NLP

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)

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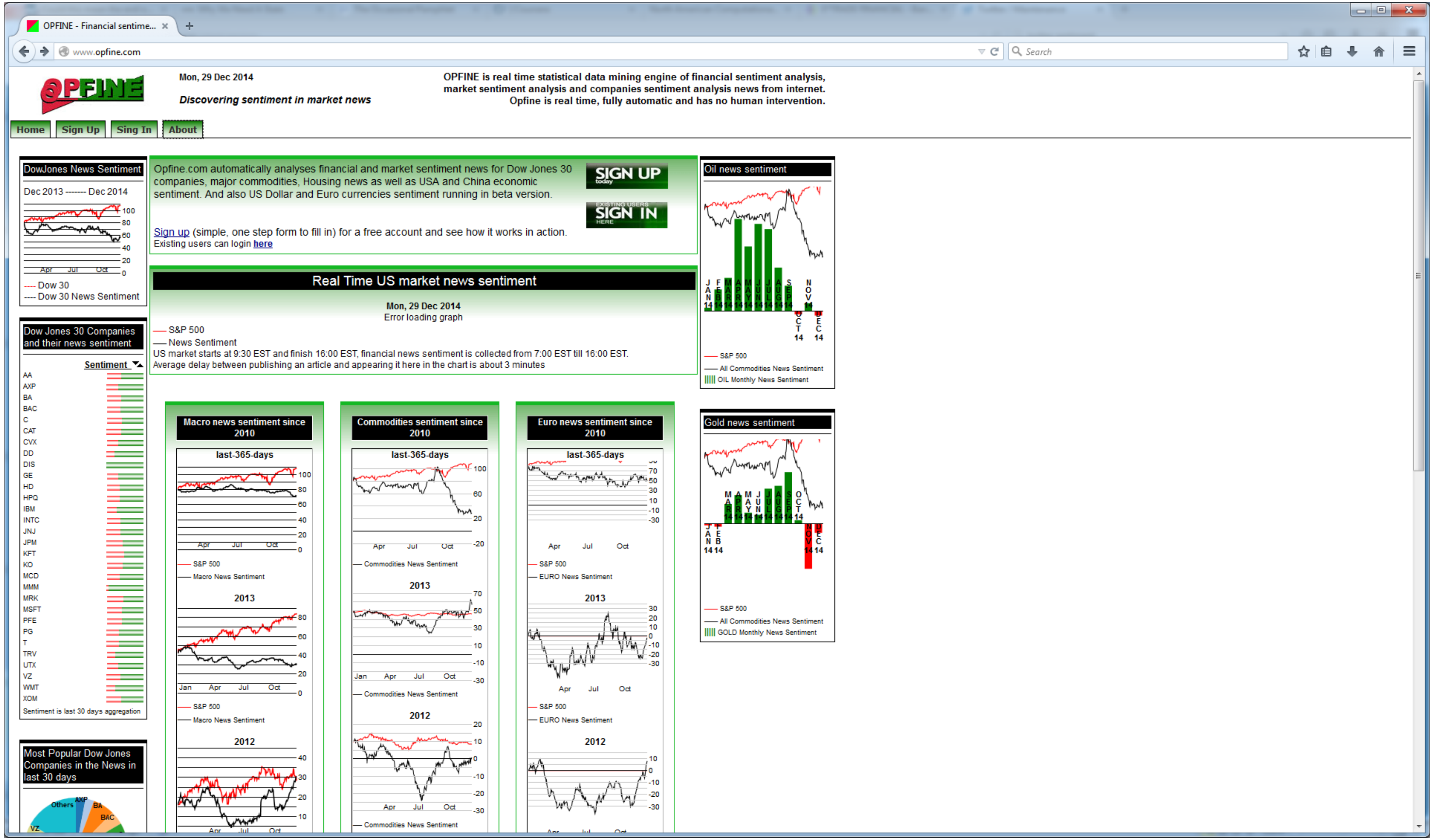
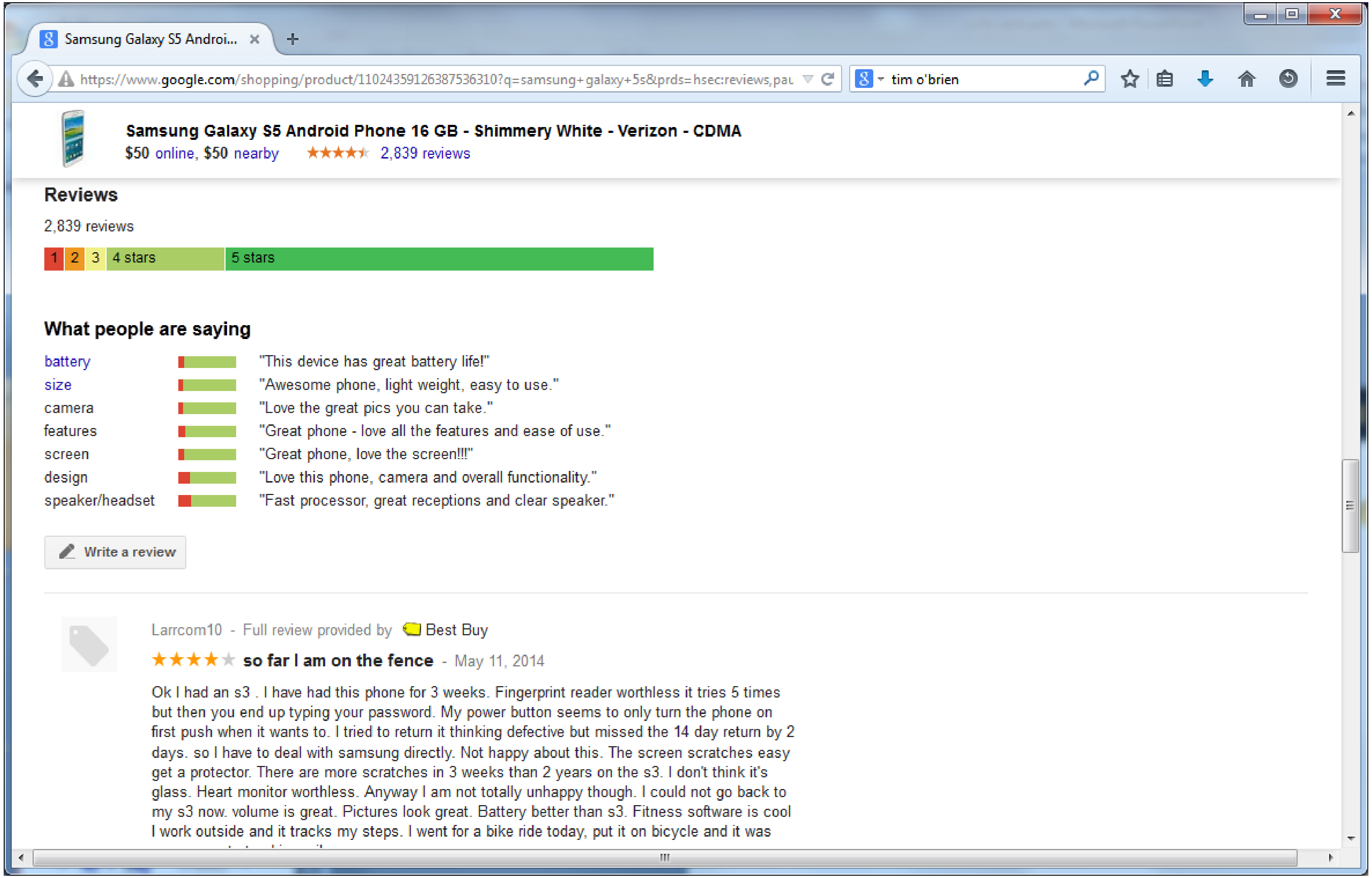
Sentiment about Companies



