Introduction to NLP

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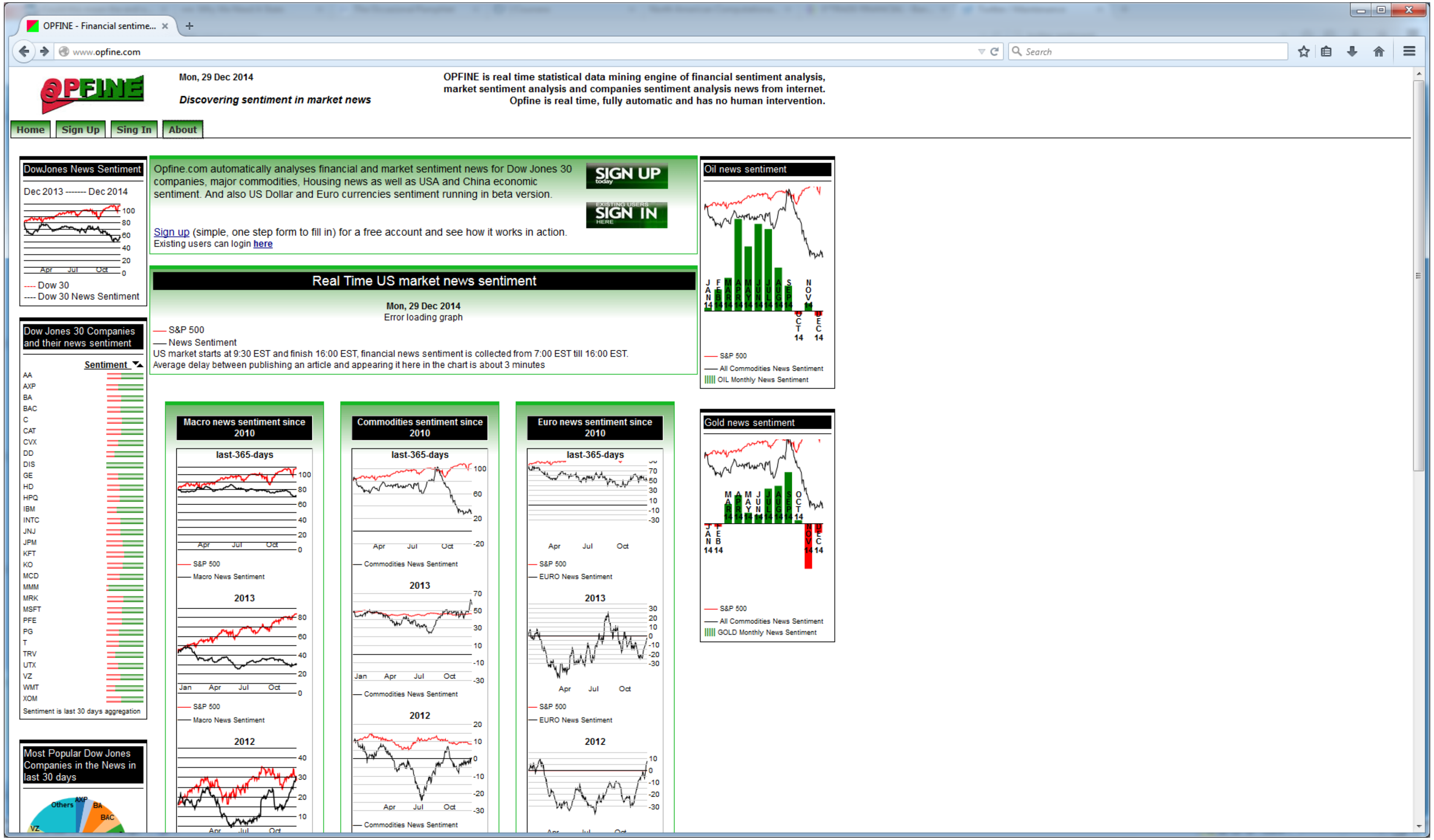
Sentiment Analysis

