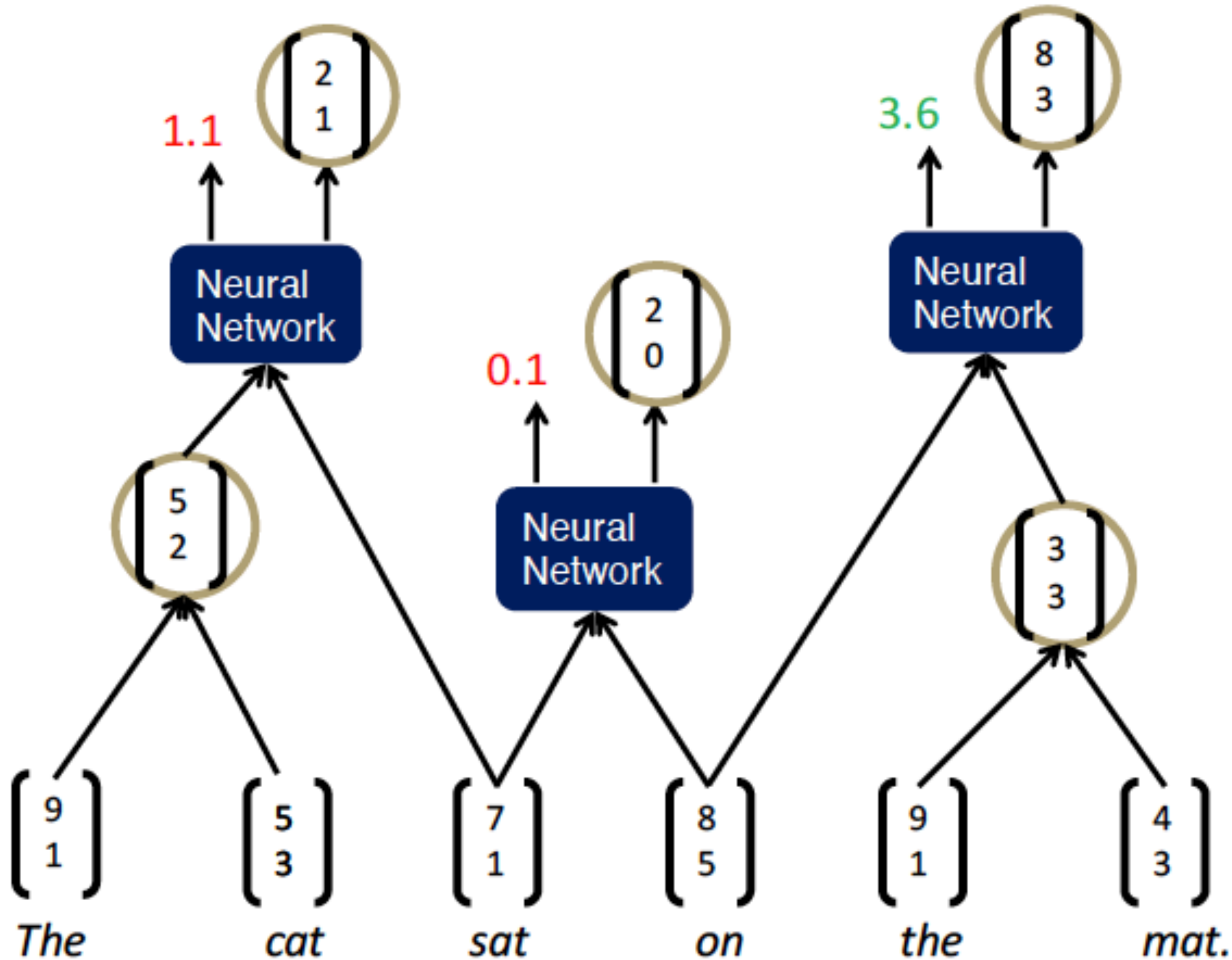
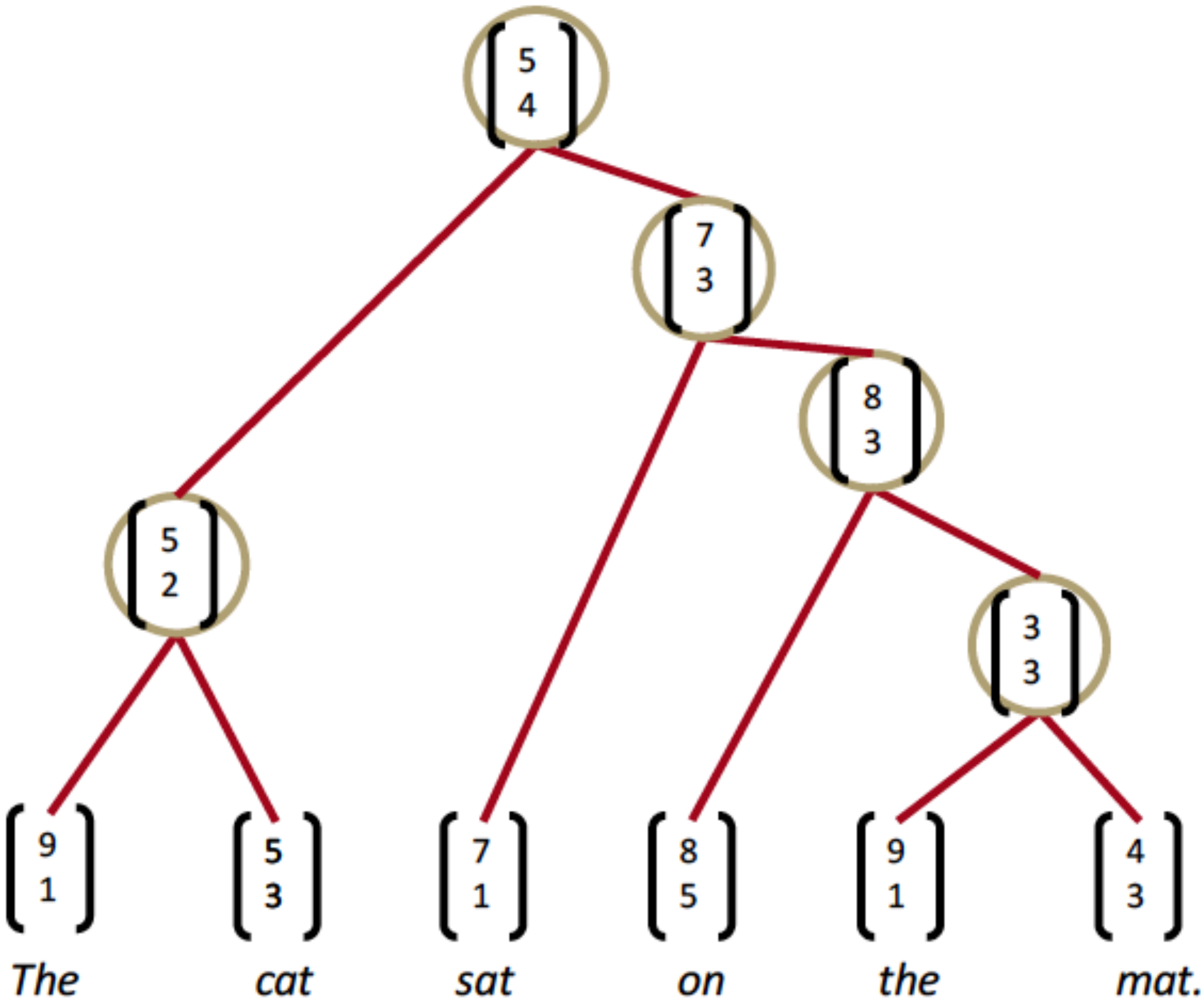
Parsing a sentence with an RNN