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

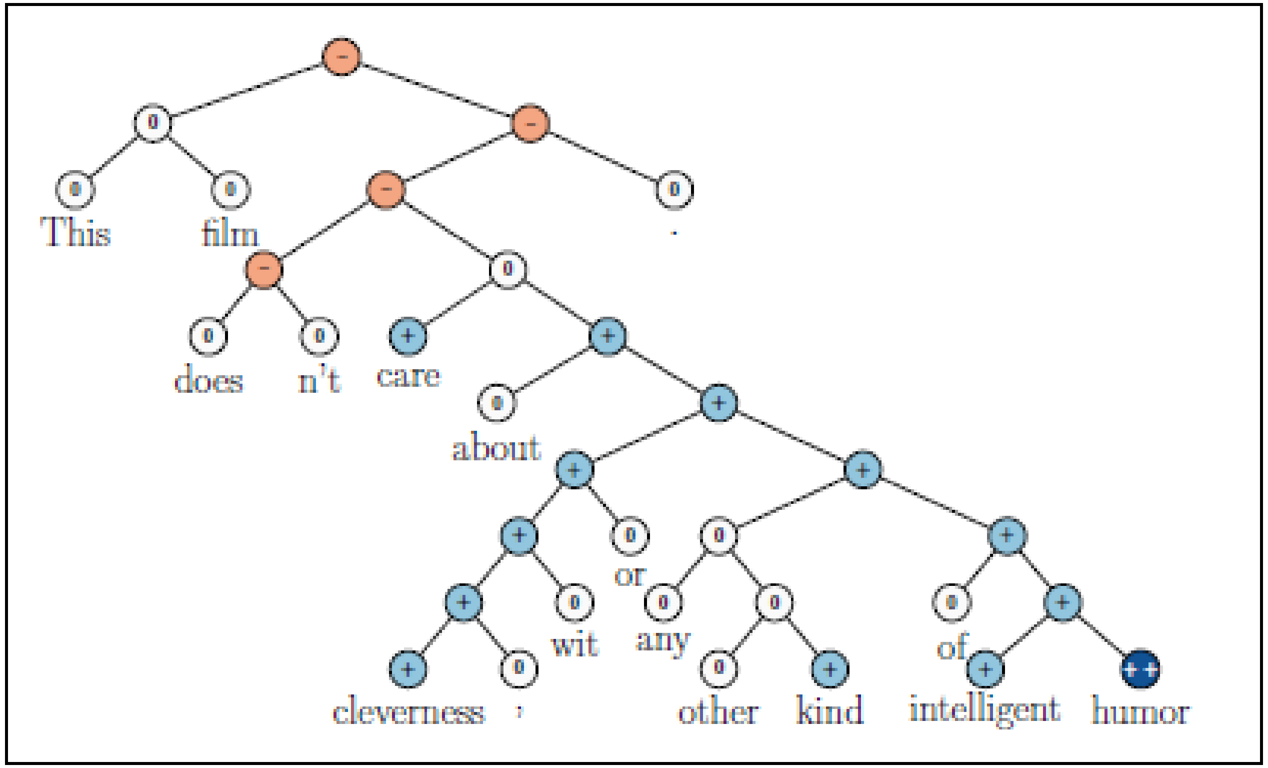

Figure 1: Example of the Recursive Neural Tensor Network accurately predicting 5 sentiment classes, very negative to very positive (– –, –, 0, +, + +), at every node of a parse tree and capturing the negation and its scope in this sentence.

[Socher et al. EMNLP 2013]

Recursive Neural Tensor Networks

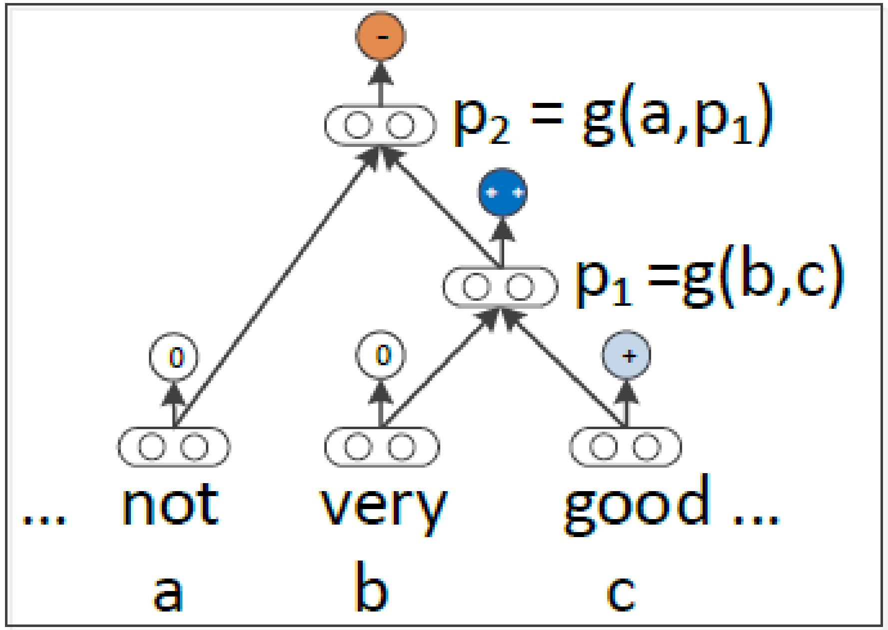

Figure 4: Approach of Recursive Neural Network models for sentiment: Compute parent vectors in a bottom up fashion using a compositionality function g and use node vectors as features for a classifier at that node. This function varies for the different models.

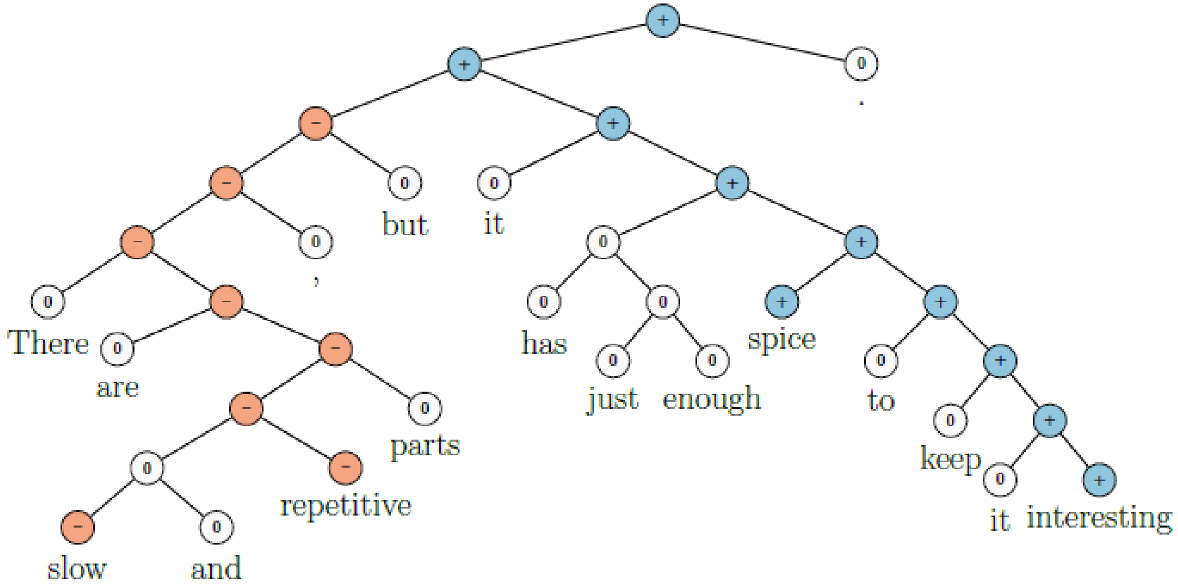

Figure 7: Example of correct prediction for contrastive conjunction X *but* Y.