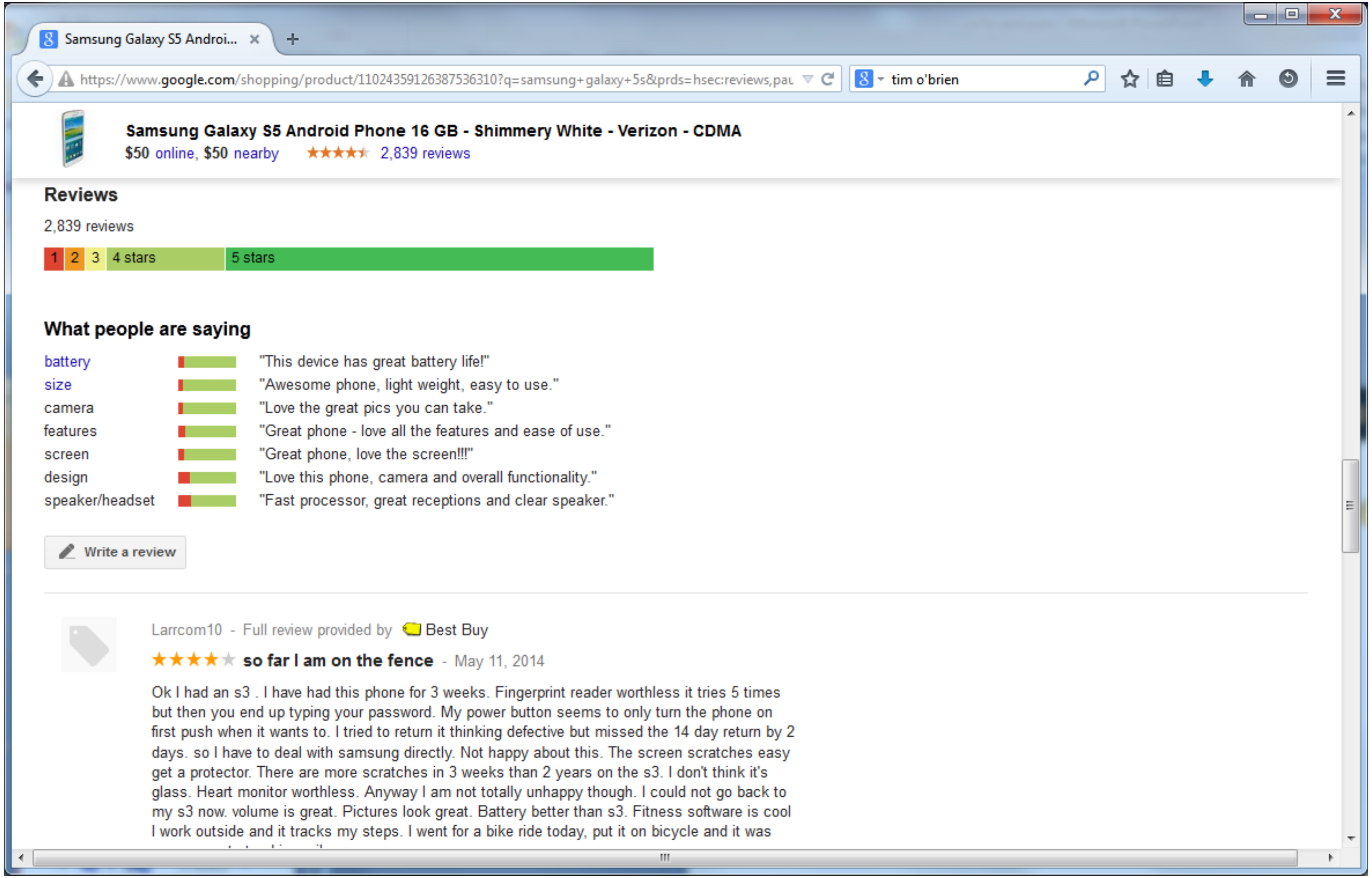
Reviews of 1Q84 by Haruki Murakami

- "*1Q84* is a tremendous feat and a triumph . . . A must-read for anyone who wants to come to terms with contemporary Japanese culture."
  —Lindsay Howell, *Baltimore Examiner*
- "Perhaps one of the most important works of science fiction of the year . . . *1Q84* does not disappoint . . . [It] envelops the reader in a shifting world of strange cults and peculiar characters that is surreal and entrancing."
  —Matt Staggs, Suvudu.com
- Ambitious, sprawling and thoroughly stunning . . . Orwellian dystopia, sci-fi, the modern world (terrorism, drugs, apathy, pop novels)—all blend in this dreamlike, strange and wholly unforgettable epic."
  —*Kirkus Reviews* (starred review)

Sentiment about Companies



Product Reviews



Introduction

- Many posts, blogs
- Expressing personal opinions
- Research questions
  - Subjectivity analysis
  - Polarity analysis (positive/negative, number of stars)
  - Viewpoint analysis (Chelsea vs. Manchester United, republican vs. democrat)
- Sentiment target
  - entity
  - aspect

Introduction

- Level of granularity
  - Document
  - Sentence
  - Attribute
- Opinion words
  - Base
  - Comparative (better, slower)
- Negation analysis
  - Just counting negative words is not enough

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Sentiment Analysis as Classification

- Feature types
  - Words
    - Presence is more important than frequency
  - Punctuation
    - Exclamation points, emoji
  - Phrases
- A lot of training data is available
  - E.g., movie review sentences and stars
- Techniques
  - Logistic Regression, SVM, Naïve Bayes

Linguistic Observations

- “very”
  - enhances the polarity of the adjective or adverb
- “raise”
  - can be negative or positive depending on the object
- “cold beer” vs. “cold coffee”
- “advanced”, “progressive”
  - positive or negative?
- Negations
  - “Not great”
- Some of these can be captured by n-grams
- Syntactic structure
  - “Soldiers shooting at militants” vs. “Militants shooting at soldiers”
  - “While it starts as fun, the movie ultimately turns out to be boring and disturbing”

Compositionality

- “inflammation”
- “reduces inflammation”, “doesn’t reduce inflammation”, “fails to reduce inflammation”, “hard to believe that it causes inflammation”
- “may reduce inflammation”
- “is reported to reduce inflammation”
- “reduces fever but not inflammation”

