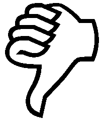
CS11-711: Algorithms for NLP

Sentiment Analysis

Yulia Tsvetkov

Carnegie Mellon University
Language Technologies Institute

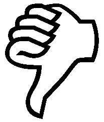
Positive or negative movie review?



- unbelievably disappointing

- Full of zany characters and richly applied satire, and some great plot twists

- this is the greatest screwball comedy ever filmed



- It was pathetic. The worst part about it was the boxing scenes.

Google Product Search

HP Officejet 6500A Plus e-All-in-One Color Ink-jet - Fax / copier / printer / scanner

$89 online, **$100** nearby ★★★★☆ 377 reviews

September 2010 - Printer - HP - Inkjet - Office - Copier - Color - Scanner - Fax - 250 sh

Reviews

Summary - Based on 377 reviews

1 star | 2 | 3 | 4 stars | 5 stars

What people are saying

ease of use	"This was very easy to setup to four computers."
value	"Appreciate good quality at a fair price."
setup	"Overall pretty easy setup."
customer service	"I DO like honest tech support people."
size	"Pretty Paper weight."
mode	"Photos were fair on the high quality mode."
colors	"Full color prints came out with great quality."

Bing Shopping

HP Officejet 6500A E710N Multifunction Printer

Product summary Find best price **Customer reviews** Specifications Related items

$121.53 - $242.39 (14 stores)

☐ Compare

Average rating ★★★½☆ (144)

★★★★★	(55)
★★★★☆	(54)
★★★☆☆	(10)
★★☆☆☆	(6)
★☆☆☆☆	(23)
☆☆☆☆☆	(0)

Most mentioned

Performance	(57)
Ease of Use	(43)
Print Speed	(39)
Connectivity	(31)

More ▼

Show reviews by source

Best Buy (140)
CNET (5)
Amazon.com (3)

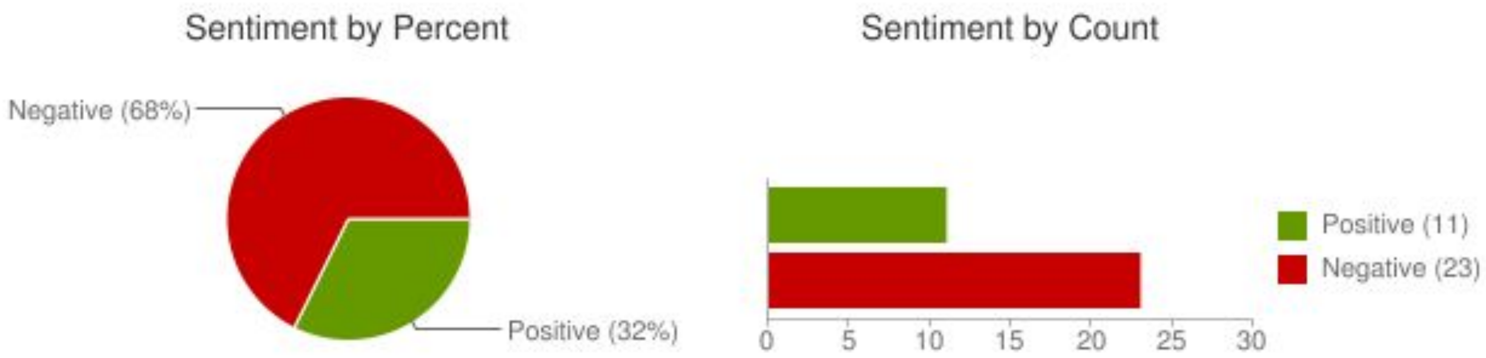
Target Sentiment on Twitter

- [Twitter Sentiment App]
- Alec Go, Richa Bhayani, Lei Huang. 2009. Twitter Sentiment Classification using Distant Supervision

Type in a word and we'll highlight the good and the bad

"united airlines" Search [Save this search]

Sentiment analysis for "united airlines"



jljacobson: OMG... Could @**United airlines** have worse customer service? W8g now 15 minutes on hold 4 questions about a flight 2DAY that need a human.
Posted 2 hours ago

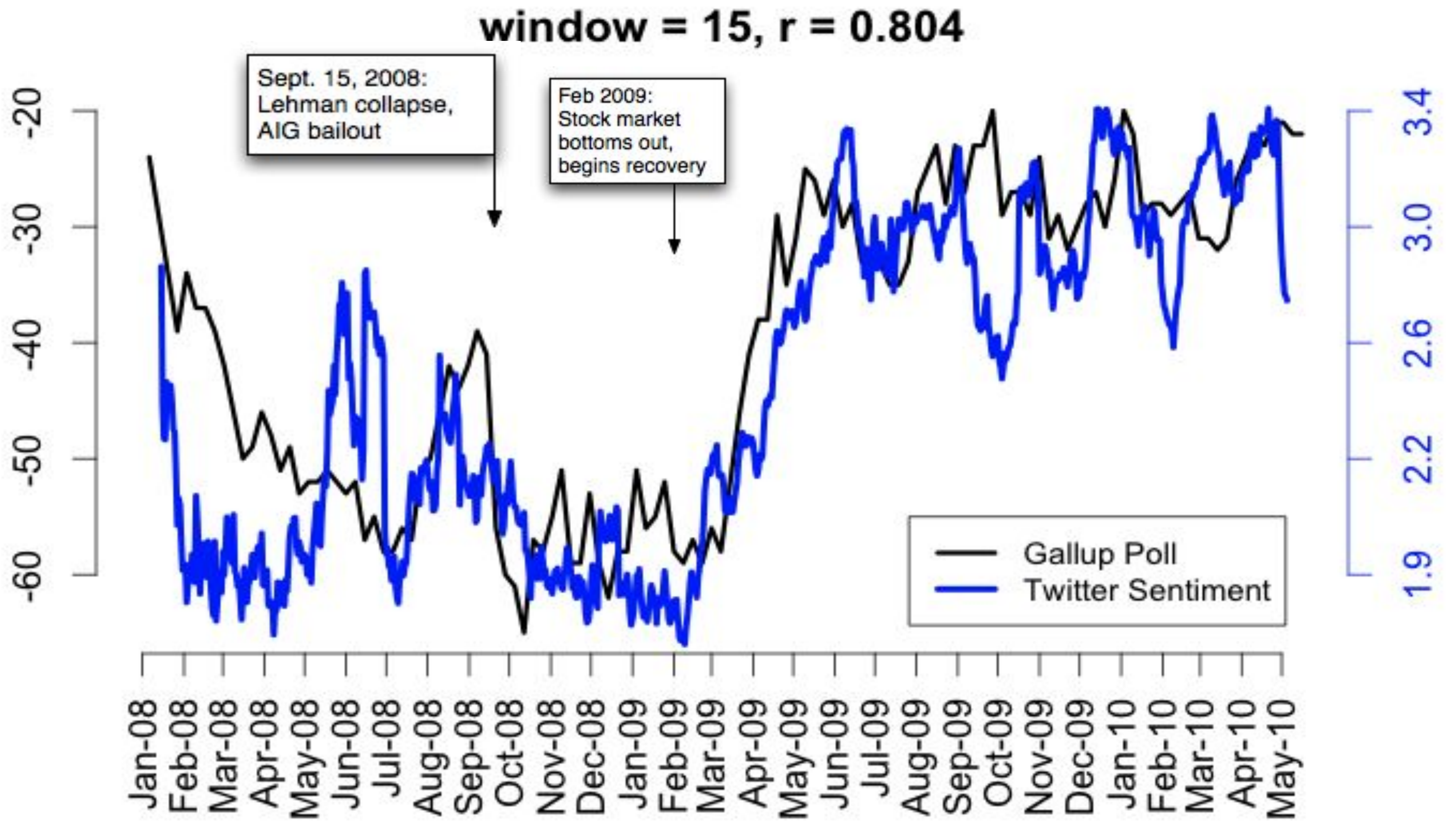
12345clumsy6789: I hate **United Airlines** Ceiling!!! Fukn impossible to get my conduit in this damn mess! ?
Posted 2 hours ago

EMLandPRGbelgiu: EML/PRG fly with Q8 **united airlines** and 24seven to an exotic destination. http://t.co/Z9QloAjF
Posted 2 hours ago

CountAdam: FANTASTIC customer service from **United Airlines** at XNA today. Is tweet more, but cell phones off now!
Posted 4 hours ago

Twitter sentiment versus Gallup Poll of Consumer Confidence

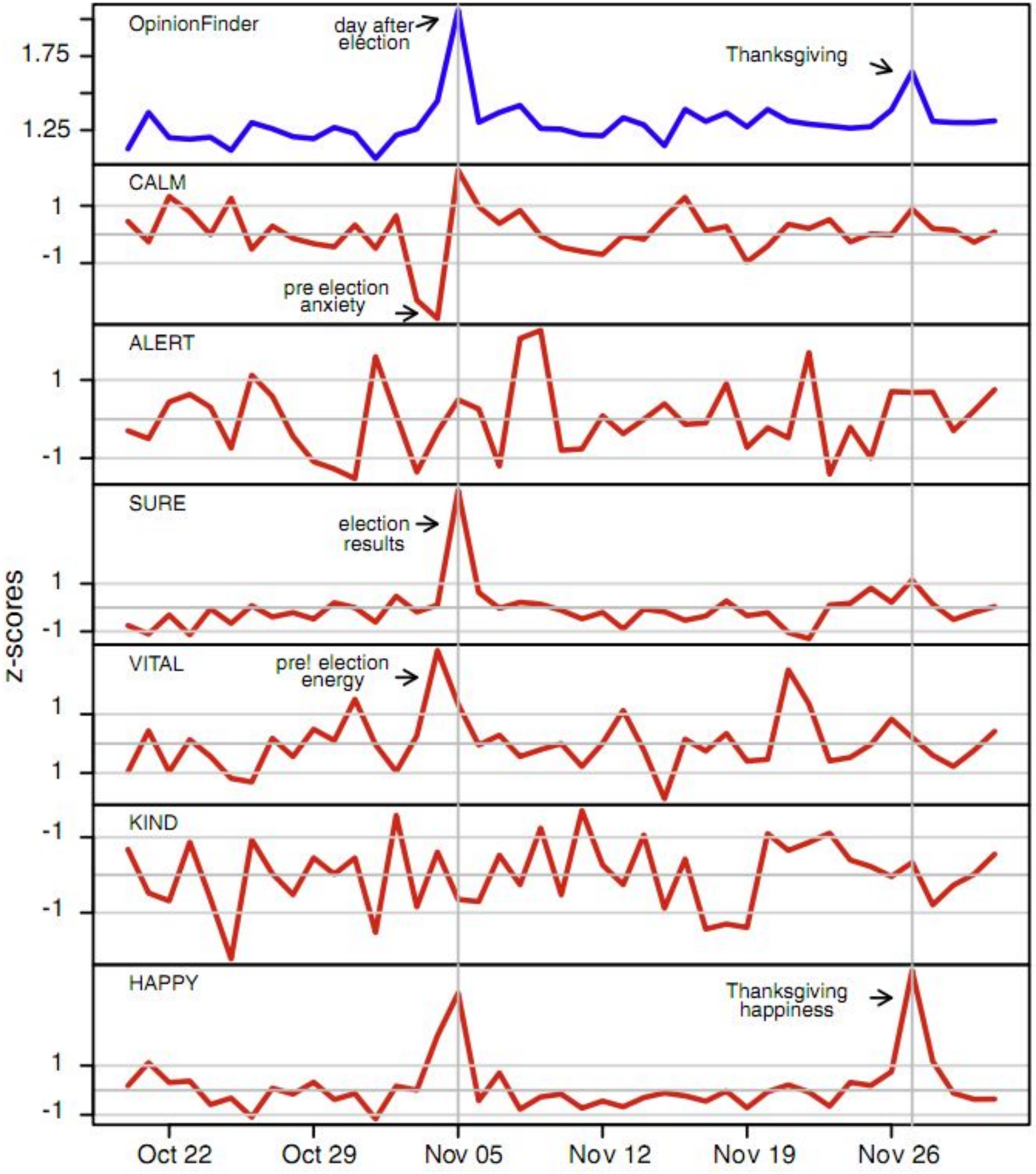
Brendan O'Connor, Ramnath Balasubramanyan, Bryan R. Routledge, and Noah A. Smith. 2010.
From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series. In ICWSM-2010



Twitter sentiment

Johan Bollen, Huina Mao, Xiaojun Zeng. 2011. [Twitter mood predicts the stock market,](#)

Journal of Computational Science 2:1, 1-8. 10.1016/j.jocs.2010.12.007.