[Socher et al. 2013]

Recursive Neural Tensor Networks

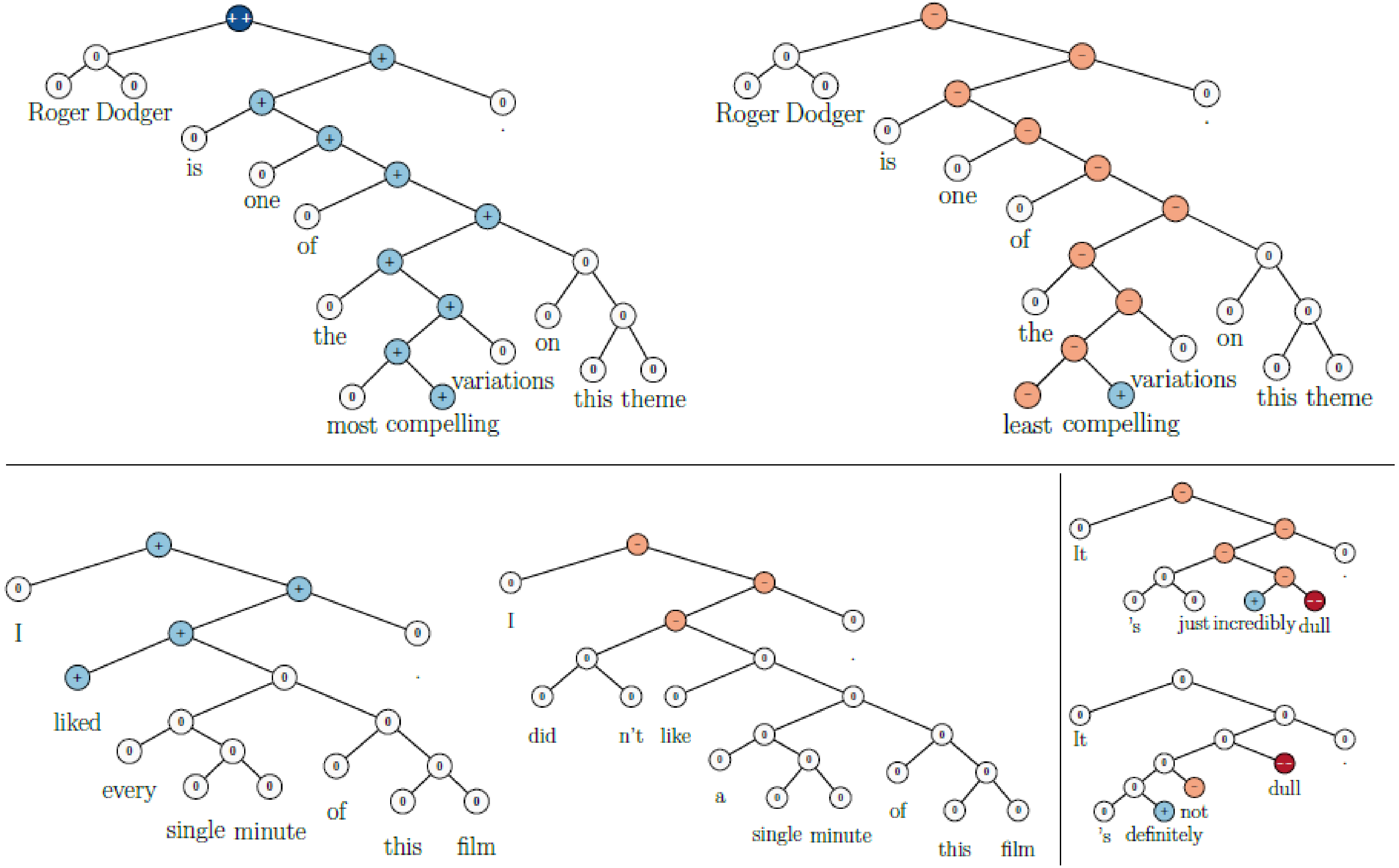

Figure 9: RNTN prediction of positive and negative (bottom right) sentences and their negation.

[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

NLP

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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).

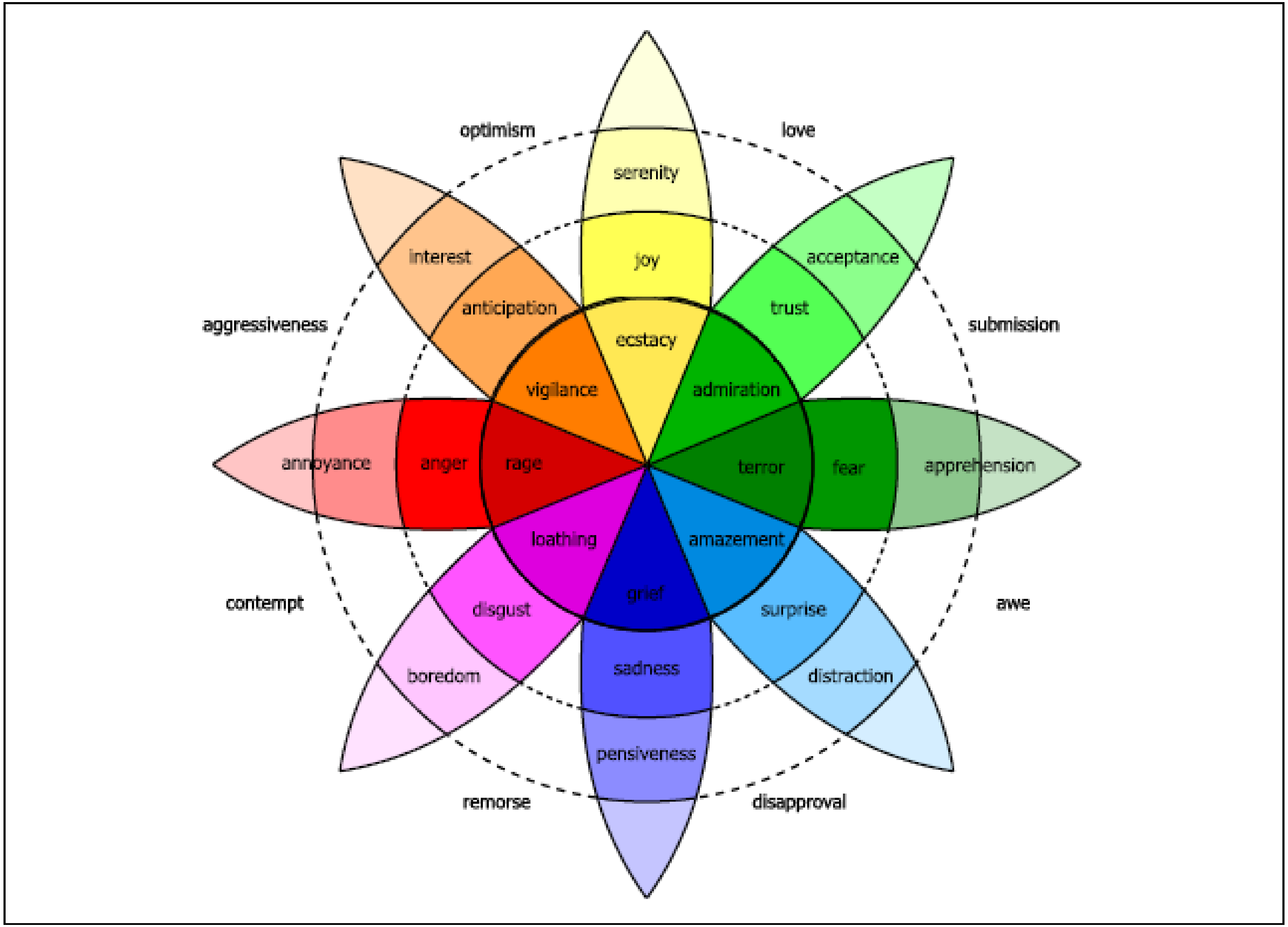


Figure 21.2 Plutchik wheel of emotion.