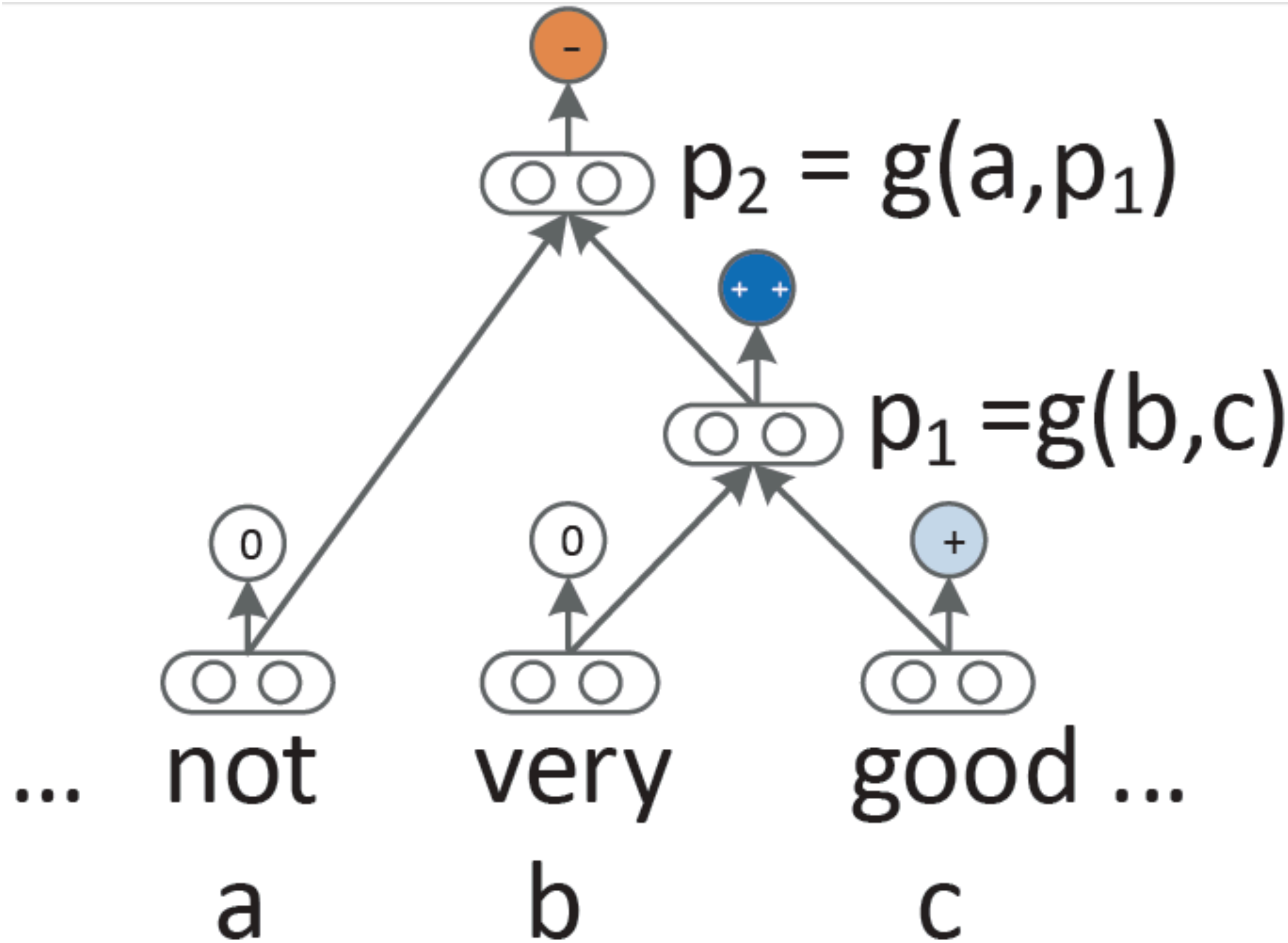
Source: http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf

Parsing a sentence with an RNN



Source: http://cs224d.stanford.edu/lectures/CS224d-Lecture10.pdf

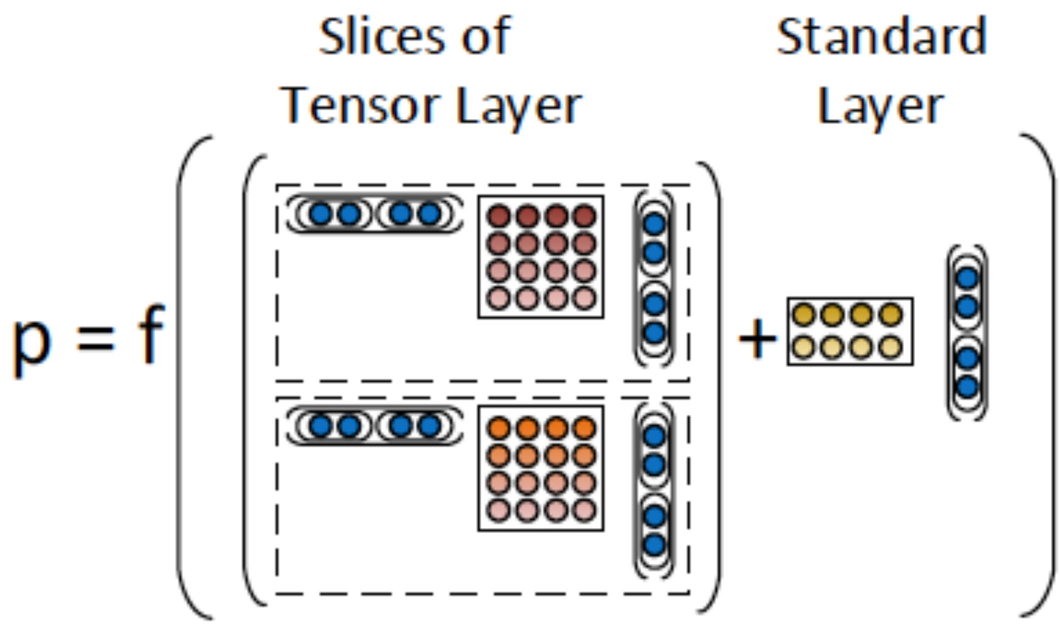
Recursive Neural Network (RNN) models for sentiment