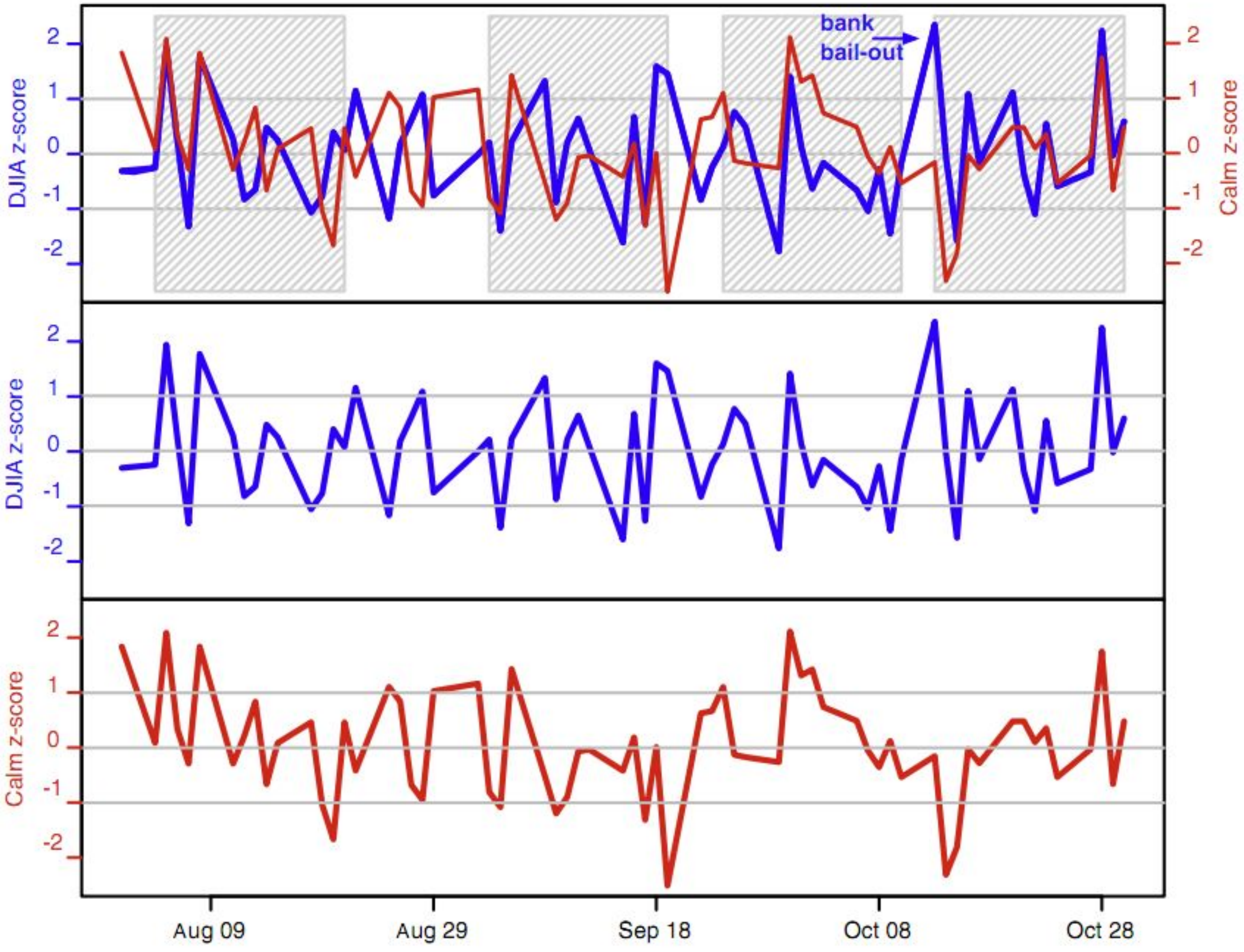


Bollen et al. (2011)

- CALM predicts DJIA 3 days later
- At least one current hedge fund uses this algorithm

Dow Jones

CALM



Sentiment analysis has many other names

- Opinion extraction
- Opinion mining
- Sentiment mining
- Subjectivity analysis

Methods for sentiment analysis broadly fall into "**text classification**" methods

Why sentiment analysis?

- *Movie*: is this review positive or negative?
- *Products*: what do people think about the new iPhone?
- *Public sentiment*: how is consumer confidence? Is despair increasing?
- *Politics*: what do people think about this candidate or issue?
- *Prediction*: predict election outcomes or market trends from sentiment

Why compute affective meaning?

- Detecting:
  - sentiment towards politicians, products, countries, ideas
  - frustration of callers to a help line
  - stress in drivers or pilots
  - depression and other medical conditions
  - confusion in students talking to e-tutors
  - emotions in novels (e.g., for studying groups that are feared over time)
- Could we generate:
  - emotions or moods for literacy tutors in the children's storybook domain
  - emotions or moods for computer games
  - personalities for dialogue systems to match the user

Scherer (1984) Typology of Affective States

- **Emotion**: brief organically synchronized … evaluation of a major event
  - *angry, sad, joyful, fearful, ashamed, proud, elated*
- **Mood**: diffuse non-caused low-intensity long-duration change in subjective feeling
  - *cheerful, gloomy, irritable, listless, depressed, buoyant*
- **Interpersonal stances**: affective stance toward another person in a specific interaction
  - *friendly, flirtatious, distant, cold, warm, supportive, contemptuous*
- **Attitudes**: enduring, affectively colored beliefs, dispositions towards objects or persons
  - *liking, loving, hating, valuing, desiring*
- **Personality traits**: stable personality dispositions and typical behavior tendencies
  - *nervous, anxious, reckless, morose, hostile, jealous*

Scherer (1984) Typology of Affective States

Type of affective state: brief definition (*examples*)	Intensity	Duration	Syn-chroni-zation	Event focus	Appraisal elicita-tion	Rapid-ity of change	Behav-ioral impact
Emotion: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an external or internal event as being of major significance (*angry, sad, joyful, fearful, ashamed, proud, elated, desperate*)	+ +–+ + +	+	+ + +	+ + +	+ + +	+ + +	+ + +
Mood: diffuse affect state, most pronounced as change in subjective feeling, of low intensity but relatively long duration, often without apparent cause (*cheerful, gloomy, irritable, listless, depressed, buoyant*)	+–+ +	++	+	+	+	++	+
Interpersonal stances: affective stance taken toward another person in a specific interaction, colouring the interpersonal exchange in that situation (*distant, cold, warm, supportive, contemptuous*)	+–+ +	+–+ +	+	++	+	+ + +	++
Attitudes: relatively enduring, affectively coloured beliefs, preferences, and predispositions towards objects or persons (*liking, loving, hating, valueing, desiring*)	0–+ +	+ +–+ + +	0	0	+	0–+	+
Personality traits: emotionally laden, stable personality dispositions and behavior tendencies, typical for a person (*nervous, anxious, reckless, morose, hostile, envious, jealous*)	0–+	+ + +	0	0	0	0	+

0: low, +: medium, ++: high, + + +: very high, –: indicates a range.

Scherer Typology of Affective States

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Sentiment Analysis

- Sentiment analysis is the detection of **attitudes**

  "enduring, affectively colored beliefs, dispositions towards objects or persons"

1. **Holder (source)** of attitude
2. **Target (aspect)** of attitude
3. **Type** of attitude
   - From a set of types
     - *Like, love, hate, value, desire,* etc.
   - Or (more commonly) simple weighted **polarity**:
     - *positive, negative, neutral,* together with *strength*
4. **Text** containing the attitude
   - Sentence or entire document

Sentiment Analysis

- Simplest task:
  - Is the attitude of this text positive or negative?
- More complex:
  - Rank the attitude of this text from 1 to 5
- Advanced:
  - Detect the target, source, or complex attitude types

Positive or negative?

- There was an earthquake in California
- The team failed to complete physical challenge. (We win/lose!)
- They said it would be great.
- They said it would be great, and they were right.
- They said it would be great, and they were wrong.
- The party fat-cats are sipping their expensive imported wines
- Oh, you're terrible!
- long-suffering fans, bittersweet memories, hilariously embarrassing moments

Examples by Chris Potts

What makes sentiment hard to classify?

- Subtlety:
  - Perfume review in *Perfumes: the Guide*:
    - "If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut."
  - Dorothy Parker on Katherine Hepburn
    - "She runs the gamut of emotions from A to B"

Why sentiment analysis?

+ an interesting use-case for modeling natural language understanding

- sentiment
- emotion, mood, attitude, personality
- perspective, intent
- negation
- metaphor, non-literal language
- sarcasm
- …

Sentiment Datasets

- Datasets from Lillian Lee's group
  - http://www.cs.cornell.edu/home/llee/data/
- Datasets from Bing Liu's group
  - https://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#datasets
- IMDb movie reviews (50K) (Maas et al. 2011)
  - http://ai.stanford.edu/~amaas/data/sentiment/index.html
- RateBeer (McAuley et al. 2012; McAuley and Leskovec 2013)
  - http://snap.stanford.edu/data/web-RateBeer.html
- Amazon Customer Review data:
  - https://s3.amazonaws.com/amazon-reviews-pds/readme.html
- Amazon Product Data (McAuley et al. 2015; He and McAuley 2016):
  - http://jmcauley.ucsd.edu/data/amazon/
- Sentiment and social networks together (West et al. 2014)
  - http://infolab.stanford.edu/~west1/TACL2014/
- Stanford Sentiment Treebank (SST; Socher et al. 2013)
  - https://nlp.stanford.edu/sentiment
- The Multilingual Amazon Reviews Corpus
  - https://docs.opendata.aws/amazon-reviews-ml/readme.html

A Baseline Algorithm: Sentiment Classification in Movie Reviews

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.
Bo Pang and Lillian Lee. 2004. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. ACL, 271-278

- Polarity detection:
  - Is an IMDB movie review positive or negative?
- Data: *Polarity Data 2.0:*
  - http://www.cs.cornell.edu/people/pabo/movie-review-data

IMDB data in the Pang and Lee database

✓

when _star wars_ came out some twenty years ago , the image of traveling throughout the stars has become a commonplace image . [...]

when han solo goes light speed , the stars change to bright lines , going towards the viewer in lines that converge at an invisible point .

cool .

october sky offers a much simpler image–that of a single white dot , traveling horizontally across the night sky . [. . .]

✗

" snake eyes " is the most aggravating kind of movie : the kind that shows so much potential then becomes unbelievably disappointing .

it's not just because this is a brian depalma film , and since he's a great director and one who's films are always greeted with at least some fanfare .

and it's not even because this was a film starring nicolas cage and since he gives a brauvara performance , this film is hardly worth his talents .