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.

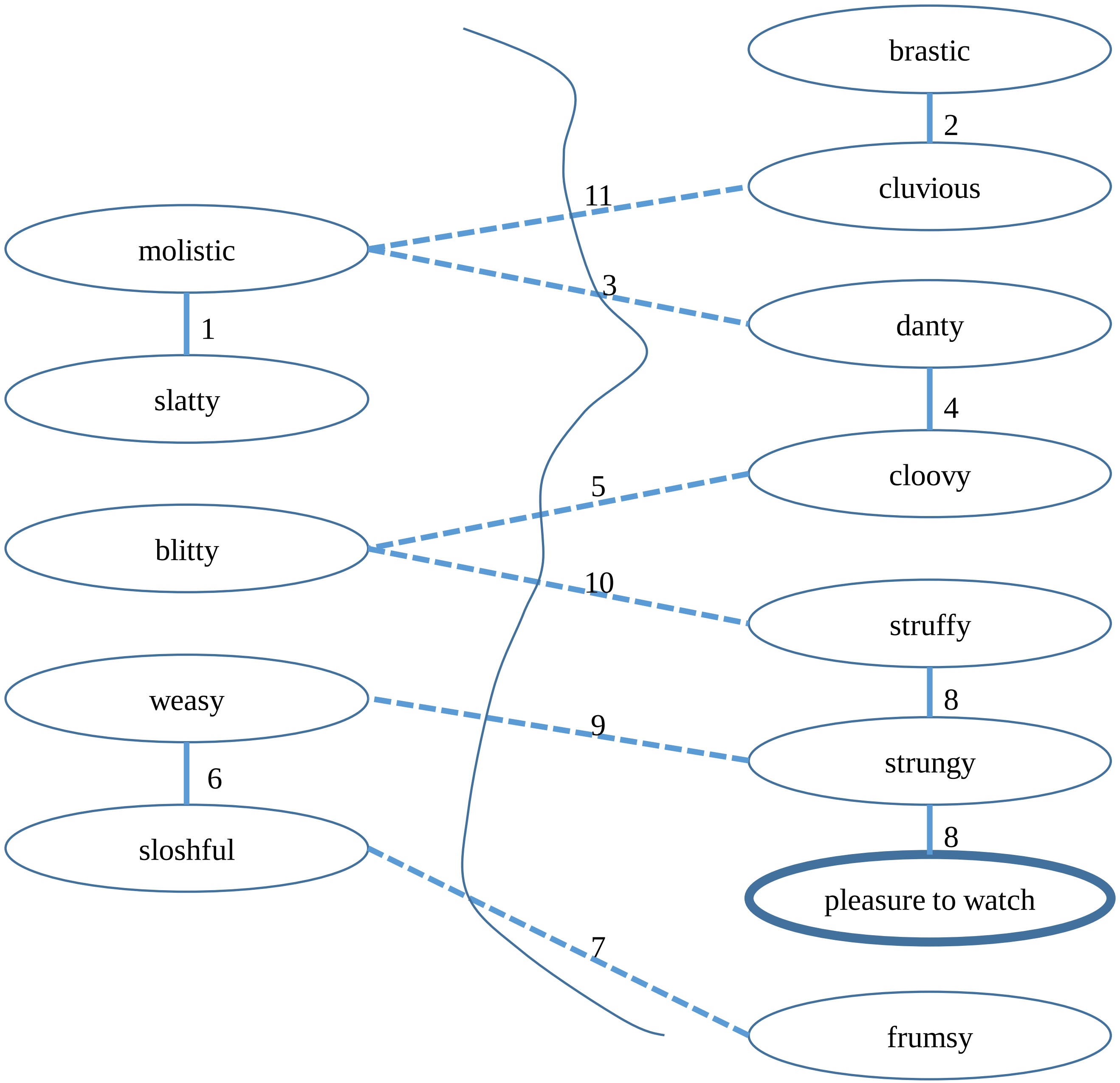
A1. Then which of the following would you be likely to hear?

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
1
slatty
3
danty
4
cloovy
5
blitty
10
struffy
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")

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

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

NLP

Text similarity

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Introduction to Text Similarity

Text Similarity

- Motivation
  - People can express the same concept (or related concepts) in many different ways. For example, “the plane leaves at 12pm” vs “the flight departs at noon”
  - Text similarity is a key component of Natural Language Processing
- Uses in NLP
  - If the user is looking for information about cats, we may want the NLP system to return documents that mention kittens even if the word “cat” is not in them.
  - If the user is looking for information about “fruit dessert”, we want the NLP system to return documents about “peach tart” or “apple cobbler”.
  - A speech recognition system should be able to tell the difference between similar sounding words like the “Dulles” and “Dallas” airports.

Types of Text Similarity

- Many types of text similarity exist:
  - Morphological similarity (e.g., respect-respectful)
  - Spelling similarity (e.g., theater-theatre)
  - Homophony (e.g., raise-raze-rays)
  - **Synonymy (e.g., talkative-chatty**), including across languages
  - **Semantic similarity (e.g., cat-tabby)**
  - Sentence similarity (e.g., paraphrases)
  - Document similarity (e.g., two news stories on the same event)

Notes

- Similarity vs. relatedness
  - car, bicycle: similar
  - car, gasoline: related, not similar
- Semantic field
  - doctor, nurse, hospital, syringe, medication, scalpel

Human Judgments of Similarity

tiger	cat	7.35
tiger	tiger	10.00
book	paper	7.46
computer	keyboard	7.62
computer	internet	7.58
plane	car	5.77
train	car	6.31
telephone	communication	7.50
television	radio	6.77
media	radio	7.42
drug	abuse	6.85
bread	butter	6.19
cucumber	potato	5.92

[Lev Finkelstein, Evgeniy Gabrilovich, Yossi Matias, Ehud Rivlin, Zach Solan, Gadi Wolfman, and Eytan Ruppin, "Placing Search in Context: The Concept Revisited", ACM Transactions on Information Systems, 20(1):116-131, January 2002]