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

Recursive Neural Tensor Network (RNTN)

Neural Tensor Layer



$$p = f\left(\begin{bmatrix} b \\ c \end{bmatrix}^T V^{[1:2]} \begin{bmatrix} b \\ c \end{bmatrix} + W \begin{bmatrix} b \\ c \end{bmatrix} \right)$$

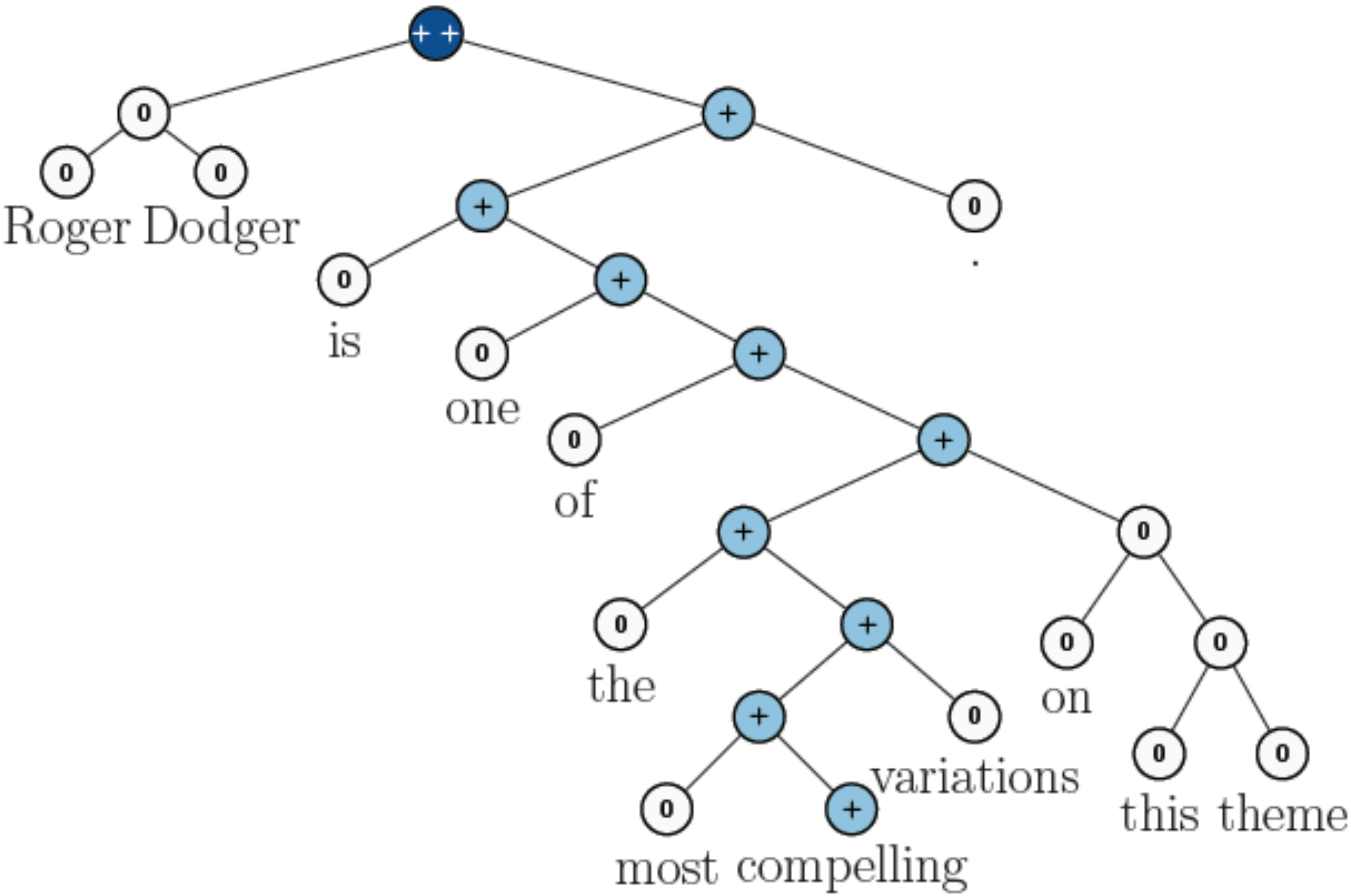
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