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- Build a classifier
  - Predict sentiment given features
  - Use “counts of lexicon categories” as a features
  - Handle negation
  - Use counts of **all** the words and bigrams in the training set

  - This is hard to beat
  - But only works if the training and test sets are very similar

Baseline Algorithm (adapted from Pang and Lee)

- Data preparation
- Feature Extraction
- Classification using different classifiers
  - Naïve Bayes
  - MaxEnt
  - SVM

Sentiment Tokenization Issues

- Deal with HTML and XML markup
- Twitter mark-up (names, hash tags)
- Capitalization (preserve for words in all caps)
- Phone numbers, dates
- Emoticons
- Useful code:
  - [Christopher Potts sentiment tokenizer]
  - [Brendan O'Connor twitter tokenizer]

Potts emoticons

```
[<>]?                          # optional hat/brow
[:;=8]                         # eyes
[\-o\*\']?                     # optional nose
[\)\]\(\[dDpP/\:\}\{@\|\\]     # mouth
|                              #### reverse orientation
[\)\]\(\[dDpP/\:\}\{@\|\\]     # mouth
[\-o\*\']?                     # optional nose
[:;=8]                         # eyes
[<>]?                          # optional hat/brow
```

Handling Negation

- How to handle negation
  - I **didn’t** like this movie

  vs
  - I really like this movie
- Intensity:
  - good <> not good; bad <> not bad
  - superb <> not superb; terrible <> not terrible
- Lexical diversity:
  - I didn't enjoy it.
  - I never enjoy it.
  - No one enjoys it.
  - I have yet to enjoy it.
  - I don't think I will enjoy it.

Negation

Das, Sanjiv and Mike Chen. 2001. Yahoo! for Amazon: Extracting market sentiment from stock message boards. In Proceedings of the Asia Pacific Finance Association Annual Conference (APFA).
Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.

Append NOT_ to every word between negation and following punctuation:

```
didn't like this movie , but I
```

```
didn't NOT_like NOT_this NOT_movie but I
```

More informative parts of speech

- Which words to use?
  - Only adjectives
  - All words

	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	"	pres.	81.0	80.4	**82.9**
(3)	unigrams+bigrams	32330	pres.	80.6	80.8	**82.7**
(4)	bigrams	16165	pres.	77.3	**77.4**	77.1
(5)	unigrams+POS	16695	pres.	81.5	80.4	**81.9**
(6)	adjectives	2633	pres.	77.0	**77.7**	75.1
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**
(8)	unigrams+position	22430	pres.	81.0	80.1	**81.6**

Figure 3: Average three-fold cross-validation accuracies, in percent. Boldface: best performance for a given setting (row). Recall that our baseline results ranged from 50% to 69%.

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Baseline algorithm: Sentiment Classification in Movie Reviews

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Computing with Affective Lexicons

- Drawing on literatures in
  - affective computing (Picard 95)
  - linguistic subjectivity (Wiebe and colleagues)
  - social psychology (Pennebaker and colleagues)
- Can we model the lexical semantics relevant to:
  - sentiment
  - emotion
  - personality
  - mood
  - attitudes, perspectives

Bing Liu Opinion Lexicon

Minqing Hu and Bing Liu. Mining and Summarizing Customer Reviews. ACM SIGKDD-2004.

- Bing Liu's Page on Opinion Mining
- http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar

- 6786 words
  - 2006 positive
  - 4783 negative

MPQA Subjectivity Cues Lexicon

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. Proc. of HLT-EMNLP-2005.

Riloff and Wiebe (2003). Learning extraction patterns for subjective expressions. EMNLP-2003.

- Home page: http://www.cs.pitt.edu/mpqa/subj_lexicon.html
- 6885 words from 8221 lemmas
  - 2718 positive
  - 4912 negative
- Each word annotated for intensity (strong, weak)
- GNU GPL

SentiWordNet

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010 SENTIWORDNET 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. LREC-2010

- Home page: http://sentiwordnet.isti.cnr.it/
- All WordNet synsets automatically annotated for degrees of positivity, negativity, and neutrality/objectiveness
- [estimable(J,3)] “may be computed or estimated”

  `Pos   0    Neg  0    Obj  1`
- [estimable(J,1)] “deserving of respect or high regard”

  `Pos  .75   Neg  0    Obj  .25`

The General Inquirer

Philip J. Stone, Dexter C Dunphy, Marshall S. Smith, Daniel M. Ogilvie. 1966. The General Inquirer: A Computer Approach to Content Analysis. MIT Press

- Home page: http://www.wjh.harvard.edu/~inquirer
- List of Categories: http://www.wjh.harvard.edu/~inquirer/homecat.htm
- Spreadsheet: http://www.wjh.harvard.edu/~inquirer/inquirerbasic.xls
- Categories:
    - Positiv (1915 words) and Negativ (2291 words)
    - Strong vs Weak, Active vs Passive, Overstated versus Understated
    - Pleasure, Pain, Virtue, Vice, Motivation, Cognitive Orientation, etc
- Free for Research Use

Scherer's typology of affective states

Emotion: relatively brief episode of synchronized response of all or most organismic subsystems in response to the evaluation of an event as being of major significance

angry, sad, joyful, fearful, ashamed, proud, desperate

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Two families of theories of emotion

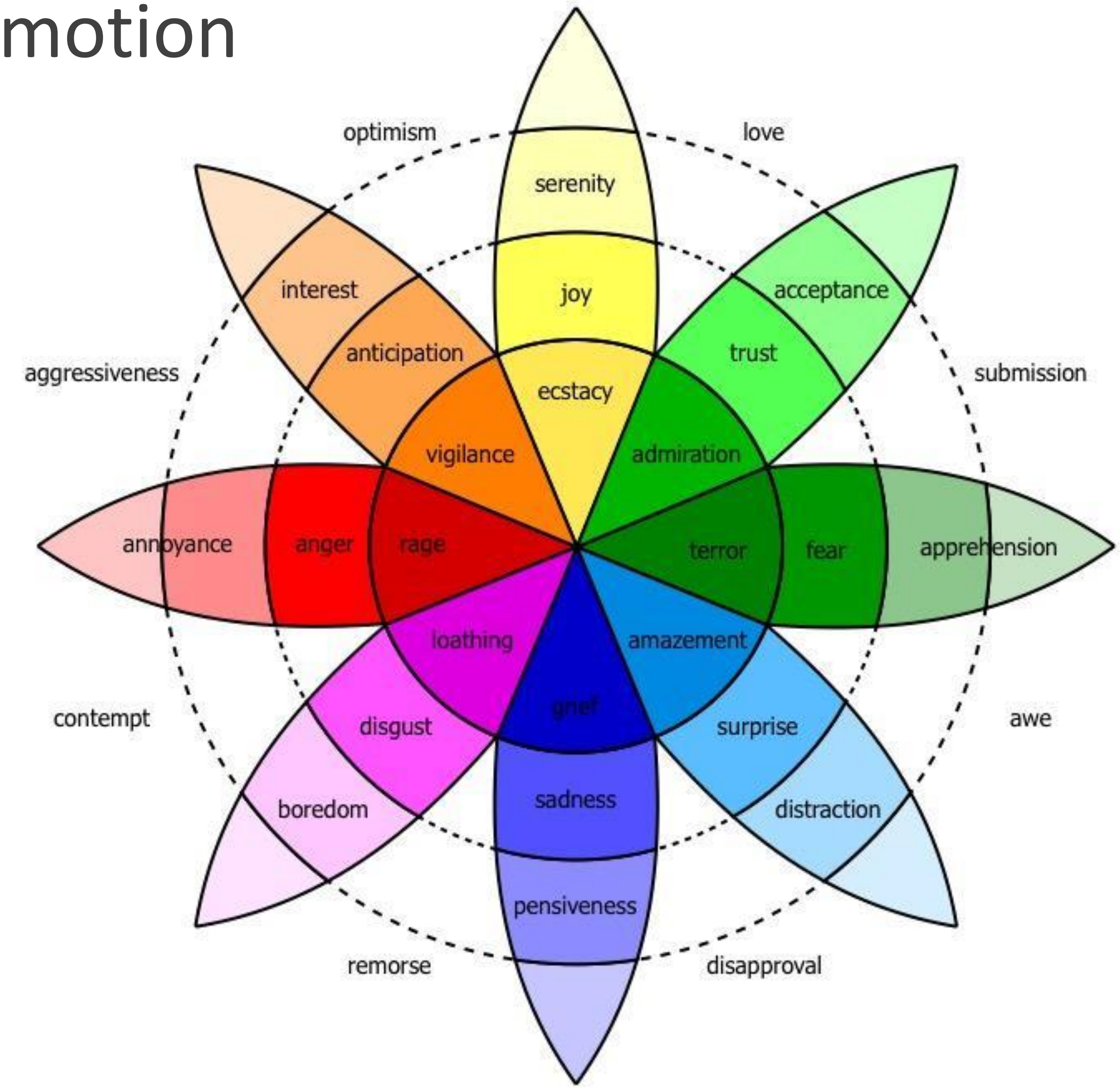
- Atomic basic emotions
  - A finite list of 6 or 8, from which others are generated
- Dimensions of emotion
  - Valence (positive negative)
  - Arousal (strong, weak)
  - Control

Ekman’s 6 basic emotions:

Surprise, happiness, anger, fear, disgust, sadness

Plutchick’s wheel of emotion

- 8 basic emotions
- in four opposing pairs:
    - joy–sadness
    - anger–fear
    - trust–disgust
    - anticipation–surprise



Atomic units vs. Dimensions

Distinctive

- Emotions are units.
- Limited number of basic emotions.
- Basic emotions are innate and universal

Dimensional

- Emotions are dimensions.
- Limited # of labels but unlimited number of emotions.
- Emotions are culturally learned.

One emotion lexicon from each paradigm!

1. 8 basic emotions:
   - NRC Word-Emotion Association Lexicon (Mohammad and Turney 2011)
2. Dimensions of valence/arousal/dominance
   - Warriner, A. B., **Kuperman**, V., and Brysbaert, M. (2013)

- Both built using Amazon Mechanical Turk

NRC Word-Emotion Association Lexicon

Mohammad and Turney 2011

- 10,000 words chosen mainly from earlier lexicons
- Labeled by Amazon Mechanical Turk
- 5 Turkers per hit
- Give Turkers an idea of the relevant sense of the word

The AMT Hit

Prompt word: *startle*

Q1. Which word is closest in meaning (most related) to *startle*?

- *automobile*
- *shake*
- *honesty*
- *entertain*

Q2. How positive (good, praising) is the word *startle*?

- *startle* is not positive
- *startle* is weakly positive
- *startle* is moderately positive
- *startle* is strongly positive

Q3. How negative (bad, criticizing) is the word *startle*?

- *startle* is not negative
- *startle* is weakly negative
- *startle* is moderately negative
- *startle* is strongly negative

Q4. How much is *startle* associated with the emotion joy? (For example, *happy* and *fun* are strongly associated with joy.)

- *startle* is not associated with joy
- *startle* is weakly associated with joy
- *startle* is moderately associated with joy
- *startle* is strongly associated with joy

Q5. How much is *startle* associated with the emotion sadness? (For example, *failure* and *heart-break* are strongly associated with sadness.)

- *startle* is not associated with sadness
- *startle* is weakly associated with sadness
- *startle* is moderately associated with sadness
- *startle* is strongly associated with sadness

Q6. How much is *startle* associated with the emotion fear? (For example, *horror* and *scary* are strongly associated with fear.)

- Similar choices as in 4 and 5 above

Q7. How much is *startle* associated with the emotion anger? (For example, *rage* and *shouting* are strongly associated with anger.)

- Similar choices as in 4 and 5 above

Q8. How much is *startle* associated with the emotion trust? (For example, *faith* and *integrity* are strongly associated with trust.)