Recursive Neural Tensor Networks

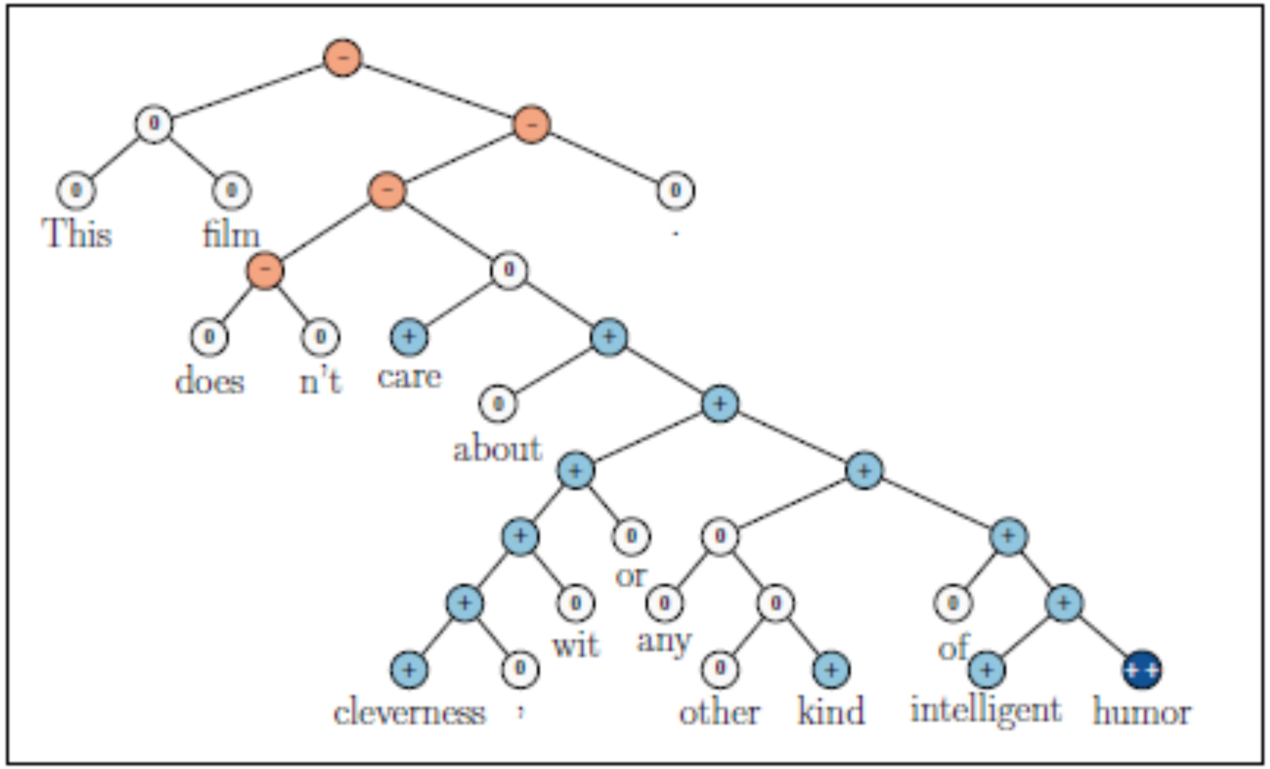

Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (– –, –, 0, +, + +), at every node of a parse tree and capturing the negation and its scope in this sentence.

[Socher et al. EMNLP 2013]

Recursive Neural Tensor Networks

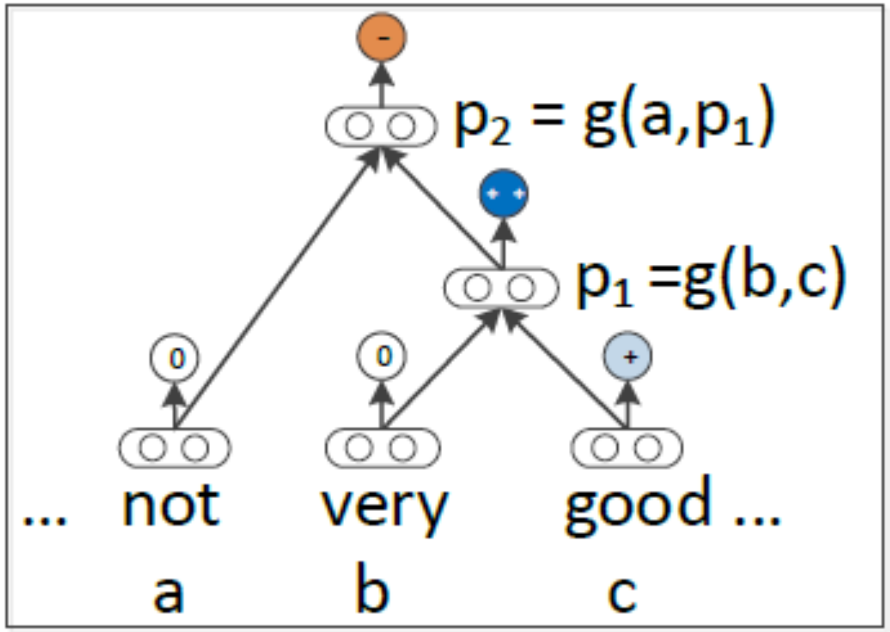

Figure 4: Approach of Recursive Neural Network models for sentiment: Compute parent vectors in a bottom up fashion using a compositionality function g and use node vectors as features for a classifier at that node. This function varies for the different models.