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

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

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

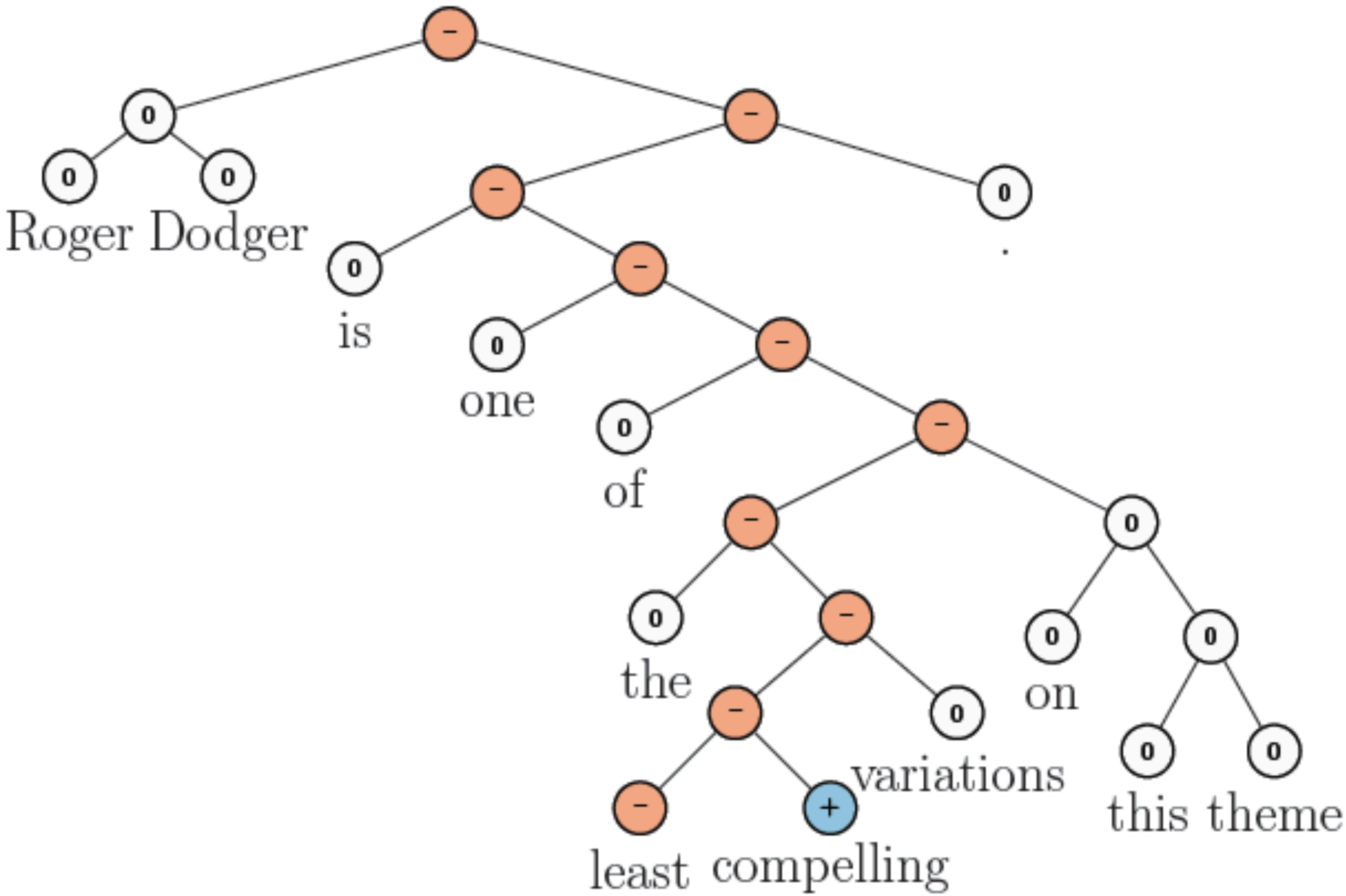
RNTN for Sentiment Analysis



Roger Dodger is one of the 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.

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

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**

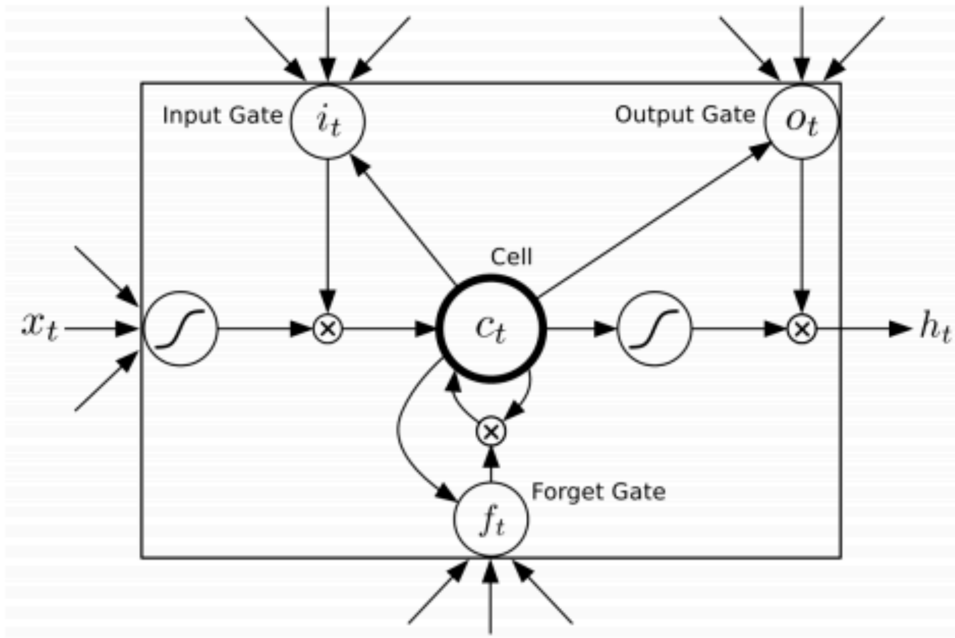
Source: Richard Socher et al. (2013) "Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank", EMNLP 2013

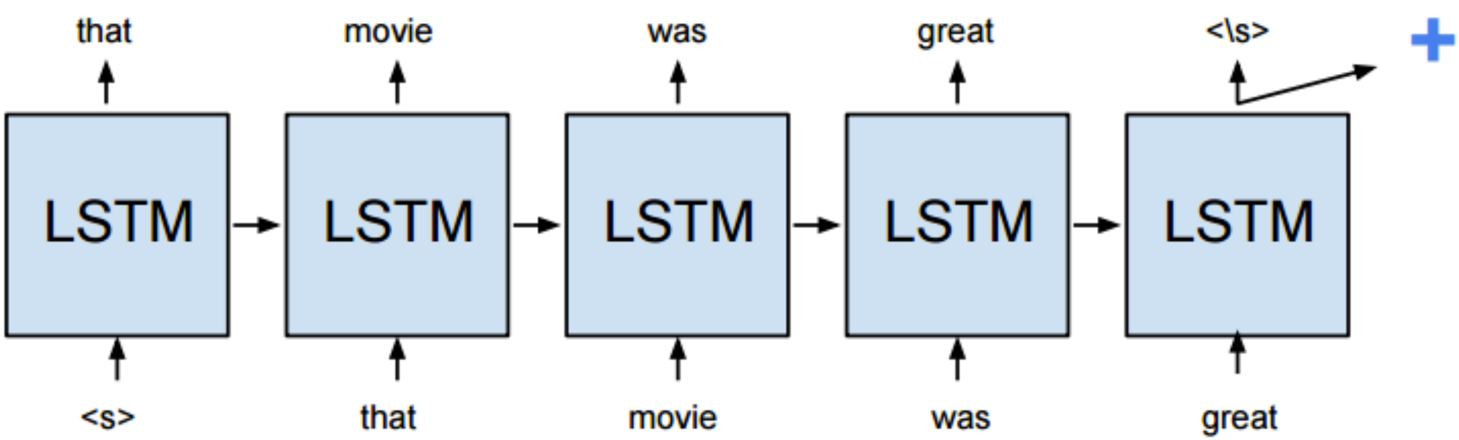
Accuracy of negation detection

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

Long Short-Term Memory (LSTM)





Source: https://cs224d.stanford.edu/reports/HongJames.pdf

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

Source: https://cs224d.stanford.edu/reports/HongJames.pdf

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]

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

Social Media Monitoring/Analysis

Existing Tools
("Social Media Monitoring/Analysis")