- Similar choices as in 4 and 5 above

Q9. How much is *startle* associated with the emotion disgust? (For example, *gross* and *cruelty* are strongly associated with disgust.)

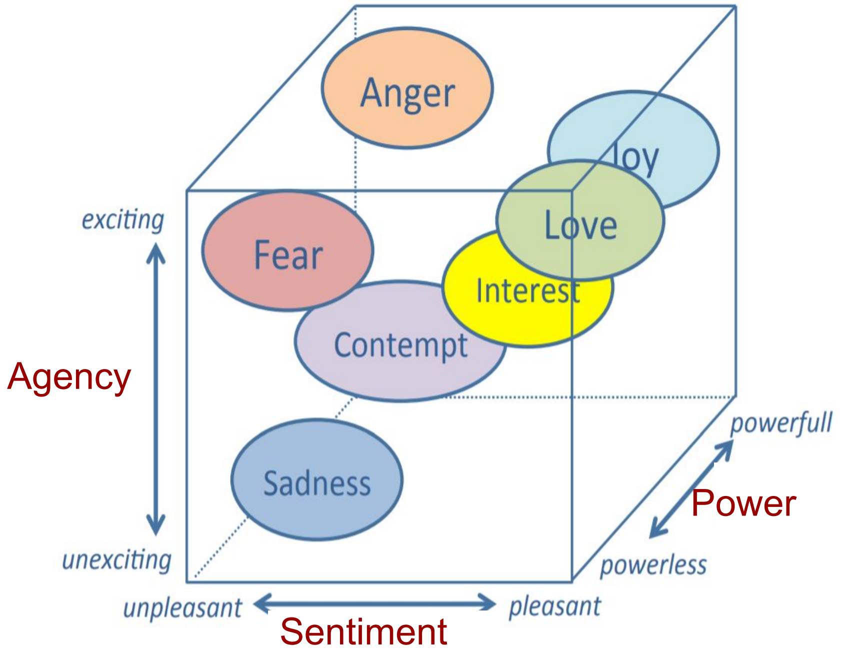
- Similar choices as in 4 and 5 above

...

Affect Control Theory

Three most important, largely independent, affective dimensions:

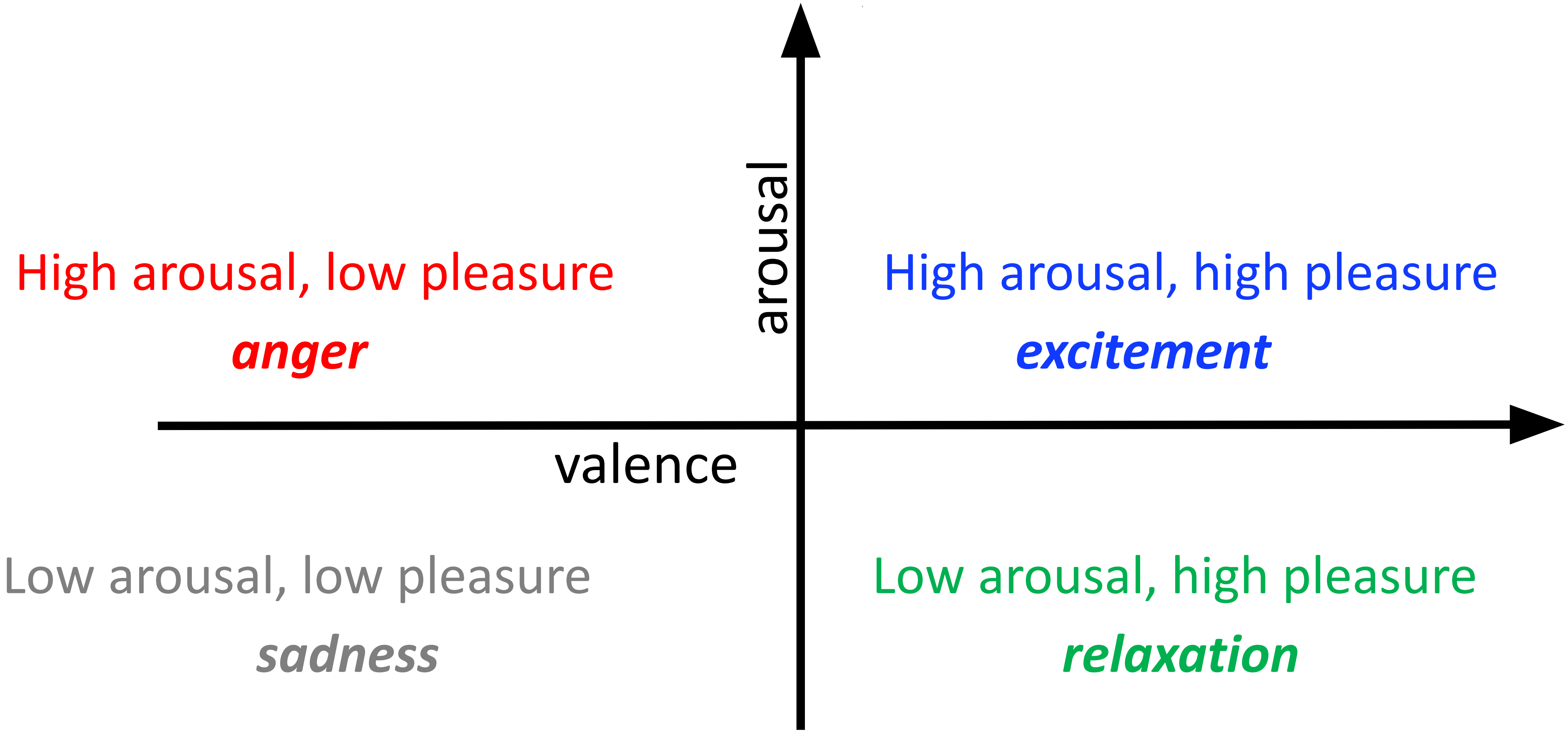
- Valence / Sentiment
  - positive–negative
  - pleasant–unpleasant
- Arousal / Agency
  - active–passive
- Dominance / Power
  - dominant–submissive



[Image credit: Tobias Schröder]

Osgood, C.; Suci, G.; and Tannenbaum, P. 1957. The Measurement of Meaning. Illini Books, IB47. University of Illinois Press
Mohammad, Saif. "Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 english words." Proc. ACL'18

Valence/Arousal Dimensions



Lexicon of valence, arousal, and dominance

- Warriner, A. B., **Kuperman**, V., and Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods 45, 1191-1207.*

- **Ratings for 14,000 words for emotional dimensions:**
  - **valence** (the pleasantness of the stimulus)
  - **arousal** (the intensity of emotion provoked by the stimulus)
  - **dominance** (the degree of control exerted by the stimulus)

Lexicon of valence, arousal, and dominance

- **valence** (the pleasantness of the stimulus)

  9: happy, pleased, satisfied, contented, hopeful

  1: unhappy, annoyed, unsatisfied, melancholic, despaired, or bored
- **arousal** (the intensity of emotion provoked by the stimulus)

  9: stimulated, excited, frenzied, jittery, wide-awake, or aroused

  1: relaxed, calm, sluggish, dull, sleepy, or unaroused;
- **dominance** (the degree of control exerted by the stimulus)

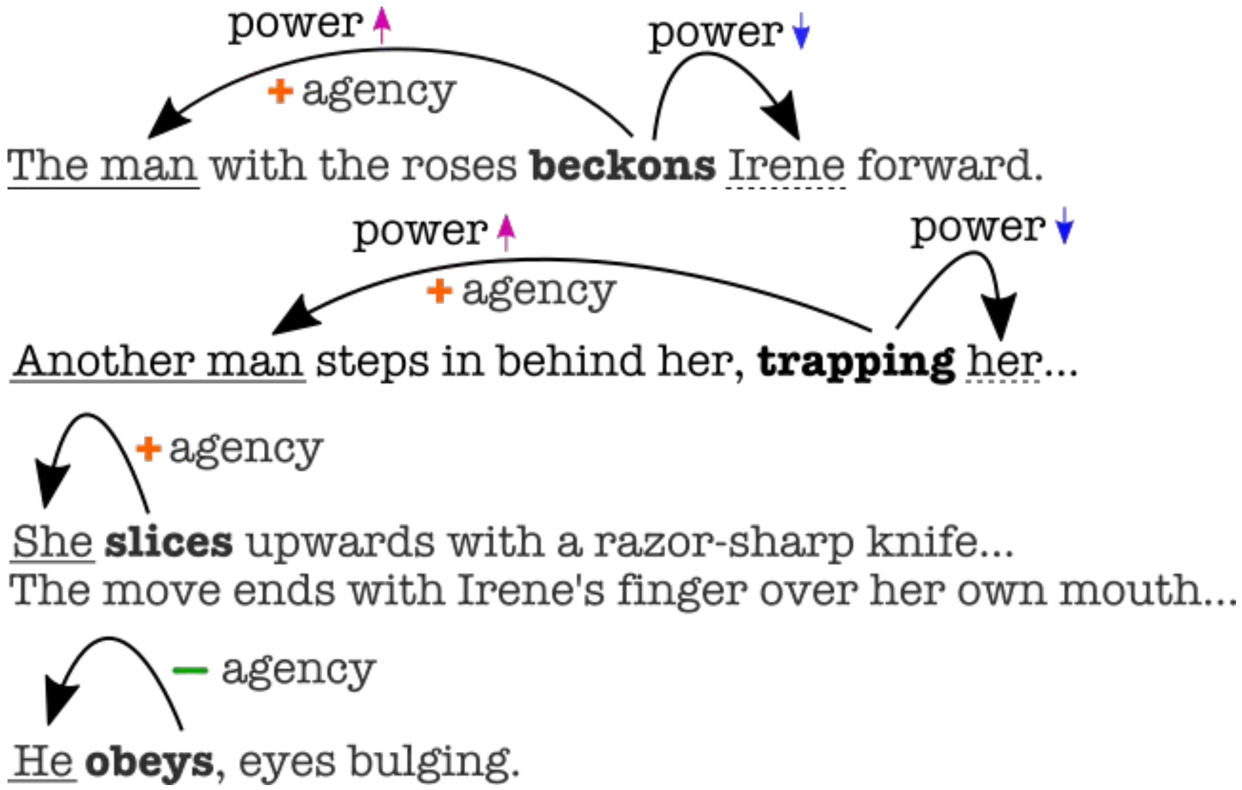
  9: in control, influential, important, dominant, autonomous, or controlling

  1: controlled, influenced, cared-for, awed, submissive, or guided
- Again produced by AMT

Lexicon of valence, arousal, and dominance: Examples

Valence		Arousal		Dominance	
vacation	8.53	rampage	7.56	self	7.74
happy	8.47	tornado	7.45	incredible	7.74
whistle	5.7	zucchini	4.18	skillet	5.33
conscious	5.53	dressy	4.15	concur	5.29
torture	1.4	dull	1.67	earthquake	2.14

Connotation frames: sentiment, power, agency



- Hannah Rashkin, Sameer Singh, Yejin Choi. 2016. Connotation Frames: A Data-Driven Investigation. ACL'16.
- Maarten Sap, Marcella Cindy Prasettio, Ari Holtzman, Hannah Rashkin, & Yejin Choi. 2017. Connotation Frames of Power and Agency in Modern Films. EMNLP'17
  - https://hrashkin.github.io/data/cf/annotated_connotation_frames.zip
  - https://homes.cs.washington.edu/~msap/movie-bias/data/FramesAgencyPower.zip

Multilingual sentiment, power, agency lexicons

English Wikipedia:
He *accepted* the option of injections of what was then called stilboestrol.