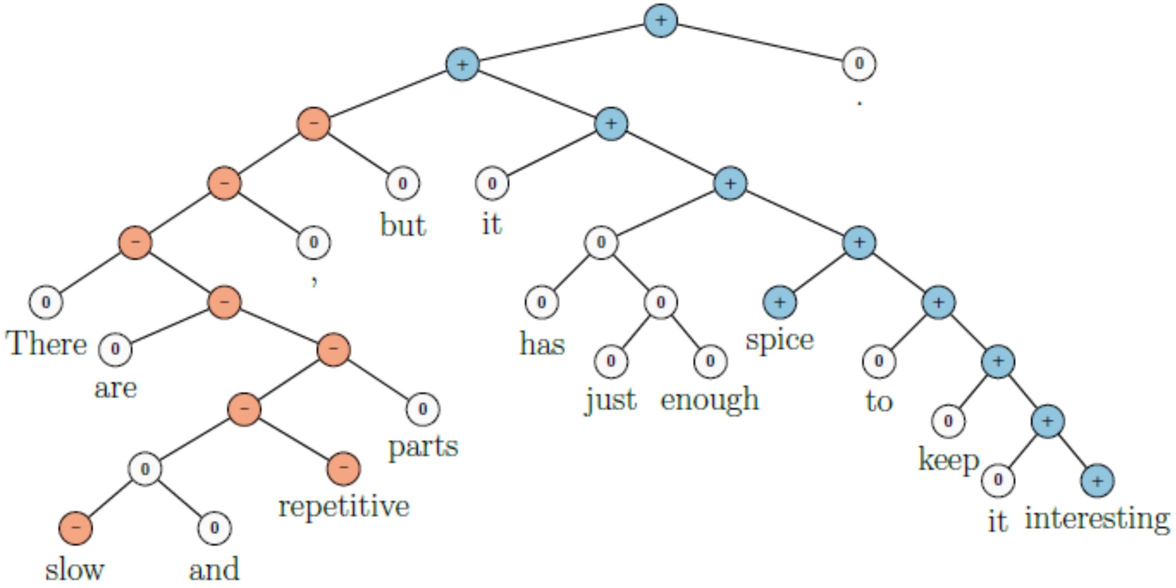

Figure 7: Example of correct prediction for contrastive conjunction X *but* Y.

[Socher et al. 2013]