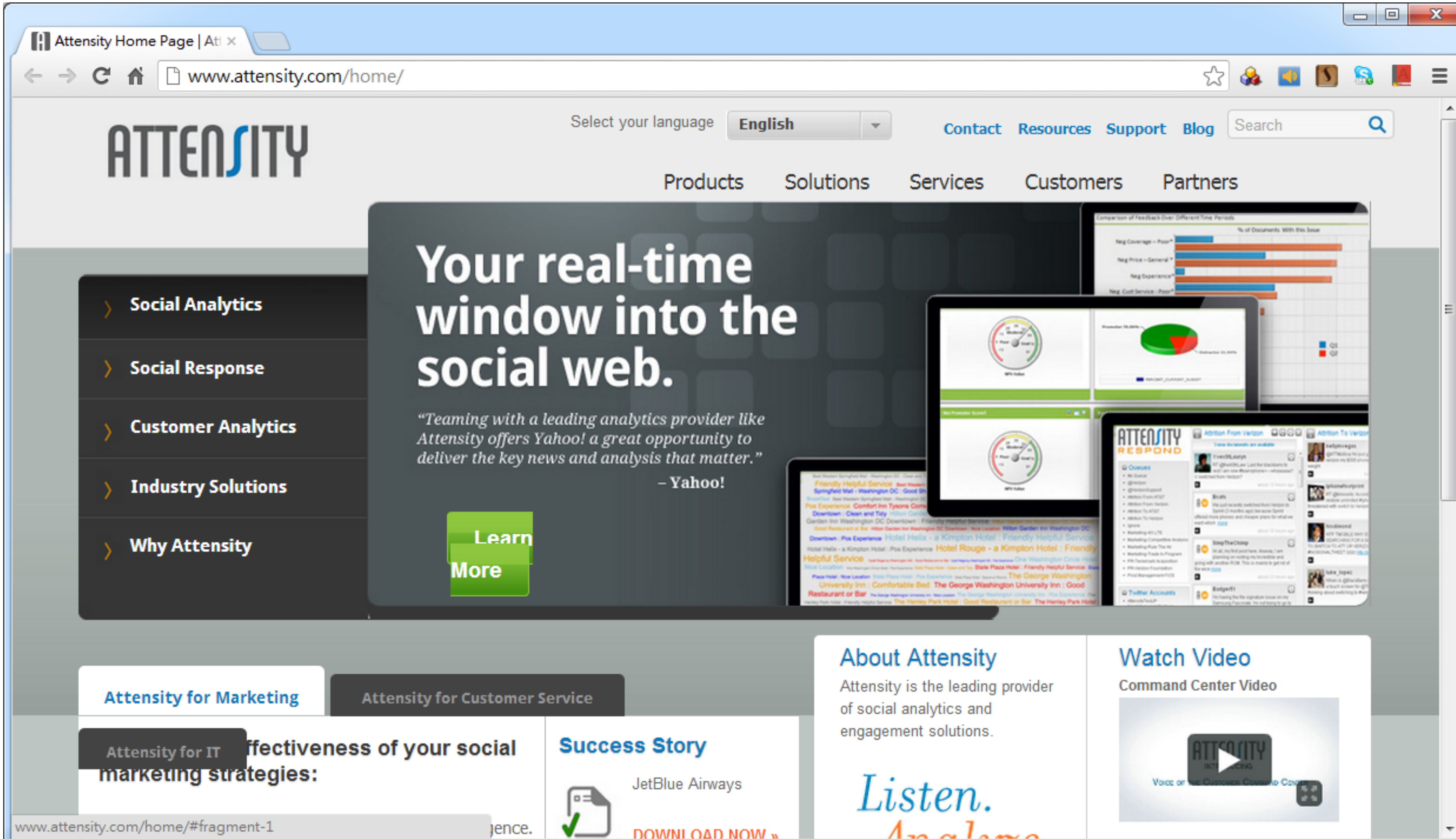
- Radian 6
- Social Mention
- Overtone OpenMic
- Microsoft Dynamics Social Networking Accelerator
- SAS Social Media Analytics
- Lithium Social Media Monitoring
- RightNow Cloud Monitor