Spanish Wikipedia:
Finalmente escogió las inyecciones de estrógenos.
Finally he chose estrogen injections.

Russian Wikipedia:
Учёный предпочёл инъекции стильбэстрола
The scientist preferred stilbestrol injections.

- Chan Young Park, Xinru Yan, Anjalie Field, Yulia Tsvetkov. Multilingual Contextual Affective Analysis of LGBT People Portrayals in Wikipedia. Forthcoming.

LIWC (Linguistic Inquiry and Word Count)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

- Home page: http://www.liwc.net/
- 2300 words, >70 classes
- **Affective Processes**
  - negative emotion (*bad, weird, hate, problem, tough*)
  - positive emotion (*love, nice, sweet*)
- **Cognitive Processes**
  - Tentative (*maybe, perhaps, guess*), Inhibition (*block, constraint*)
- **Pronouns, Negation** (*no, never*), **Quantifiers** (*few, many*)
- $30 or $90 fee

Sample LIWC Features

LIWC (Linguistic Inquiry and Word Count)

Pennebaker, J.W., Booth, R.J., & Francis, M.E. (2007). Linguistic Inquiry and Word Count: LIWC 2007. Austin, TX

Feature	Type	Example
Anger words	LIWC	hate, kill, pissed
Metaphysical issues	LIWC	God, heaven, coffin
Physical state/function	LIWC	ache, breast, sleep
Inclusive words	LIWC	with, and, include
Social processes	LIWC	talk, us, friend
Family members	LIWC	mom, brother, cousin
Past tense verbs	LIWC	walked, were, had
References to friends	LIWC	pal, buddy, coworker

Sentiment lexicon induction

- Manually annotated lexicons are accurate but sparse
- Need to expand the lexicons:
  - To induce domain-specific lexicons
  - To increase the coverage (more words)
- Intuition: use seeds and supervised/semi-supervised learning to induce lexicons
  - Start with a seed set of words (‘good’, ‘poor’)
    - Find other words that have similar polarity:
      - Using heuristics: “and” and “but”
      - Using distributional hypothesis: words that occur nearby in the similar documents
      - Using lexicons: WordNet synonyms and antonyms
      - Using graph-based semi-supervised learning
    - Use annotated lexicons for lexicon expansion in supervised approaches

Hatzivassiloglou and McKeown identifying word polarity

Vasileios Hatzivassiloglou and Kathleen R. McKeown. 1997. Predicting the Semantic Orientation of Adjectives. ACL, 174–181

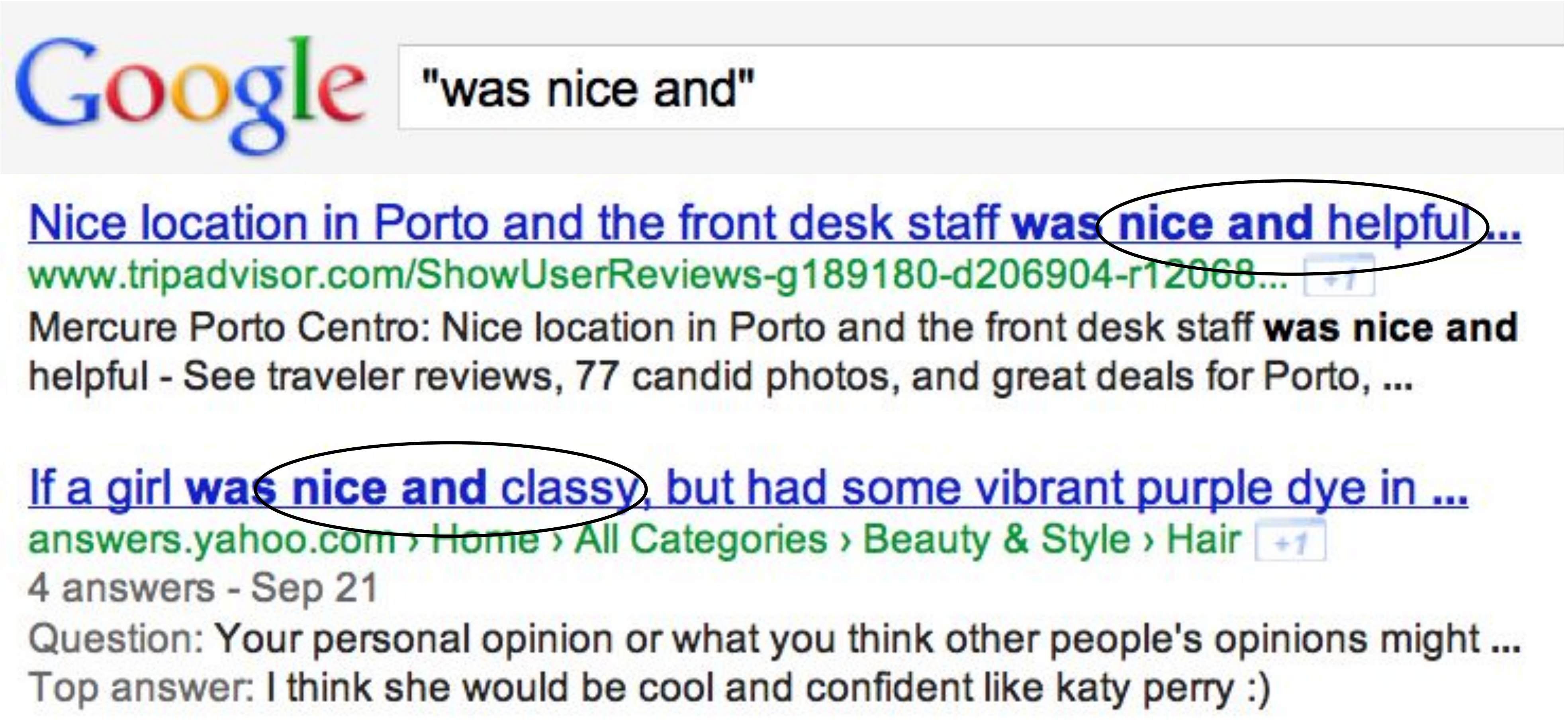
- Adjectives conjoined by "*and*" have same polarity
  - Fair **and** legitimate, corrupt **and** brutal
  - *fair **and** brutal, *corrupt **and** legitimate
- Adjectives conjoined by "*but*" do not
  - fair **but** brutal

Hatzivassiloglou & McKeown 1997
Step 1

- Label **seed set** of 1336 adjectives (all >20 in 21 million word WSJ corpus)
  - 657 positive
    - adequate central clever famous intelligent remarkable reputed sensitive slender thriving…
  - 679 negative
    - contagious drunken ignorant lanky listless primitive strident troublesome unresolved unsuspecting…

Hatzivassiloglou & McKeown 1997
Step 2

- Expand seed set to conjoined adjectives

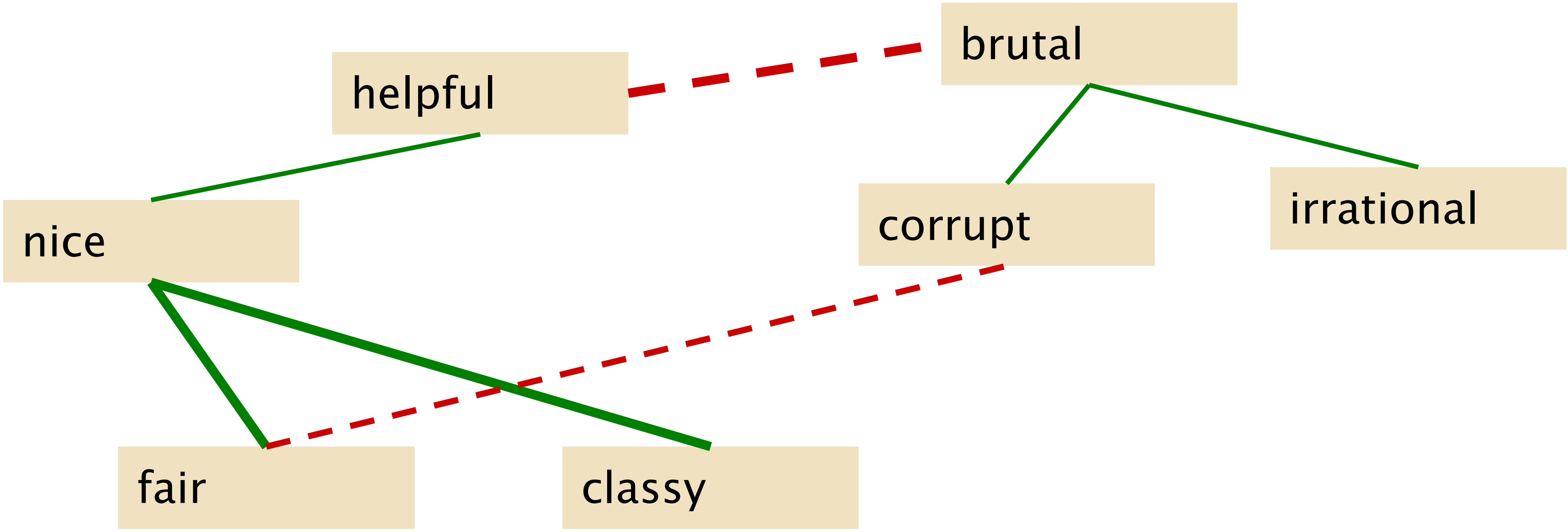


nice, helpful

nice, classy

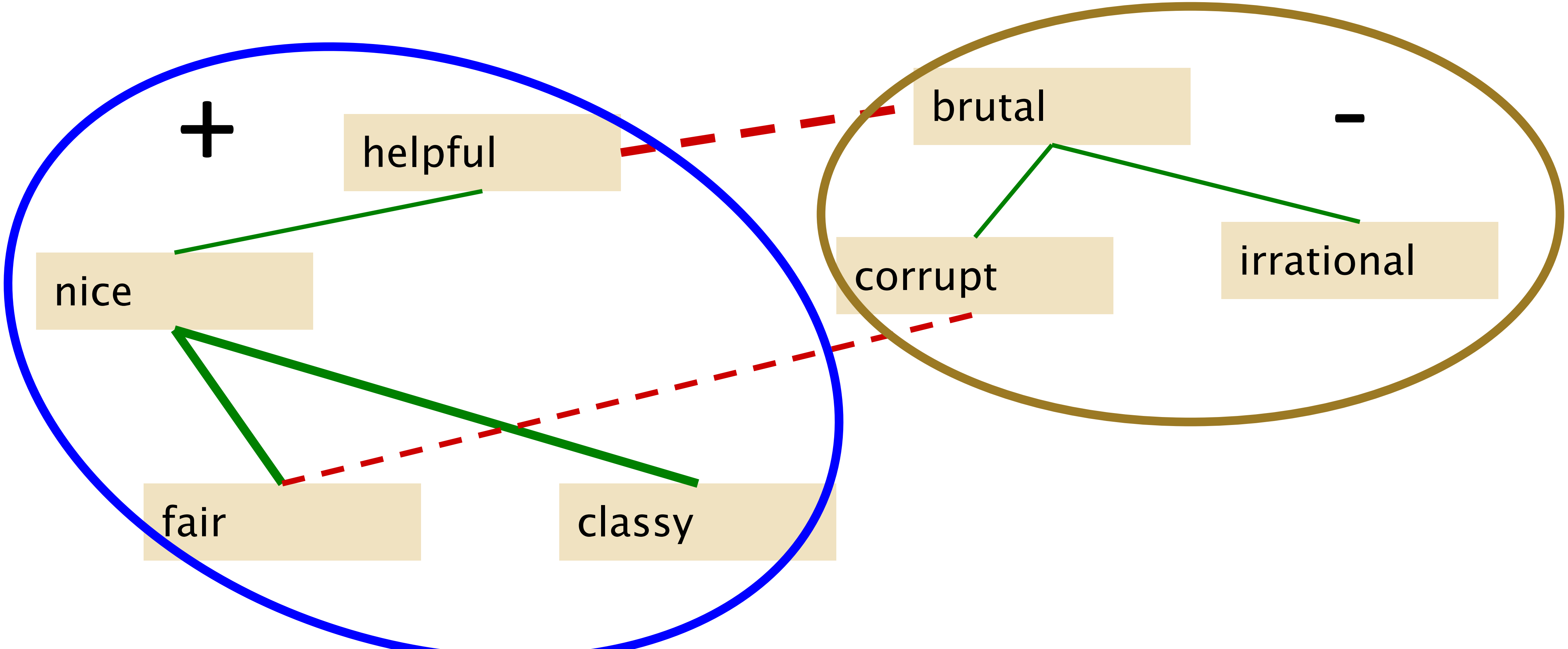
Hatzivassiloglou & McKeown 1997
Step 3

- Supervised classifier assigns "polarity similarity" to each word pair, resulting in graph:



Hatzivassiloglou & McKeown 1997
Step 4

- Clustering for partitioning the graph into two



Output polarity lexicon

- Positive
  - bold decisive **disturbing** generous good honest important large mature patient peaceful positive proud sound stimulating straightforward **strange** talented vigorous witty…
- Negative
  - ambiguous **cautious** cynical evasive harmful hypocritical inefficient insecure irrational irresponsible minor **outspoken pleasant** reckless risky selfish tedious unsupported vulnerable wasteful…

Turney Algorithm

Turney (2002): Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews

1. Extract a *phrasal lexicon* from reviews
2. Learn polarity of each phrase
3. Rate a review by the average polarity of its phrases

Extract two-word phrases with adjectives

First Word	Second Word	Third Word (not extracted)
JJ	NN or NNS	anything
RB, RBR, RBS	JJ	Not NN nor NNS
JJ	JJ	Not NN or NNS
NN or NNS	JJ	Nor NN nor NNS
RB, RBR, or RBS	VB, VBD, VBN, VBG	anything

How to measure polarity of a phrase?

- Positive phrases co-occur more with *"excellent"*
- Negative phrases co-occur more with *"poor"*
- To measure co-occurrence use PMI

$$\mathrm{PMI}(word_1, word_2) = \log_2 \frac{P(word_1, word_2)}{P(word_1)P(word_2)}$$

$$\mathrm{Polarity}(phrase) = \mathrm{PMI}(phrase, \text{"excellent"}) - \mathrm{PMI}(phrase, \text{"poor"})$$

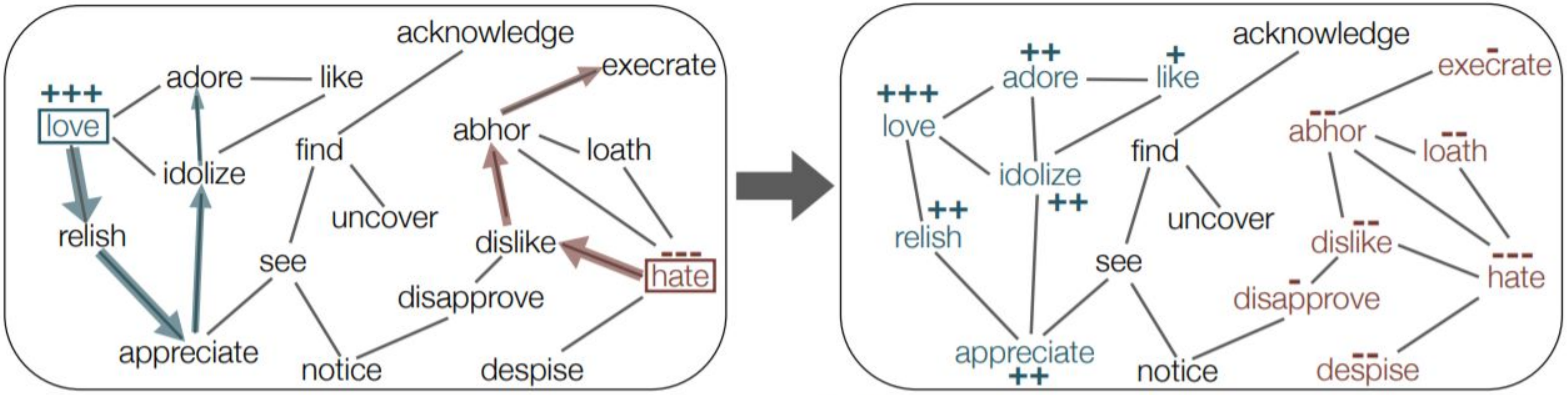
Using WordNet to learn polarity

S.M. Kim and E. Hovy. 2004. Determining the sentiment of opinions. COLING 2004
M. Hu and B. Liu. Mining and summarizing customer reviews. In Proceedings of KDD, 2004

- WordNet: online thesuarus
- Create positive ("good") and negative seed-words ("terrible")
- Find Synonyms and Antonyms
  - Positive Set: Add synonyms of positive words ("well") and antonyms of negative words
  - Negative Set: Add synonyms of negative words ("awful") and antonyms of positive words (”evil")
- Repeat, following chains of synonyms
- Filter

Graph-Based Approaches

[William L. Hamilton, Kevin Clark, Jure Leskovec, Dan Jurafsky 2016. Inducing Domain-Specific Sentiment Lexicons from Unlabeled Corpora. In Proceedings of EMNLP]



a. Run random walks from seed words. **b. Assign polarity scores based on frequency of random walk visits.**

Figure 3: Visual summary of the SENTPROP algorithm.

Domain-specific Seed Lexicons

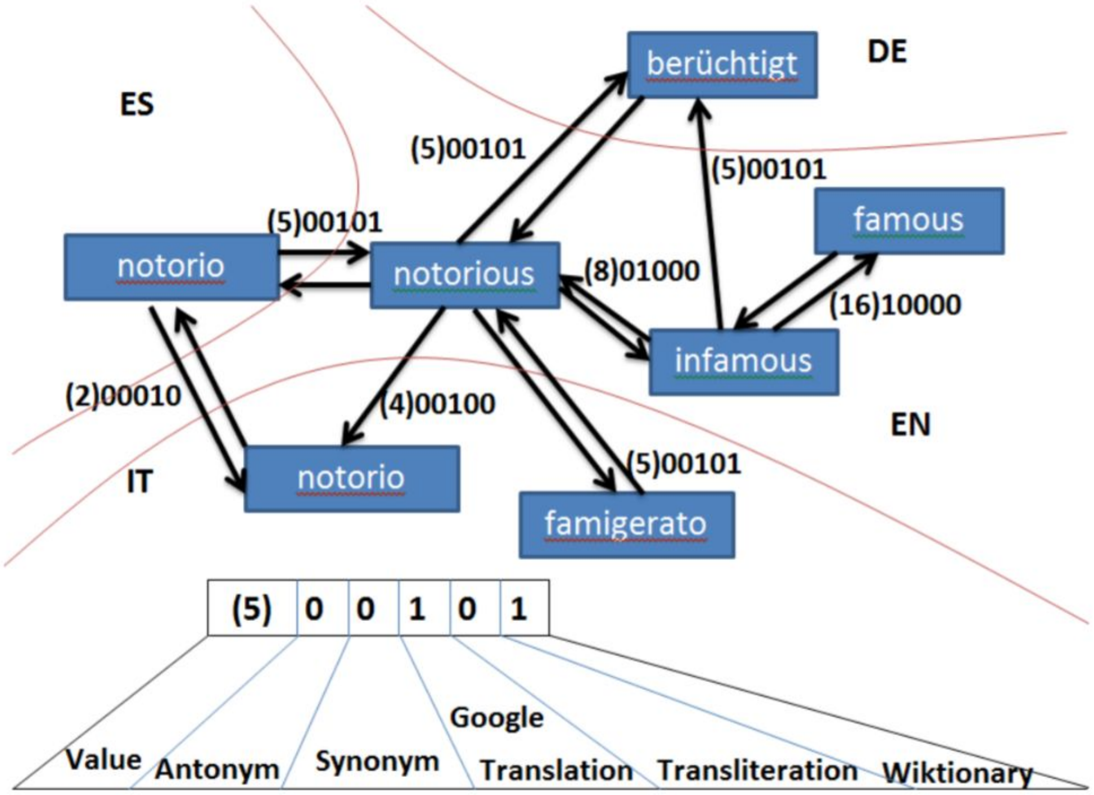
Domain	Positive seed words	Negative seed words
Standard English	good, lovely, excellent, fortunate, pleasant, delightful, perfect, loved, love, happy	bad, horrible, poor, unfortunate, unpleasant, disgusting, evil, hated, hate, unhappy
Finance	successful, excellent, profit, beneficial, improving, improved, success, gains, positive	negligent, loss, volatile, wrong, losses, damages, bad, litigation, failure, down, negative
Twitter	love, loved, loves, awesome, nice, amazing, best, fantastic, correct, happy	hate, hated, hates, terrible, nasty, awful, worst, horrible, wrong, sad

Table 1: Seed words. The seed words were manually selected to be context insensitive (without knowledge of the test lexicons).

Multilingual Sentiment Lexicons

https://polyglot.readthedocs.io/en/latest/Sentiment.html

Building Sentiment Lexicons for All Major Languages
Yanqing Chen and Steven Skiena
ACL 2014

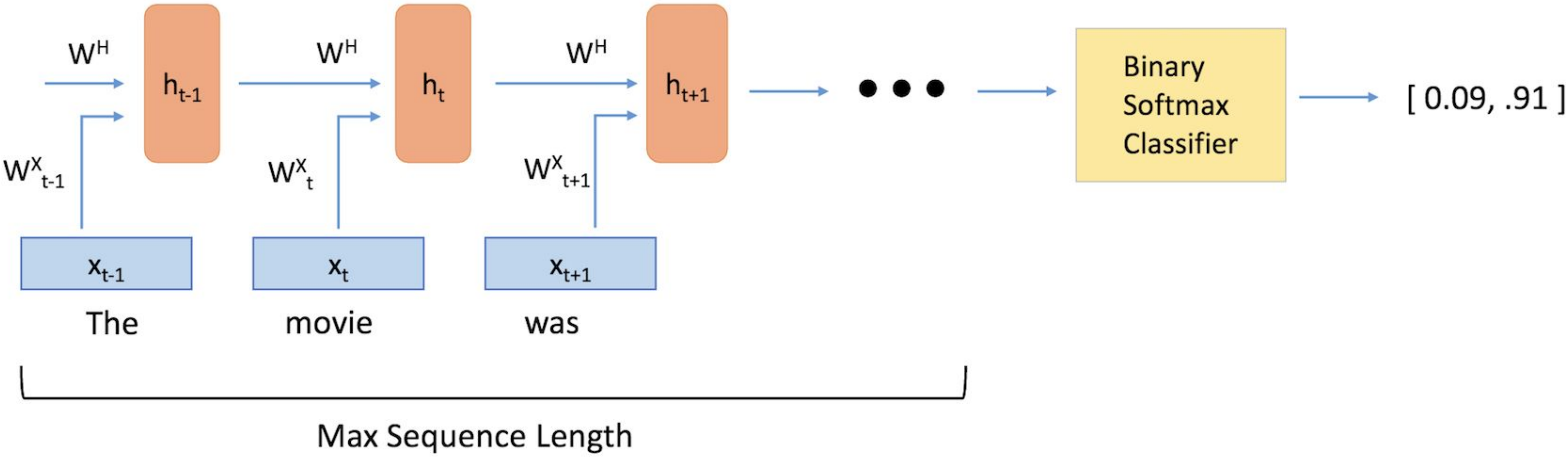


Languages Coverage

```
from polyglot.downloader import downloader
print(downloader.supported_languages_table("sentiment2", 3))
```