Recursive Neural Tensor Networks

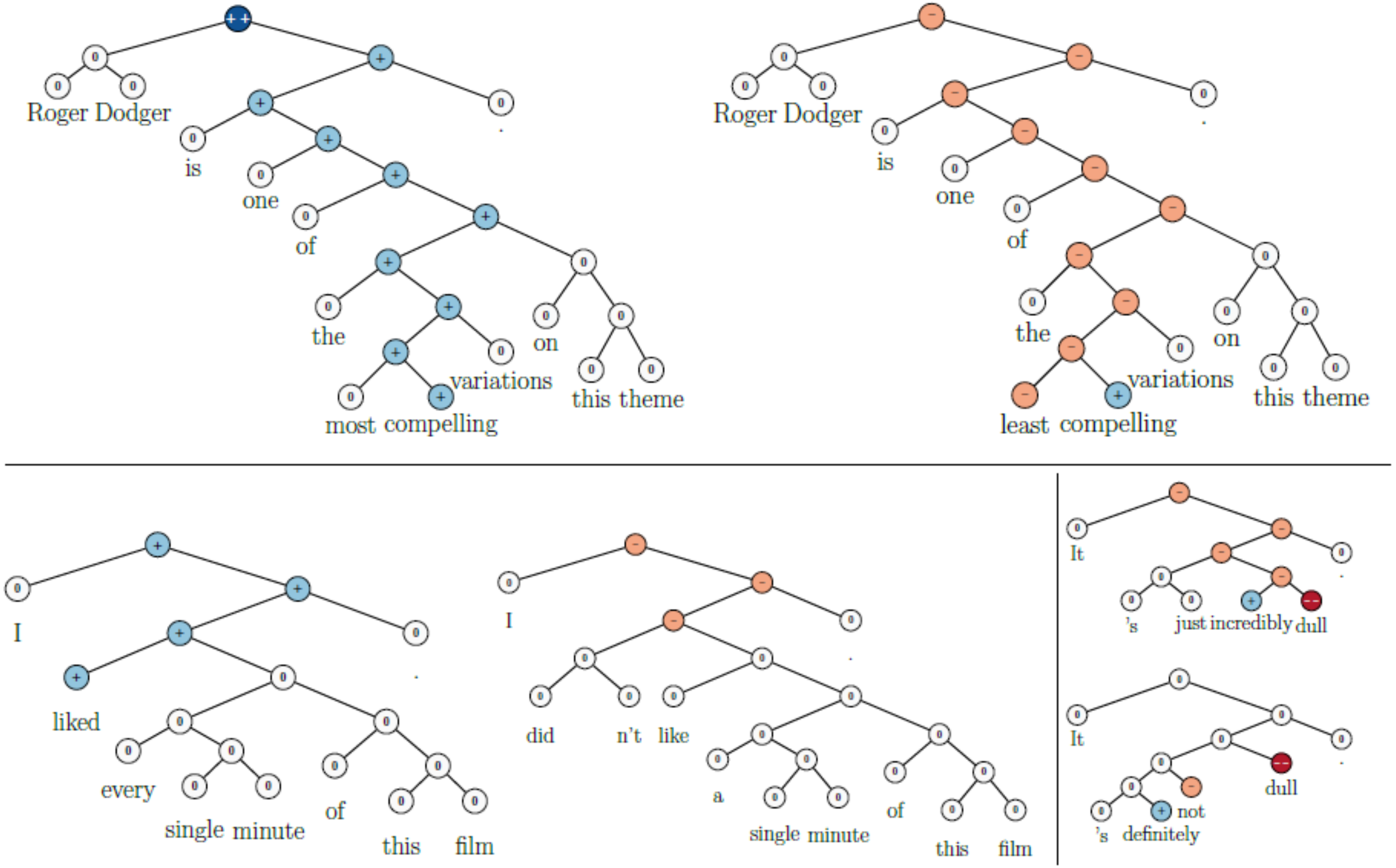

Figure 9: RNTN prediction of positive and negative (bottom right) sentences and their negation.

[Socher et al. 2013]

Recursive Neural Tensor Networks

n	Most positive n-grams	Most negative n-grams
1	engaging; best; powerful; love; beautiful	bad; dull; boring; fails; worst; stupid; painfully
2	excellent performances; A masterpiece; masterful film; wonderful movie; marvelous performances	worst movie; very bad; shapeless mess; worst thing; instantly forgettable; complete failure
3	an amazing performance; wonderful all-ages triumph; a wonderful movie; most visually stunning	for worst movie; A lousy movie; a complete failure; most painfully marginal; very bad sign
5	nicely acted and beautifully shot; gorgeous imagery, effective performances; the best of the year; a terrific American sports movie; refreshingly honest and ultimately touching	silliest and most incoherent movie; completely crass and forgettable movie; just another bad movie. A cumbersome and cliche-ridden movie; a humorless, disjointed mess
8	one of the best films of the year; A love for films shines through each frame; created a masterful piece of artistry right here; A masterful film from a master filmmaker,	A trashy, exploitative, thoroughly unpleasant experience ; this sloppy drama is an empty vessel.; quickly drags on becoming boring and predictable.; be the worst special-effects creation of the year

Table 3: Examples of n-grams for which the RNTN predicted the most positive and most negative responses.

[Socher et al. 2013]

Common Data Sets

- Movie sentiment analysis (IMDB)
  - Binary
  - Five-way

IMDb

The IMDb dataset is a binary sentiment analysis dataset consisting of 50,000 reviews from the Internet Movie Database (IMDb) labeled as positive or negative. The dataset contains an even number of positive and negative reviews. Only highly polarizing reviews are considered. A negative review has a score ≤ 4 out of 10, and a positive review has a score ≥ 7 out of 10. No more than 30 reviews are included per movie. Models are evaluated based on accuracy.

Model	Accuracy	Paper / Source
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

https://github.com/sebastianruder/NLP-progress/blob/master/english/sentiment_analysis.md

Results

SST

The Stanford Sentiment Treebank contains of 215,154 phrases with fine-grained sentiment labels in the parse trees of 11,855 sentences in movie reviews. Models are evaluated either on fine-grained (five-way) or binary classification based on accuracy.

Fine-grained classification (SST-5, 94,2k examples):

Model	Accuracy	Paper / Source
BCN+ELMo (Peters et al., 2018)	54.7	Deep contextualized word representations
BCN+Char+CoVe (McCann et al., 2017)	53.7	Learned in Translation: Contextualized Word Vectors

Binary classification (SST-2, 56.4k examples):

Model	Accuracy	Paper / Source
Block-sparse LSTM (Gray et al., 2017)	93.2	GPU Kernels for Block-Sparse Weights
bmLSTM (Radford et al., 2017)	91.8	Learning to Generate Reviews and Discovering Sentiment
BCN+Char+CoVe (McCann et al., 2017)	90.3	Learned in Translation: Contextualized Word Vectors
Neural Semantic Encoder (Munkhdalai and Yu, 2017)	89.7	Neural Semantic Encoders
BLSTM-2DCNN (Zhou et al., 2017)	89.5	Text Classification Improved by Integrating Bidirectional LSTM with Two-dimensional Max Pooling

Other Difficult Problems

- Subtlety
- Concession
- Manipulation
- Sarcasm and irony
- Affect
- Emotions

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Sentiment Lexicons

Sentiment Lexicons

- SentiWordNet
  - http://sentiwordnet.isti.cnr.it/
- General Inquirer
  - 2,000 positive words and 2,000 negative words
  - http://www.wjh.harvard.edu/~inquirer/
- LIWC
  - http://liwc.wpengine.com/
- Bing Liu's opinion dataset
  - http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar
- MPQA subjectivity lexicon
  - http://mpqa.cs.pitt.edu/lexicons/subj_lexicon/