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

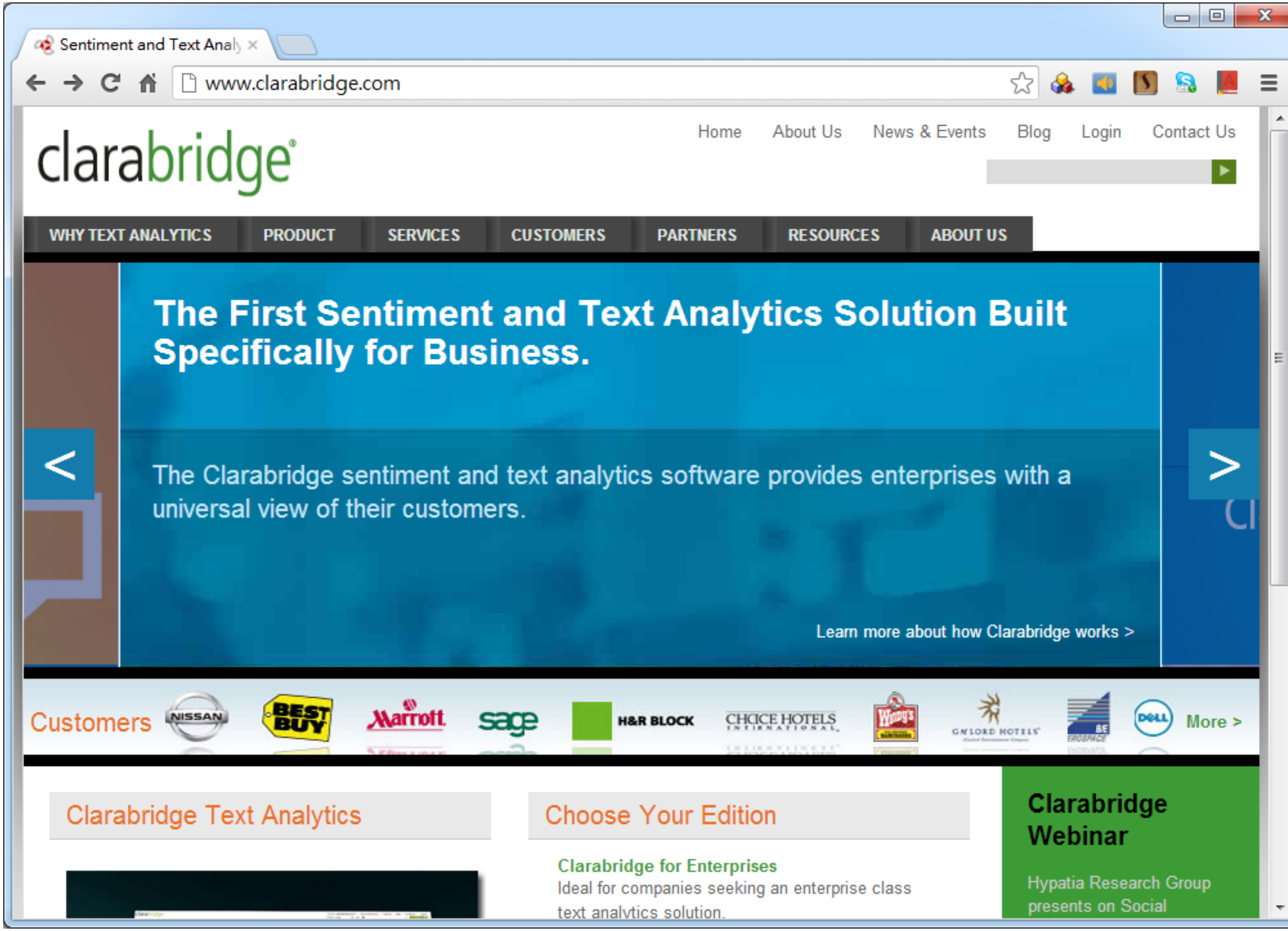
http://www.attensity.com/



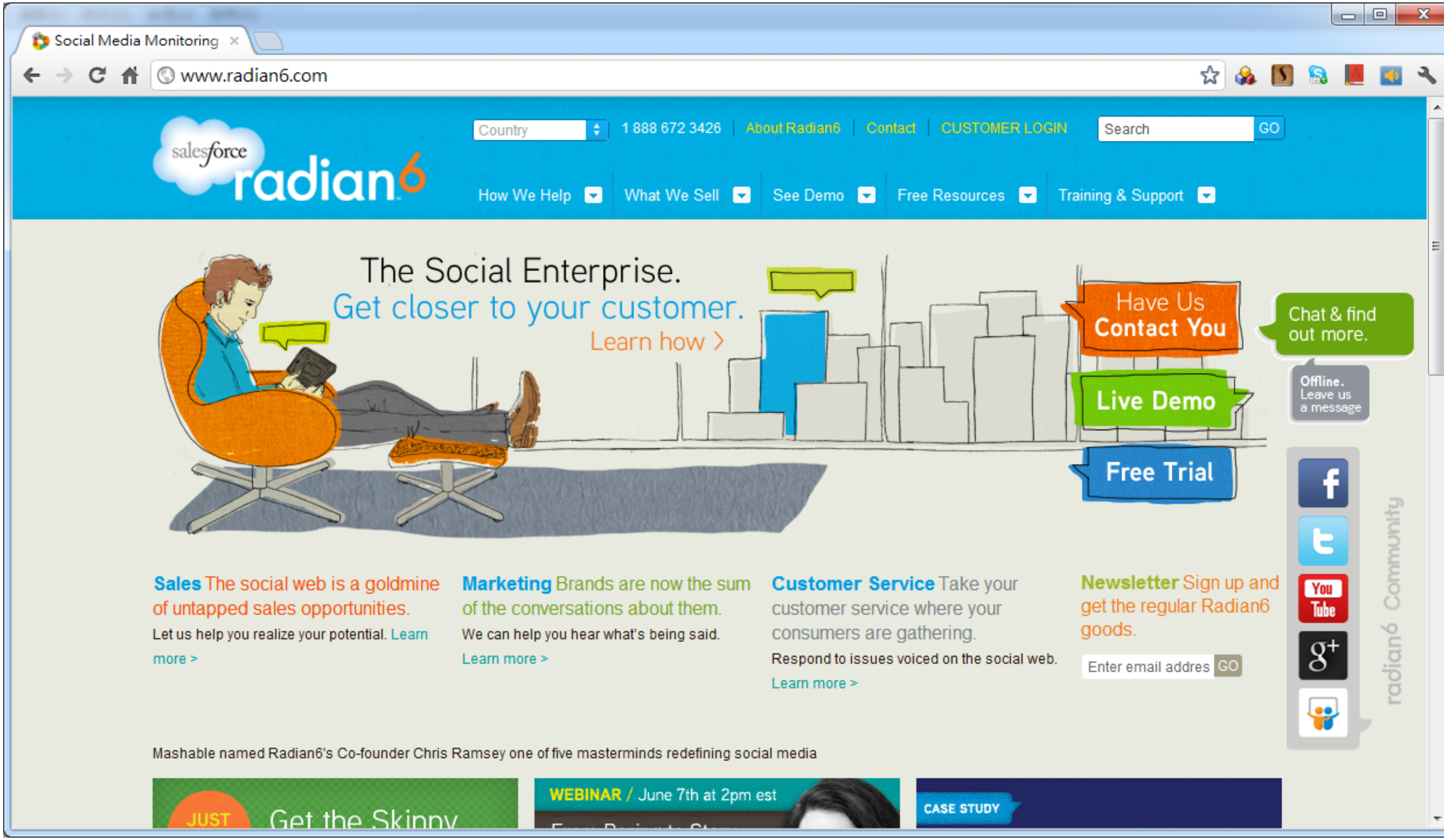
http://www.youtube.com/watch?v=4goxmBEg2Iw#!