1. Turkmen	2. Thai	3. Latvian
4. Zazaki	5. Tagalog	6. Tamil
7. Tajik	8. Telugu	9. Luxembourgish, Letzeb...
10. Alemannic	11. Latin	12. Turkish
13. Limburgish, Limburgan...	14. Egyptian Arabic	15. Tatar
16. Lithuanian	17. Spanish; Castilian	18. Basque
19. Estonian	20. Asturian	21. Greek, Modern
22. Esperanto	23. English	24. Ukrainian
25. Marathi (Marāṭhī)	26. Maltese	27. Burmese
28. Kapampangan	29. Uighur, Uyghur	30. Uzbek
31. Malagasy	32. Yiddish	33. Macedonian
34. Urdu	35. Malayalam	36. Mongolian
37. Breton	38. Bosnian	39. Bengali
40. Tibetan Standard, Tib...	41. Belarusian	42. Bulgarian
43. Bashkir	44. Vietnamese	45. Volapük
46. Gan Chinese	47. Manx	48. Gujarati
49. Yoruba	50. Occitan	51. Scottish Gaelic; Gaelic
52. Irish	53. Galician	54. Ossetian, Ossetic
55. Oriya	56. Walloon	57. Swedish
58. Silesian	59. Lombard language	60. Divehi; Dhivehi; Mald...
61. Danish	62. German	63. Armenian
64. Haitian; Haitian Creole	65. Hungarian	66. Croatian
67. Bishnupriya Manipuri	68. Hindi	69. Hebrew (modern)
70. Portuguese	71. Afrikaans	72. Pashto, Pushto
73. Amharic	74. Aragonese	75. Bavarian
76. Assamese	77. Panjabi, Punjabi	78. Polish
79. Azerbaijani	80. Italian	81. Arabic
82. Icelandic	83. Ido	84. Scots
85. Sicilian	86. Indonesian	87. Chinese Word
88. Interlingua	89. Waray-Waray	90. Piedmontese language
91. Quechua	92. French	93. Dutch
94. Norwegian Nynorsk	95. Norwegian	96. Western Frisian
97. Upper Sorbian	98. Nepali	99. Persian
100. Ilokano	101. Finnish	102. Faroese
103. Romansh	104. Javanese	105. Romanian, Moldavian, ...
106. Malay	107. Japanese	108. Russian
109. Catalan; Valencian	110. Fiji Hindi	111. Chinese
112. Cebuano	113. Czech	114. Chuvash
115. Welsh	116. West Flemish	117. Kirghiz, Kyrgyz
118. Kurdish	119. Kazakh	120. Korean
121. Kannada	122. Khmer	123. Georgian
124. Sakha	125. Serbian	126. Albanian
127. Swahili	128. Chechen	129. Sundanese
130. Sanskrit (Saṁskṛta)	131. Venetian	132. Northern Sami

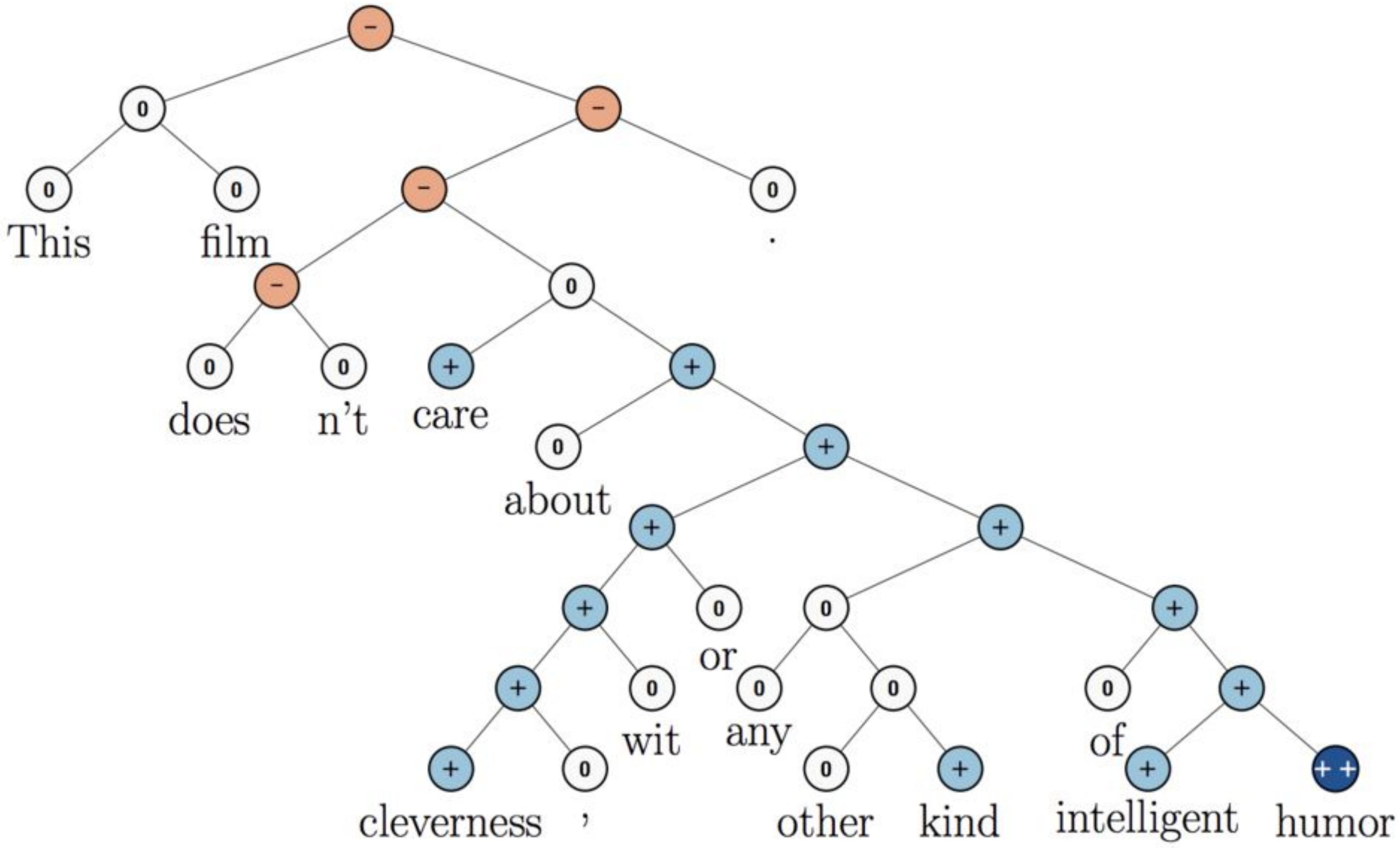
Sentiment Classification with Neural Nets



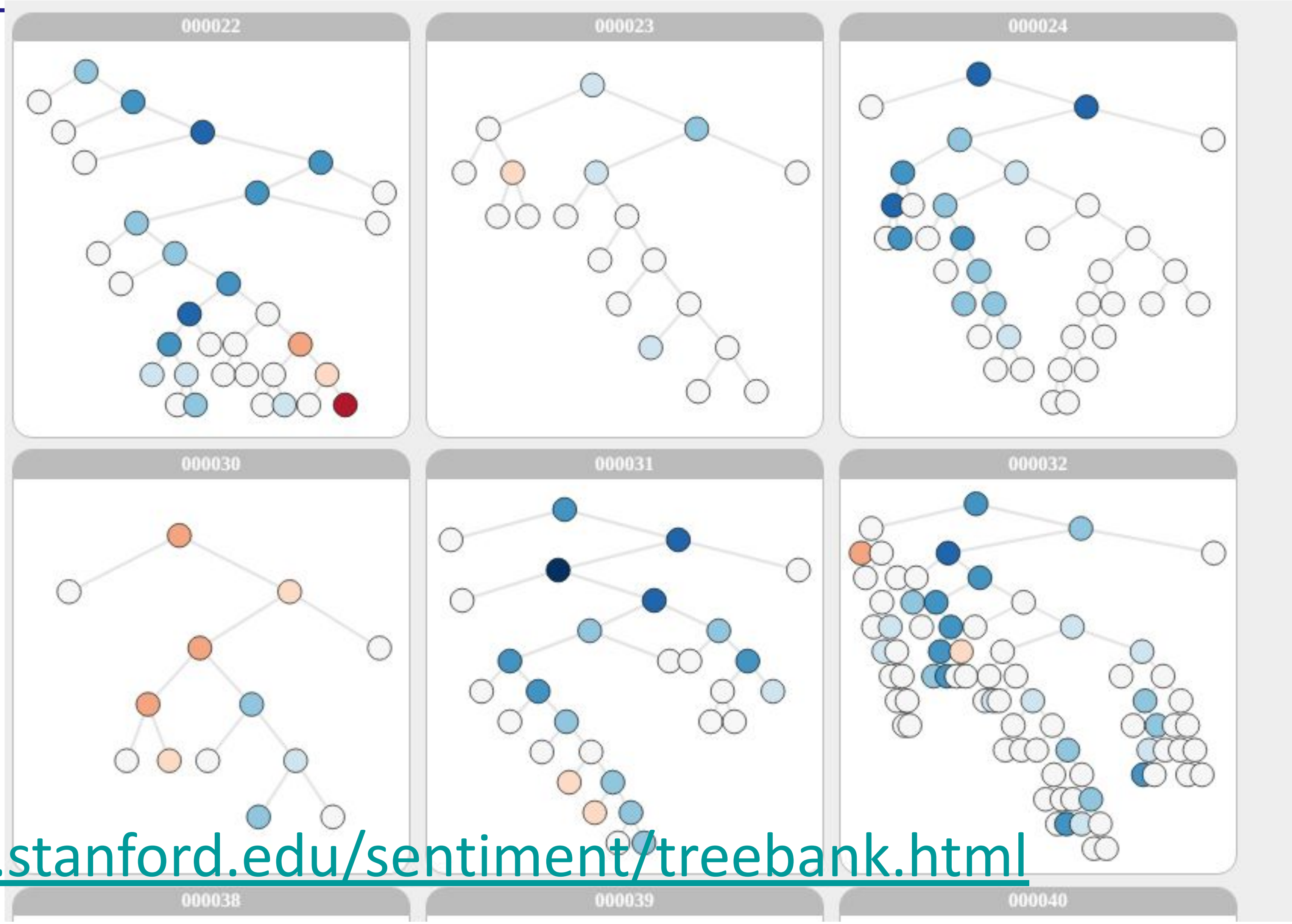
- "This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it **can't hold up**."
- Well as usual Keanu Reeves is nothing special, but surprisingly, the very talented Laurence Fishbourne is **not so good** either, I was surprised.