Positive Emotion	Negative Emotion	Insight	Inhibition	Family	Negate
appreciat*	anger*	aware*	avoid*	brother*	aren't
comfort*	bore*	believe	careful*	cousin*	cannot
great	cry	decid*	hesitat*	daughter*	didn't
happy	despair*	feel	limit*	family	neither
interest	fail*	figur*	oppos*	father*	never
joy*	fear	know	prevent*	grandf*	no
perfect*	griev*	knew	reluctan*	grandm*	nobod*
please*	hate*	means	safe*	husband	none
safe*	panic*	notice*	stop	mom	nor
terrific	suffers	recogni*	stubborn*	mother	nothing
value	terrify	sense	wait	niece*	nowhere
wow*	violent*	think	wary	wife	without

Figure 21.6 Samples from 5 of the 73 lexical categories in LIWC (Pennebaker et al., 2007). The * means the previous letters are a word prefix and all words with that prefix are included in the category.

Positive	admire, amazing, assure, celebration, charm, eager, enthusiastic, excellent, fancy, fantastic, frolic, graceful, happy, joy, luck, majesty, mercy, nice, patience, perfect, proud, rejoice, relief, respect, satisfactorily, sensational, super, terrific, thank, vivid, wise, wonderful, zest
Negative	abominable, anger, anxious, bad, catastrophe, cheap, complaint, condescending, deceit, defective, disappointment, embarrass, fake, fear, filthy, fool, guilt, hate, idiot, inflict, lazy, miserable, mourn, nervous, objection, pest, plot, reject, scream, silly, terrible, unfriendly, vile, wicked

Figure 21.3 Some samples of words with consistent sentiment across three sentiment lexicons: the General Inquirer (Stone et al., 1966), the MPQA Subjectivity lexicon (Wilson et al., 2005), and the polarity lexicon of Hu and Liu (2004).

Valence		Arousal		Dominance	
vacation	.840	enraged	.962	powerful	.991
delightful	.918	party	.840	authority	.935
whistle	.653	organized	.337	saxophone	.482
consolation	.408	effortless	.120	discouraged	.0090
torture	.115	napping	.046	weak	.045

Figure 21.4 Samples of the values of selected words on the three emotional dimensions from Mohammad (2018a).

Anger		Fear		Joy		Sadness	
outraged	0.964	horror	0.923	superb	0.864	sad	0.844
violence	0.742	anguish	0.703	cheered	0.773	guilt	0.750
coup	0.578	pestilence	0.625	rainbow	0.531	unkind	0.547
oust	0.484	stressed	0.531	gesture	0.387	difficulties	0.421
suspicious	0.484	failing	0.531	warms	0.391	beggar	0.422
nurture	0.059	confident	0.094	hardship	.031	sing	0.017

Figure 21.5 Sample emotional intensities for words for anger, fear, joy, and sadness from Mohammad (2018b).

General Inquirer

- Annotations
  - Strong Power Weak Submit Active Passive Pleasur Pain Feel Arousal EMOT Virtue Vice Ovrst Undrst Academ Doctrin Econ@ Exch ECON Exprsv Legal Milit Polit@ POLIT Relig Role COLL Work Ritual SocRel Race Kin@ MALE Female Nonadlt HU ANI PLACE Social Region Route Aquatic Land Sky Object Tool Food Vehicle BldgPt ComnObj NatObj BodyPt ComForm COM Say Need Goal Try Means Persist Complet Fail NatrPro Begin Vary Increas Decreas Finish Stay Rise Exert Fetch Travel Fall Think Know Causal Ought Perceiv Compare Eval@ EVAL Solve Abs@ ABS Quality Quan NUMB ORD CARD FREQ DIST Time@ TIME Space POS DIM Rel COLOR Self Our You Name Yes No Negate Intrj IAV DAV SV IPadj IndAdj PowGain PowLoss PowEnds PowAren PowCon PowCoop PowAuPt PowPt PowDoct PowAuth PowOth PowTot RcEthic RcRelig RcGain RcLoss RcEnds RcTot RspGain RspLoss RspOth RspTot AffGain AffLoss AffPt AffOth AffTot WltPt WltTran WltOth WltTot WlbGain WlbLoss WlbPhys WlbPsyc WlbPt WlbTot EnlGain EnlLoss EnlEnds EnlPt EnlOth EnlTot SklAsth SklPt SklOth SklTot TrnGain TrnLoss TranLw MeansLw EndsLw ArenaLw PtLw Nation Anomie NegAff PosAff SureLw If NotLw TimeSpc
- http://www.webuse.umd.edu:9090/tags
  - Positive: able, accolade, accuracy, adept, adequate…
  - Negative: addiction, adversity, adultery, affliction, aggressive…

Affective Meaning (Osgood et al. 1957)

	Valence	Arousal	Dominance
courageous	8.05	5.5	7.38
music	7.67	5.57	6.5
heartbreak	2.45	5.65	3.58
cub	6.71	3.95	4.24
life	6.68	5.59	5.89

Emotion: Relatively brief episode of 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 stance: Affective stance taken toward another person in a specific interaction, coloring the interpersonal exchange in that situation.
(*distant, cold, warm, supportive, contemptuous, friendly*)

Attitude: Relatively enduring, affectively colored beliefs, preferences, and predispositions towards objects or persons.
(*liking, loving, hating, valuing, desiring*)

Personality traits: Emotionally laden, stable personality dispositions and behavior tendencies, typical for a person.
(*nervous, anxious, reckless, morose, hostile, jealous*)

Figure 21.1 The Scherer typology of affective states (Scherer, 2000).