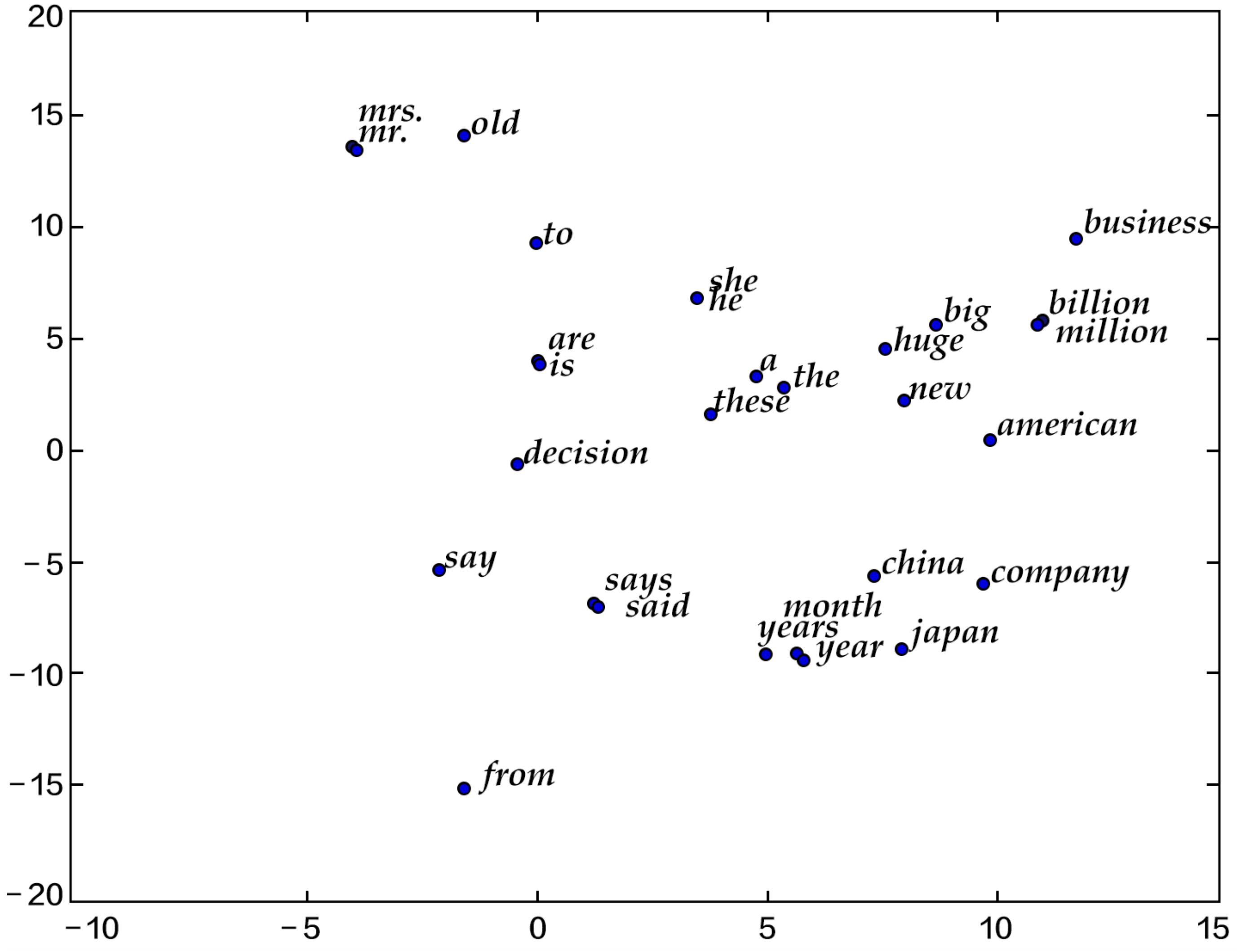
http://wordvectors.org/suite.php

Automatic Similarity Computation

spain	0.679
belgium	0.666
netherlands	0.652
italy	0.633
switzerland	0.622
luxembourg	0.610
portugal	0.577
russia	0.572
germany	0.563
catalonia	0.534

- Words most similar to “France”
- Computed using word2vec
  - [Mikolov et al. 2013]

Two-dimensional Representations



NLP

Natural Language Processing

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Semantic Similarity

Synonyms and paraphrases

- Example: post-close market announcements

The S&P 500 climbed 6.93, or 0.56 percent, to 1,243.72, its best close since June 12, 2001.

The Nasdaq gained 12.22, or 0.56 percent, to 2,198.44 for its best showing since June 8, 2001.

The DJIA rose 68.46, or 0.64 percent, to 10,705.55, its highest level since March 15.

Synonyms

- Different words (and also word compounds) can have similar meanings.
  - *tepid* and *lukewarm* have very similar meanings and can be substituted for one another (*tepid water* vs. *lukewarm water).*
- True synonyms are actually relatively rare.
  - even though *big* and *large* are often thought of as synonyms, consider the difference between *Big Leagues* and *Large Leagues*. ☺
- The verbs *sweat* and *perspire* are also near synonyms.
  - However, they differ in their frequency of use and the type of text in which they are likely to appear.

Polysemy


SWEARING
Two electric windmills are standing in a field.
One turns to the other and asks "What kind of music do you like?"
The second one replies "I'm a huge metal fan".

Polysemy

- Polysemy is the property of words to have multiple senses.
- For example, the noun *book* can refer to the following:
  - A literary work (e.g., “Anna Karenina”)
  - A stack of pages (e.g., a notebook)
  - A record of business transactions (think “bookkeeper”)
  - A record of bets (think “bookmaker”)
  - A list of buy and sell orders in a financial market

Polysemy

- The same word can also have multiple parts of speech, each with its own set of senses. For example, the word *book*, as a verb can mean “make a reservation for” or “occupy”.
- The different senses of the same word don’t have to be equally frequent.
- Some of the senses may overlap (e.g., the first two senses of *book* on the previous slide). That’s partially why different dictionaries list different sets of word senses for the same word.
  - “My favorite books are Anna Karenina and my father’s checkbook” ☺
- Some words can be highly polysemous (e.g., the verb “get” has at least 35 different meanings, according to Wordnet).

Other Semantic Relations

- Antonymy (near opposites)
  - *raise-lower*
- Hypernymy
  - a *deer* is a hypernym for *elk*
- Hyponymy (the inverse of hypernymy)
- Membership Meronymy:
  - a *flock* includes *sheep* (or *birds)*
- Part Meronymy:
  - a *table* has *legs*

Synsets

- Semantic relations hold between word senses, not between words.
- Examples:
  - the antonym of *hot* can be either *mild* or *cold* (or *unattractive)* depending on the specific sense of *hot*.
  - the immediate hypernym of *bar* can be one of the following, among others: *room*, *musical notation*, *obstruction*, *profession*, depending on the sense of *bar*.
- The term *synset* is used to group together all synonyms of the same word. If a word is polysemous, it may be associated with multiple synsets.

NLP

Text Similarity

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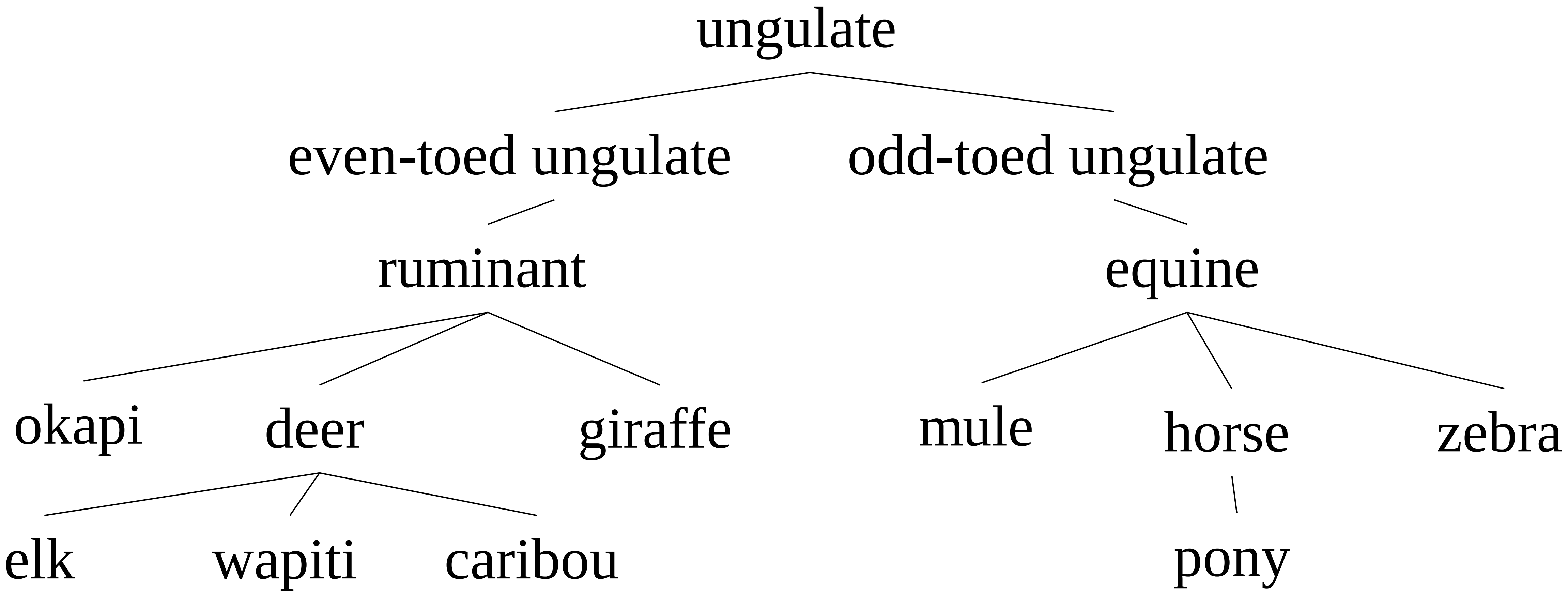
Wordnet