Sentiment Classification with Recursive Neural Networks

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)

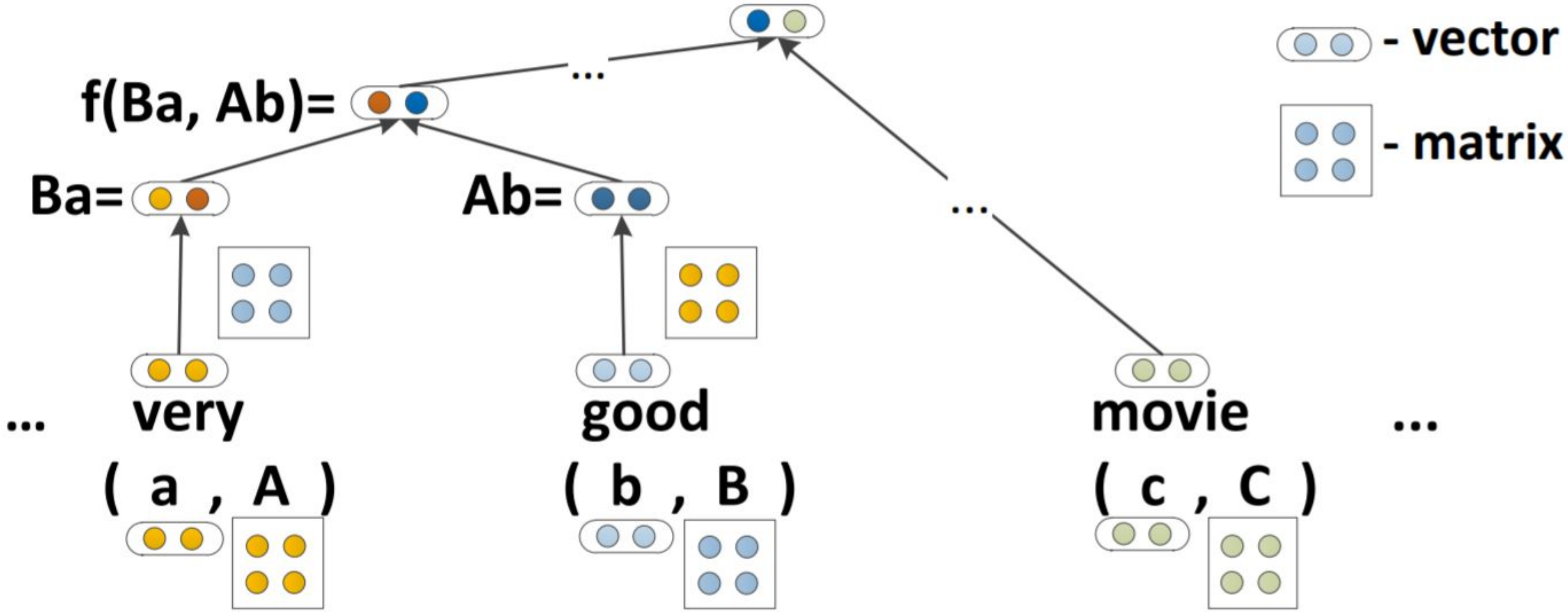


Stanford Sentiment Treebank



https://nlp.stanford.edu/sentiment/treebank.html

Recursive Neural Networks



Sentiment Classification with Recursive Neural Networks

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**

Table 1: Accuracy for fine grained (5-class) and binary predictions at the sentence level (root) and for all nodes.

SOTA Methods

SemEval Competitions: 2007, 2010, 2014, 2015, 2016, 2017

http://alt.qcri.org/semeval2016

SemEval-2016 : Semantic Evaluation Exercises

International Workshop on Semantic Evaluation (SemEval-2016)

Track II. Sentiment Analysis Track

- Task 4: Sentiment Analysis in Twitter
- Task 5: Aspect-Based Sentiment Analysis
- Task 6: Detecting Stance in Tweets
- Task 7: Determining Sentiment Intensity of English and Arabic Phrases

SemEval 2016

SwissCheese at SemEval-2016 Task 4: Sentiment Classification Using an Ensemble of Convolutional Neural Networks with Distant Supervision

Jan Deriu*
ETH Zurich
Switzerland
jderiu@student.ethz.ch

Maurice Gonzenbach*
ETH Zurich
Switzerland
mauriceg@student.ethz.ch

Fatih Uzdilli
Zurich University of Applied Sciences
Switzerland
uzdi@zhaw.ch

Aurelien Lucchi
ETH Zurich
Switzerland
alucchi@inf.ethz.ch

Valeria De Luca
ETH Zurich
Switzerland
vdeluca@vision.ee.ethz.ch

Martin Jaggi
ETH Zurich
Switzerland
jaggi@inf.ethz.ch

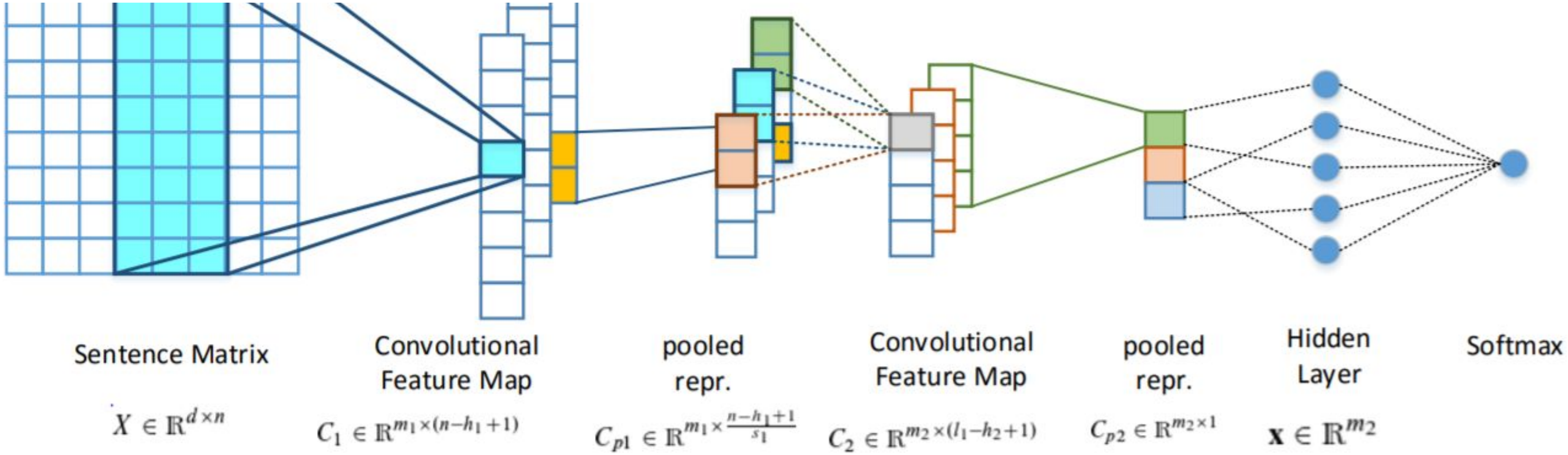
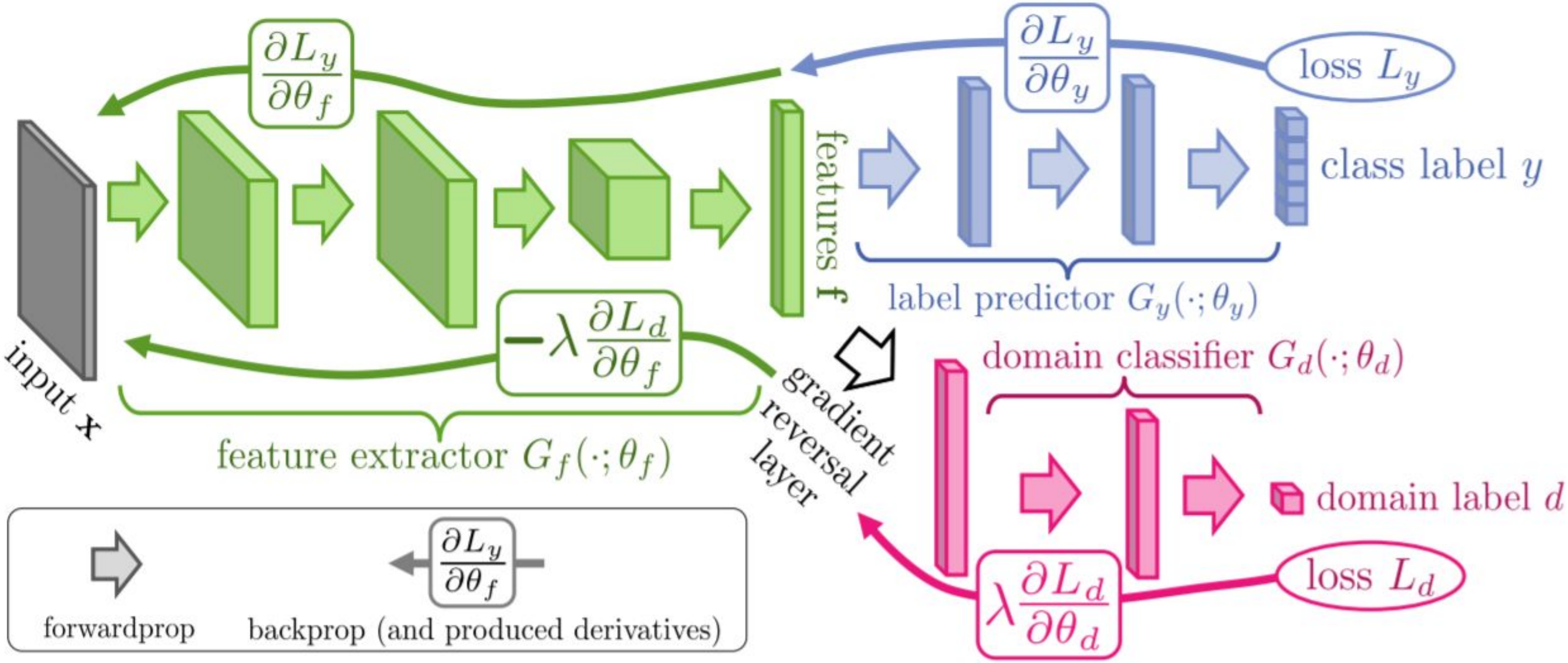


Figure 1: The architecture of the CNNs used in our approach.

Cross-Domain Sentiment Classification

[Domain-Adversarial Training of Neural Networks
Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, Victor Lempitsky
Journal of Machine Learning Research 2016, vol. 17, p. 1-35]



http://nlpprogress.com/english/sentiment_analysis.html

Model	Accuracy	Paper / Source
XLNet (Yang et al., 2019)	96.21	XLNet: Generalized Autoregressive Pretraining for Language Understanding
BERT_large+ITPT (Sun et al., 2019)	95.79	How to Fine-Tune BERT for Text Classification?
BERT_base+ITPT (Sun et al., 2019)	95.63	How to Fine-Tune BERT for Text Classification?
ULMFiT (Howard and Ruder, 2018)	95.4	Universal Language Model Fine-tuning for Text Classification
Block-sparse LSTM (Gray et al., 2017)	94.99	GPU Kernels for Block-Sparse Weights
oh-LSTM (Johnson and Zhang, 2016)	94.1	Supervised and Semi-Supervised Text Categorization using LSTM for Region Embeddings
Virtual adversarial training (Miyato et al., 2016)	94.1	Adversarial Training Methods for Semi-Supervised Text Classification
BCN+Char+CoVe (McCann et al., 2017)	91.8	Learned in Translation: Contextualized Word Vectors

Related tasks in affective computing

▪ Subjectivity	(Pang & Lee 2008)
▪ Bias	(Recasend et al. 2013)
▪ Stance	(Anand et al. 2011)
▪ Hate-speech	(Nobata et al. 2016)
▪ Sarcasm	(Khodak et al. 2017)
▪ Deception and betrayal	(Niculae et al. 2015)
▪ Online trolls	(Cheng et al. 2017)
▪ Polarization	(Demszky et al. 2019)
▪ Politeness	(Danescu-Niculescu-Mizil et al. 2013)
▪ Linguistic alignment	(Doyle el al. 2016)

Summary

- Lexicons
- Lexicon learning
- Sentiment classification
- Sentiment analysis ++
  - More labels
  - Aspect-based sentiment
  - Stance detection
  - Emotion classification
  - Sentiment + syntactic parsing
  - Sentiment + semantic frames
  - Multilingual sentiment analysis