Clarabridge: Sentiment and Text Analytics Software

http://www.clarabridge.com/

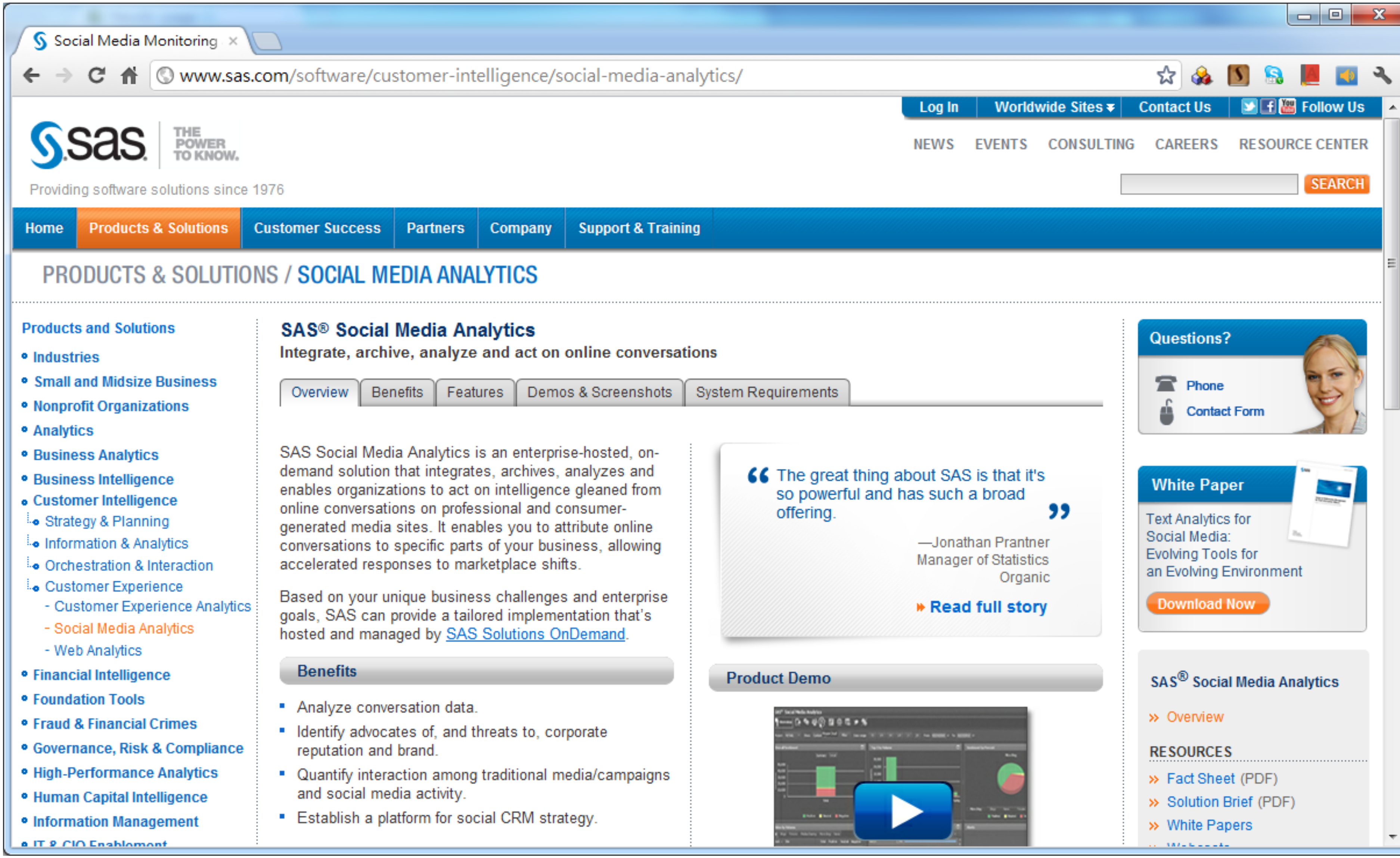


http://www.youtube.com/watch?v=IDHudt8M9P0 http://www.radian6.com/



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

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



http://www.tweetfeel.com

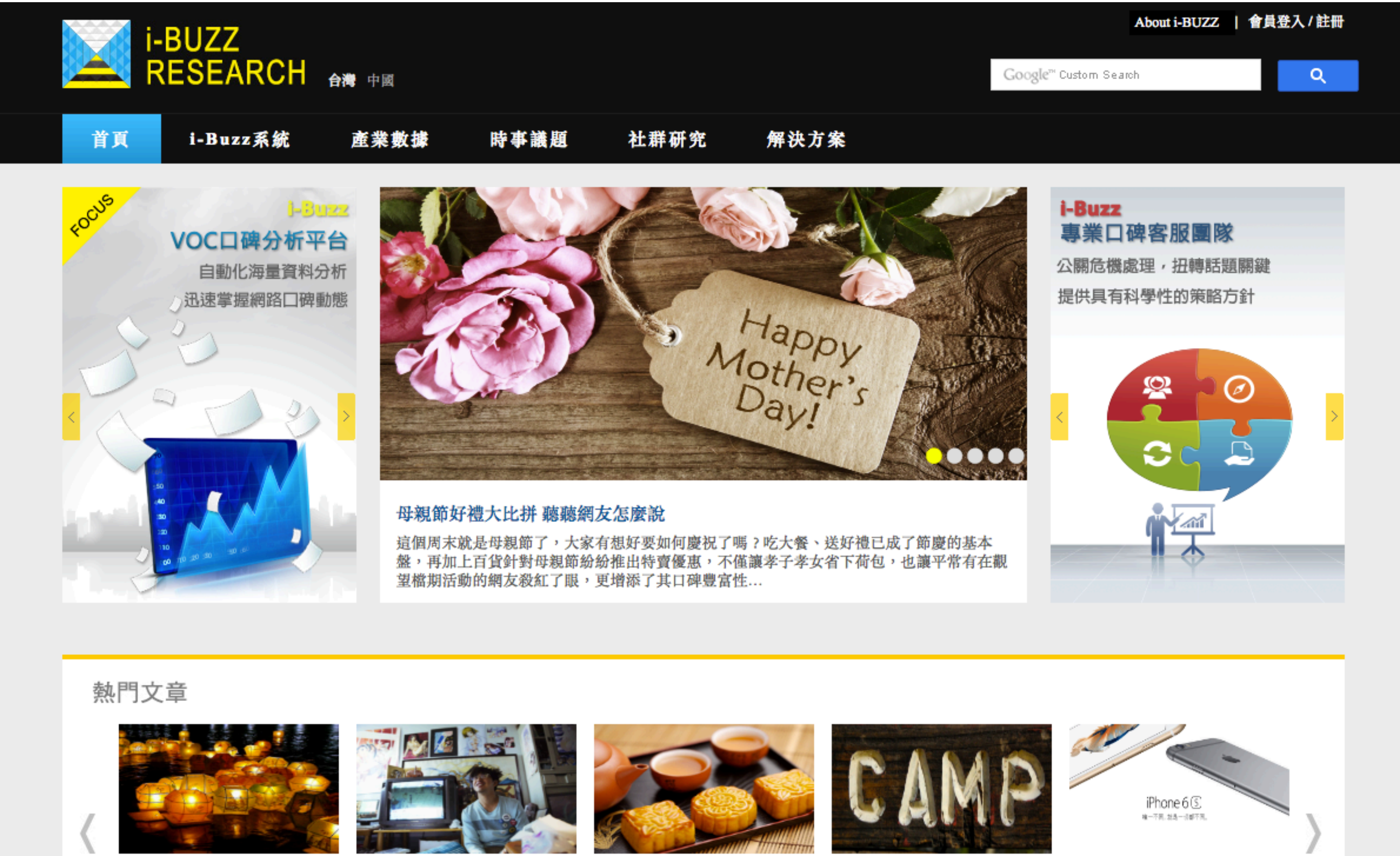
eLand

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

OpView

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

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



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)

Source: Bo Pang and Lillian Lee (2008), "Opinion mining and sentiment analysis," Foundations and Trends in Information Retrieval

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

Source: http://www.keenage.com/html/c_bulletin_2007.htm

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

Source: http://www.keenage.com/html/c_bulletin_2007.htm

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 ...

Source: http://www.keenage.com/html/c_bulletin_2007.htm

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...

Source: http://www.keenage.com/html/c_bulletin_2007.htm

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

Source: http://www.keenage.com/html/c_bulletin_2007.htm

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)

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

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.