Wordnet

- Wordnet is a project run by George Miller (1920-2012) and Christiane Fellbaum at Princeton University.
- It includes a database of words (mainly nouns and verbs but also adjectives and adverbs) and semantic relations between them.
- The main relation is hypernymy, so the overall structure of the database is more tree-like (see next slide).
- References:
  - George A. Miller (1995). WordNet: A Lexical Database for English. Communications of the ACM Vol. 38, No. 11: 39-41.
  - Christiane Fellbaum (1998, ed.) WordNet: An Electronic Lexical Database. Cambridge, MA: MIT Press.

Sample Noun Taxonomy



Wordnet Example (1/6)

The **noun** bar has 11 senses
1. barroom, bar, saloon, ginmill, taproom -- (a room where alcoholic drinks are served over a counter)
2. bar -- (a counter where you can purchase food or drink)
3. bar -- (a rigid piece of metal)
4. measure, bar -- (notation for a repeating pattern of musical beats; written followed by a vertical bar)
5. bar -- (usually metal placed in windows to prevent escape)
6. prevention, bar -- (the act of preventing)
7. bar -- (a unit of pressure equal to a million dynes per square centimeter)
8. bar -- (a submerged (or partly submerged) ridge in a river or along a shore)
9. legal profession, bar, legal community -- (the body of individuals qualified to practice law)
10. cake, bar -- (a block of soap or wax)
11. bar -- ((law) a railing that encloses the part of the courtroom where the the judges and lawyers sit and the case is tried)

The **verb** bar has 4 senses
1. bar, debar, exclude -- (prevent from entering; keep out; "He was barred from membership in the club")
2. barricade, block, blockade, block off, block up, bar -- (render unsuitable for passage; "block the way"; "barricade the streets")
3. banish, relegate, bar -- (expel, as if by official decree; "he was banished from his own country")
4. bar -- (secure with, or as if with, bars; "He barred the door")

Wordnet Example (2/6)

Sense 1
barroom, bar, saloon, ginmill, taproom
=> room
=> area
=> structure, construction
=> artifact, artefact
=> object, physical object
=> entity, something

Sense 2
bar
=> counter
=> table
=> furniture, piece of furniture, article of furniture
=> furnishings
=> instrumentality, instrumentation
=> artifact, artefact
=> object, physical object
=> entity, something

Wordnet Example (3/6)

Sense 3
bar
=> implement
=> instrumentality, instrumentation
=> artifact, artefact
=> object, physical object
=> entity, something

Sense 4
measure, bar
=> musical notation
=> notation, notational system
=> writing, symbolic representation
=> written communication, written language
=> communication
=> social relation
=> relation
=> abstraction

Wordnet Example (4/6)

Sense 5
bar
    => obstruction, impediment, impedimenta
        => structure, construction
            => artifact, artefact
                => object, physical object
                    => entity, something

Sense 6
prevention, bar
    => hindrance, interference, interfering
        => act, human action, human activity

Sense 7
bar
    => pressure unit
        => unit of measurement, unit
            => definite quantity
                => measure, quantity, amount, quantum
                    => abstraction

Wordnet Example (5/6)

```
Sense 8
bar
       => ridge
           => natural elevation, elevation
               => geological formation, geology, formation
                   => natural object
                       => object, physical object
                           => entity, something
       => barrier
           => mechanism
               => natural object
                   => object, physical object
                       => entity, something
```

Wordnet Example (6/6)

Sense 9
legal profession, bar, legal community
    => profession, community
        => occupation, vocation, occupational group
            => body
                => gathering, assemblage
                    => social group
                        => group, grouping

Sense 10
cake, bar
    => block
        => artifact, artefact
            => object, physical object
                => entity, something

Top-Level Categories

Noun

GROUP	1469	*place*
PERSON	1202	*people*
ARTIFACT	971	*car*
COGNITION	771	*way*
FOOD	766	*food*
ACT	700	*service*
LOCATION	638	*area*
TIME	530	*day*
EVENT	431	*experience*
COMMUNIC.*	417	*review*
POSSESSION	339	*price*
ATTRIBUTE	205	*quality*
QUANTITY	102	*amount*
ANIMAL	88	*dog*
BODY	87	*hair*
STATE	56	*pain*
NATURAL OBJ.	54	*flower*
RELATION	35	*portion*
SUBSTANCE	34	*oil*
FEELING	34	*discomfort*
PROCESS	28	*process*
MOTIVE	25	*reason*
PHENOMENON	23	*result*
SHAPE	6	*square*
PLANT	5	*tree*
OTHER	2	*stuff*

Verb

STATIVE	2922	*is*
COGNITION	1093	*know*
COMMUNIC.*	974	*recommend*
SOCIAL	944	*use*
MOTION	602	*go*
POSSESSION	309	*pay*
CHANGE	274	*fix*
EMOTION	249	*love*
PERCEPTION	143	*see*
CONSUMPTION	93	*have*
BODY	82	*get...done*
CREATION	64	*cook*
CONTACT	46	*put*
COMPETITION	11	*win*
WEATHER	0	—

[Example from J&M, based on Schneider and Smith 2013]

Noun Relations in WordNet

Relation	Also Called	Definition	Example
Hypernym	Superordinate	From concepts to superordinates	$breakfast^1 \rightarrow meal^1$
Hyponym	Subordinate	From concepts to subtypes	$meal^1 \rightarrow lunch^1$
Instance Hypernym	Instance	From instances to their concepts	$Austen^1 \rightarrow author^1$
Instance Hyponym	Has-Instance	From concepts to their instances	$composer^1 \rightarrow Bach^1$
Part Meronym	Has-Part	From wholes to parts	$table^2 \rightarrow leg^3$
Part Holonym	Part-Of	From parts to wholes	$course^7 \rightarrow meal^1$
Antonym		Semantic opposition between lemmas	$leader^1 \iff follower^1$
Derivation		Lemmas w/same morphological root	$destruction^1 \iff destroy^1$