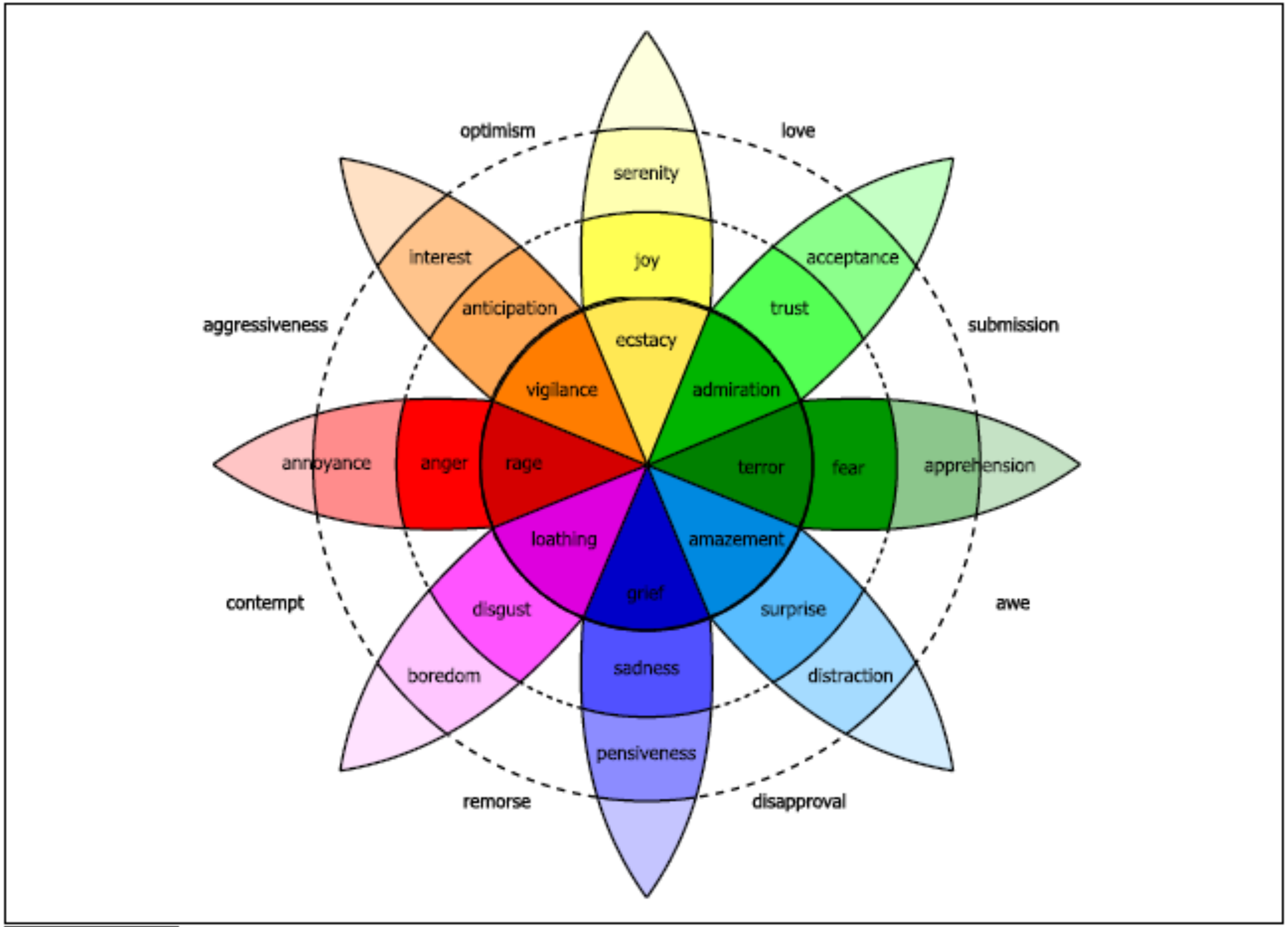


Figure 21.2 Plutchik wheel of emotion.

Dictionary-based Methods

- Start from known seeds
  - e.g., happy, angry
- Expand using WordNet
  - synonyms
  - hypernyms
- Random-walk based methods
  - words with known polarity as absorbing boundary

Automatic Extraction of Sentiment Words

- Semi-supervised method
- Look for pairs of adjectives that appear together in a conjunction

Vasileios Hatzivassiloglou and Kathleen R. McKeown, ACL 1997

Molistic

NACLO problem (2007)

Imagine that you have heard these sentences:

Jane is molistic and slatty.
Jennifer is cluvious and brastic.
Molly and Kyle are slatty but danty.
The teacher is danty and cloovy.
Mary is blitty but cloovy.
Jeremiah is not only sloshful but also weasy.
Even though frumsy, Jim is sloshful.
Strungy and struffy, Diane was a pleasure to watch.
Even though weasy, John is strungy.
Carla is blitty but struffy.
The salespeople were cluvious and not slatty.