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

Forms of Opinion spam

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

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

Fake Review Detection

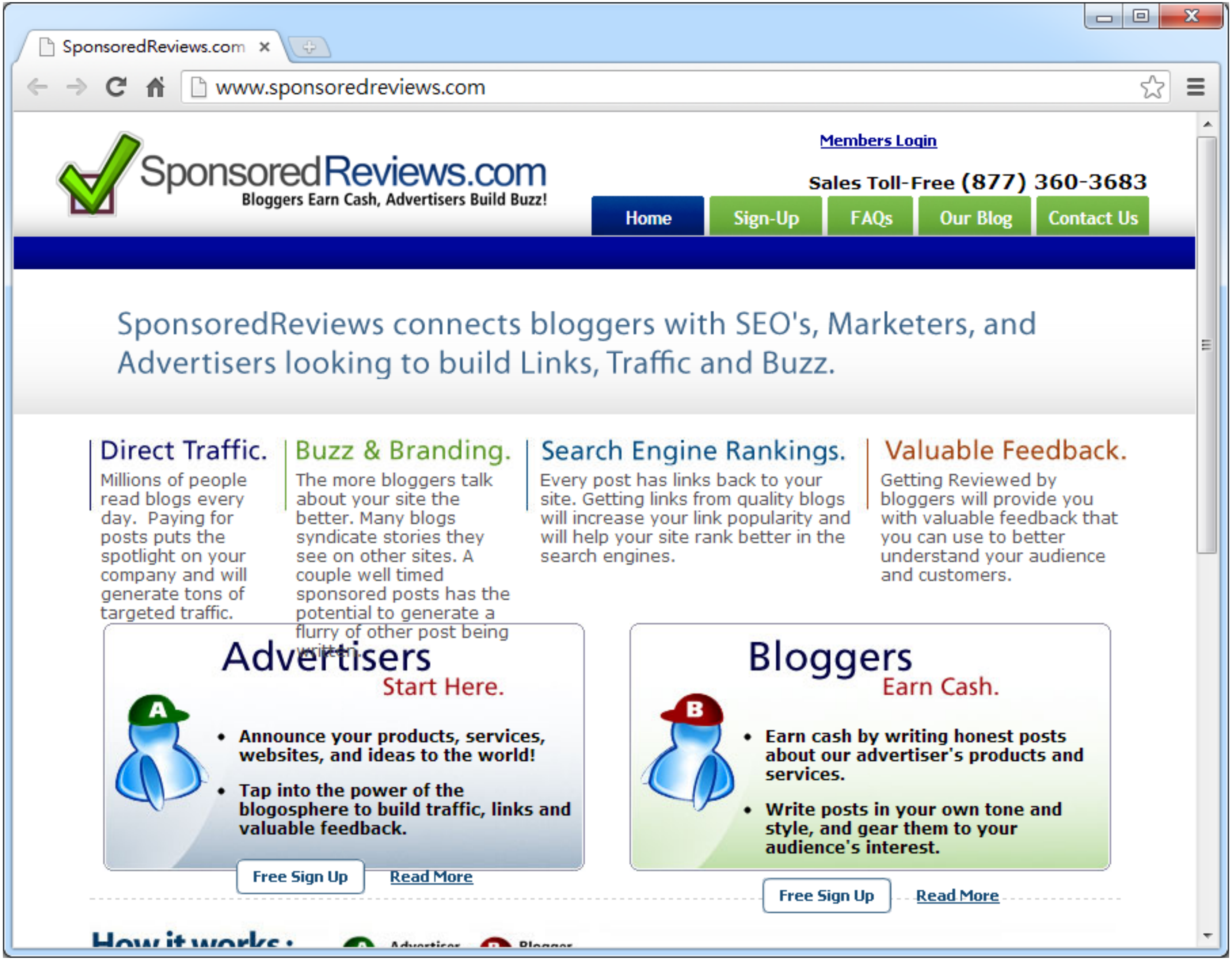
- Methods
  - supervised learning
  - pattern discovery
  - graph-based methods
  - relational modeling
- Signals
  - Review content
  - Reviewer abnormal behaviors
  - Product related features
  - Relationships

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

Professional Fake Review Writing Services (some Reputation Management companies)

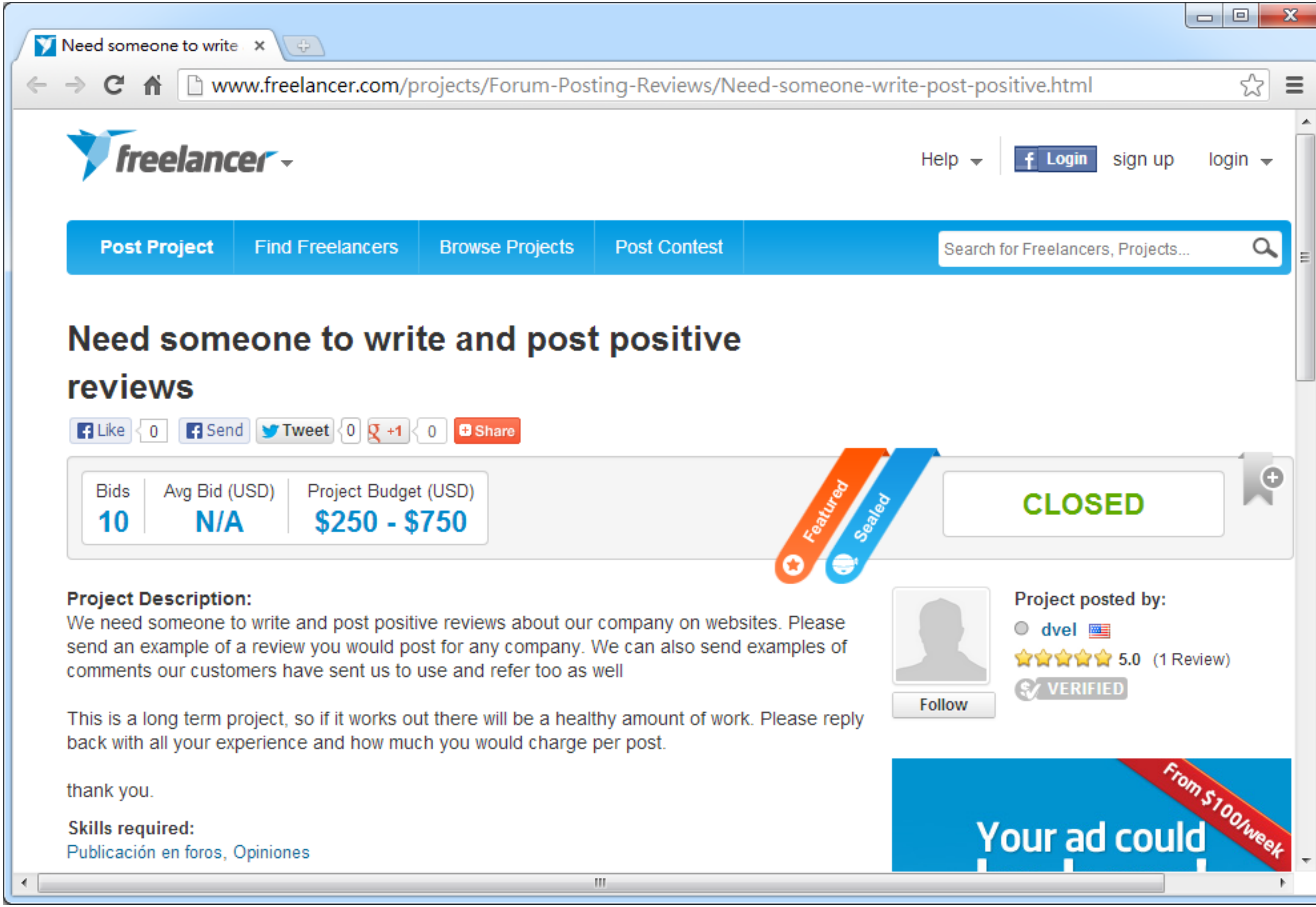
- Post positive reviews
- Sponsored reviews
- Pay per post
- Need someone to write positive reviews about our company (budget: $250-$750 USD)
- Fake review writer
- Product review writer for hire
- Hire a content writer
- Fake Amazon book reviews (hiring book reviewers)
- People are just having fun (not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

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



Source: http://www.sponsoredreviews.com/

Source: https://payperpost.com/



Source:http://www.freelancer.com/projects/Forum-Posting-Reviews/Need-someone-write-post-positive.html

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.

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

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- Guandong Xu, Yanchun Zhang, Lin Li (2011), Web Mining and Social Networking: Techniques and Applications, 2011, Springer

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