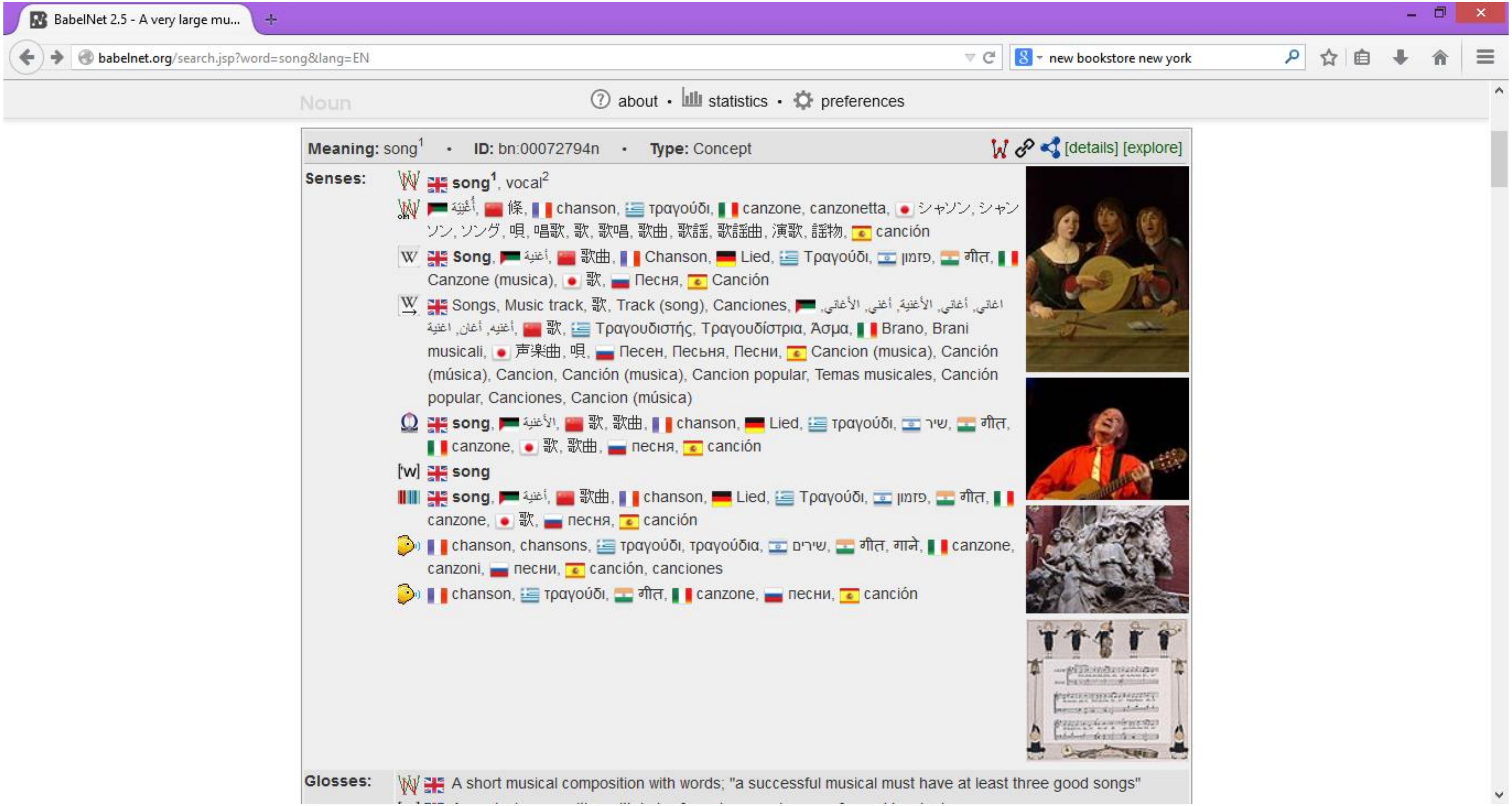
Figure 19.3 Some of the noun relations in WordNet.

Verb Relations in WordNet

Relation	Definition	Example
Hypernym	From events to superordinate events	$\mathit{fly}^9 \rightarrow \mathit{travel}^5$
Troponym	From events to subordinate event	$\mathit{walk}^1 \rightarrow \mathit{stroll}^1$
Entails	From verbs (events) to the verbs (events) they entail	$\mathit{snore}^1 \rightarrow \mathit{sleep}^1$
Antonym	Semantic opposition between lemmas	$\mathit{increase}^1 \Longleftrightarrow \mathit{decrease}^1$

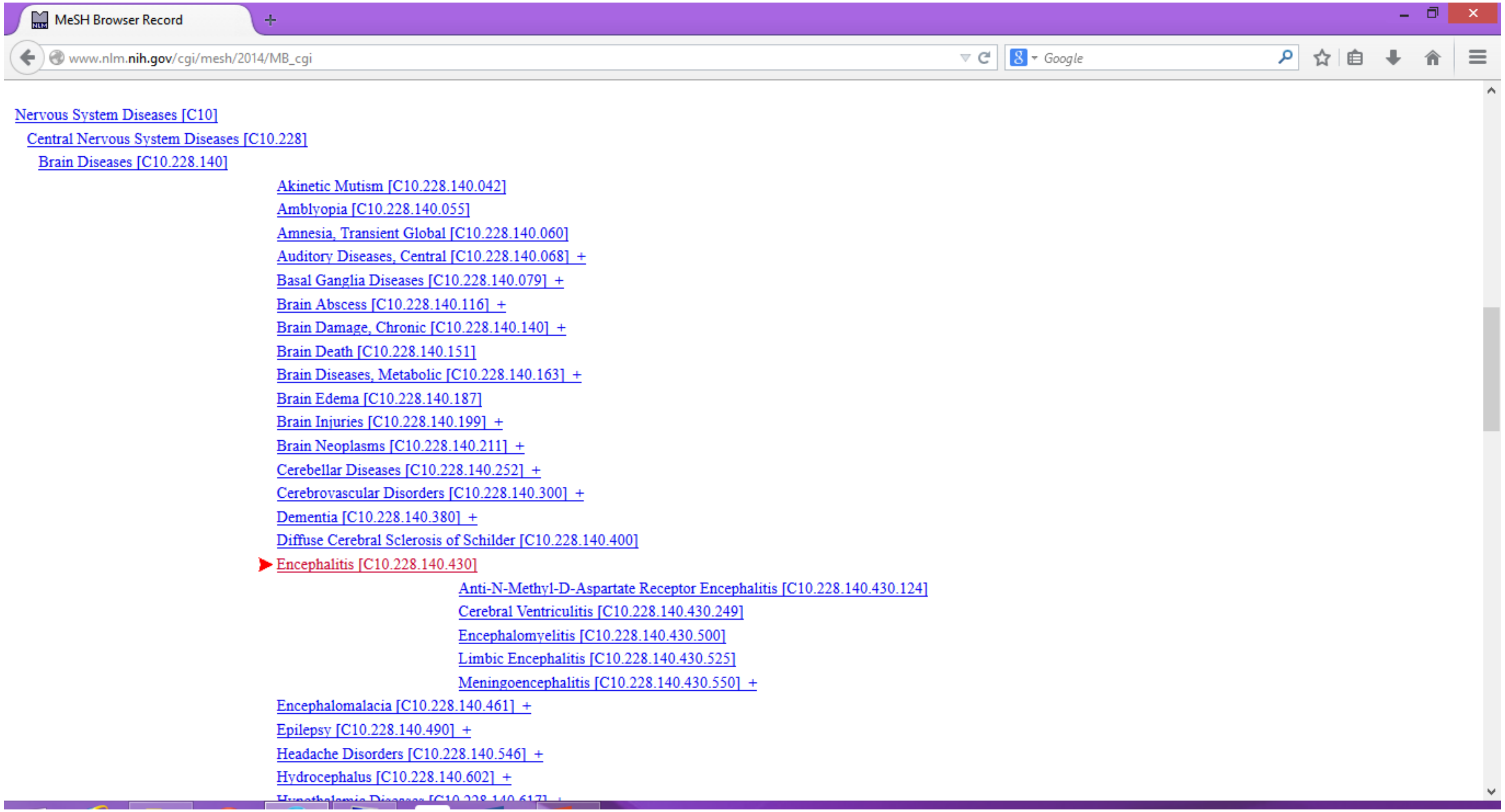
Figure 19.4 Some verb relations in WordNet.