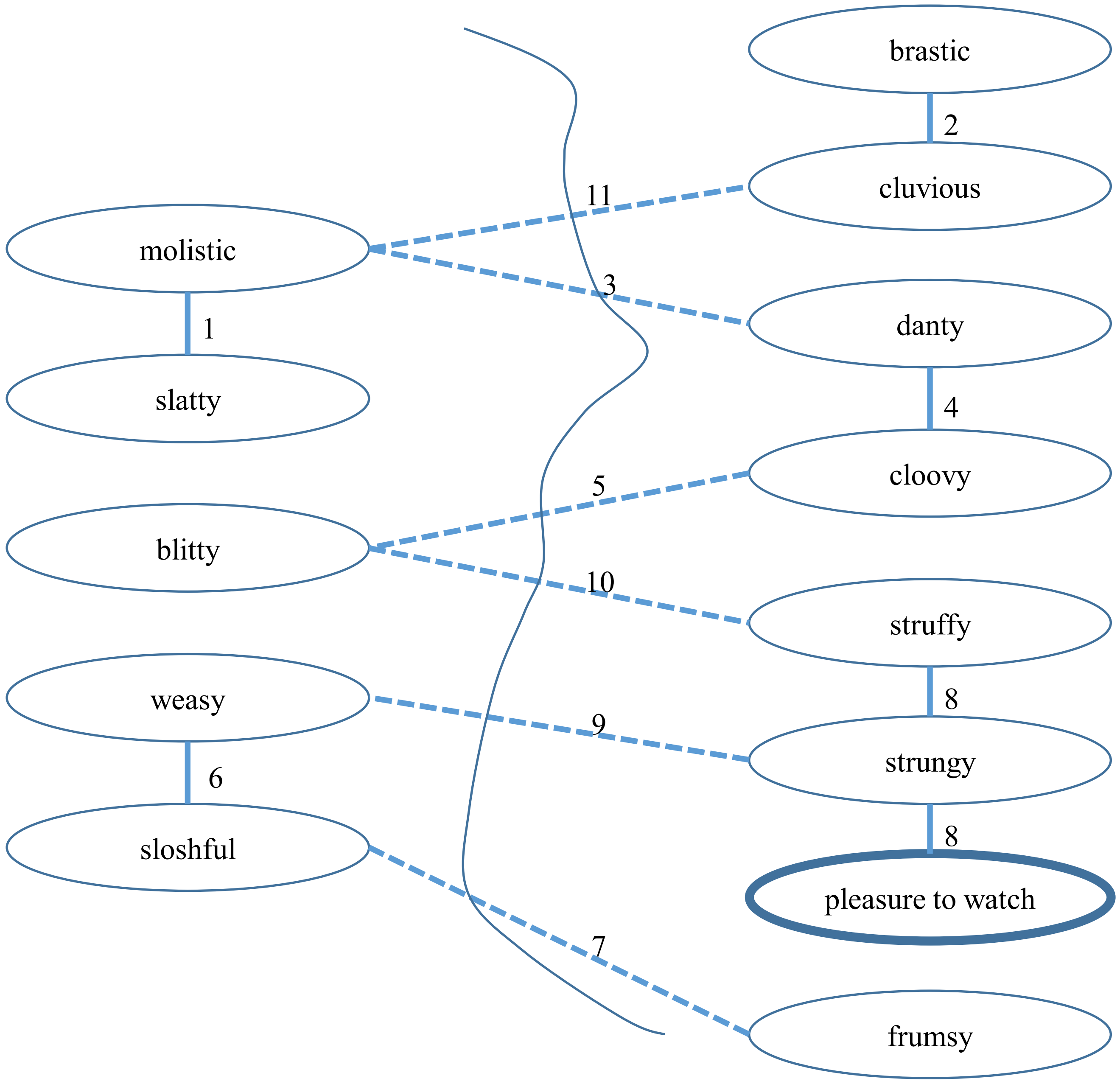
A1. Then which of the following would you be likely to hear?

a. Meredith is blitty and brastic.
b. The singer was not only molistic but also cluvious.
c. May found a dog that was danty but sloshful.

A2. What quality or qualities would you be looking for in a person?

a. blitty
b. weasy
c. sloshful

Molistic


brastic
2
cluvious
11
molistic
3
danty
1
slatty
4
cloovy
5
blitty
10
stuffy
8
weasy
9
strungy
6
8
sloshful
pleasure to watch
7
frumsy

PMI (Turney)

- PMI = pointwise mutual information
- Check how often a given unlabeled word appears with a known positive word (“excellent”)
- Same for a known negative word (“poor”)

$$\mathrm{PMI}(word_1, word_2) = \log_2 \frac{hits(word_1 \;\mathrm{NEAR}\; word_2)}{hits(word_1)\,hits(word_2)}$$

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