BabelNet Example



MeSH

Medical Subject Headings



http://www.nlm.nih.gov/mesh/MBrowser.html

External Links

- EuroWordNet
  - http://www.illc.uva.nl/EuroWordNet/
- Open Thesaurus
  - http://www.openthesaurus.de/
- Freebase
  - http://www.freebase.com
- DBPedia
  - http://www.dbpedia.org
- BabelNet
  - http://babelnet.org
- Various thesauri
  - https://sites.google.com/site/openrogets/

NLP

Text Similarity

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Thesaurus-based Word Similarity Methods

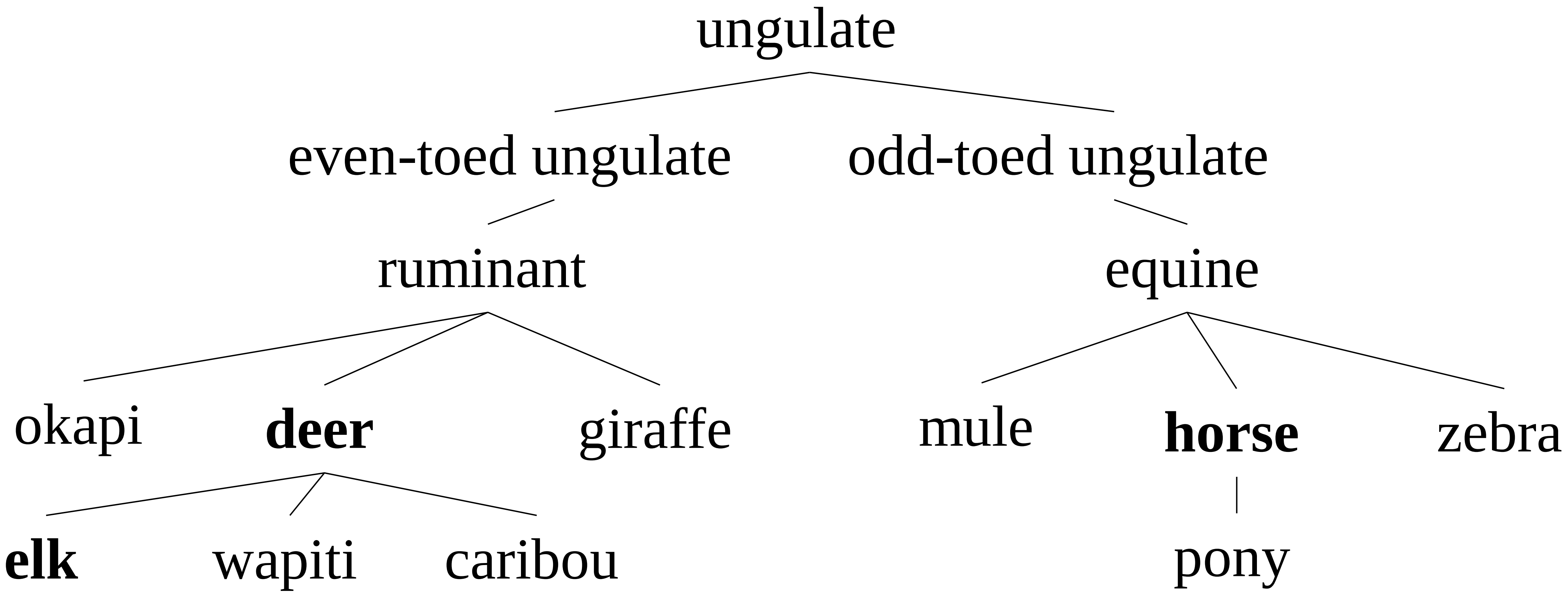
Quiz

- Which pair of words exhibits the greatest similarity?
  - 1. Deer-elk
  - 2. Deer-horse
  - 3. Deer-mouse
  - 4. Deer-roof

Quiz Answer

- Which pair of words exhibits the greatest similarity?
  - **1. Deer-elk**
  - 2. Deer-horse
  - 3. Deer-mouse
  - 4. Deer-roof
- Why?

Remember Wordnet



Path Similarity

- Version 1
  - Sim (v,w) = - pathlength (v,w)
- Version 2
  - Sim (v,w) = - log pathlength (v,w)

Problems with this Approach

- There may be no tree for the specific domain or language
- A specific word (e.g., a term or a proper noun) may not be in any tree
- IS-A (hypernym) edges are not all equally apart in similarity space

Path similarity between two words

- Version 3 (Philip Resnik)

    Sim (v,w) = - log *P*(LCS(v,w))

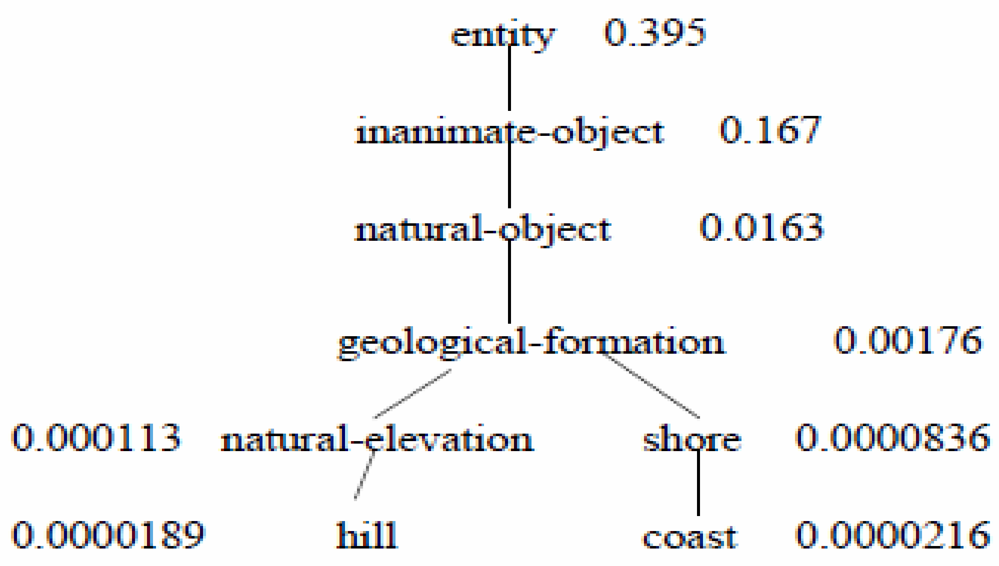
    where LCS = lowest common subsumer, e.g.,

        ungulate for deer and horse

        deer for deer and elk

Information content

- Version 4 (Dekang Lin)
  - Wordnet augmented with probabilities (Lin 1998)
  - IC(c) = -log P(c)
  - Sim (v,w) = 2 x log *P*(LCS(v,w)) / (log *P*(v) + log *P*(w))



$$\mathrm{sim}(\mathrm{Hill}, \mathrm{Coast}) = \frac{2 \times \log P(\mathrm{Geological\text{-}Formation})}{\log P(\mathrm{Hill}) + \log P(\mathrm{Coast})}$$

$$= 0.59$$

NLP

Text Similarity

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The Vector Space Model

Vectors, Matrices, and Tensors

- $X = <x_1, x_2, \ldots, x_n>$: a vector of n dimensions.
  - $x_1, \ldots, x_n$ can take either binary values {0, 1}, or real values
- Vectors and matrices provide a natural way to represent the occurrence of words in a document/query.
  - In text analysis, n is usually the size of the vocabulary, so each dimension corresponds to a unique word
  - X can be used to represent a document, or a query, or …
  - So x_i indicates either "whether the i-th word in the vocabulary appears" (binary value), or "how many times does the i-th word appear" (real value).
- The entire collection is thus represented as a matrix.
  - Next slide

Example of Document Vectors

- Doc 1= “information retrieval”
- Doc 2 = “computer information retrieval”
- Doc 3 = “computer retrieval”

- Vocabulary: information, retrieval, computer
- Doc 1 = <1, 1, 0>
- Doc 2 = <1, 1, 1>
- Doc 3 = <0, 1, 1>

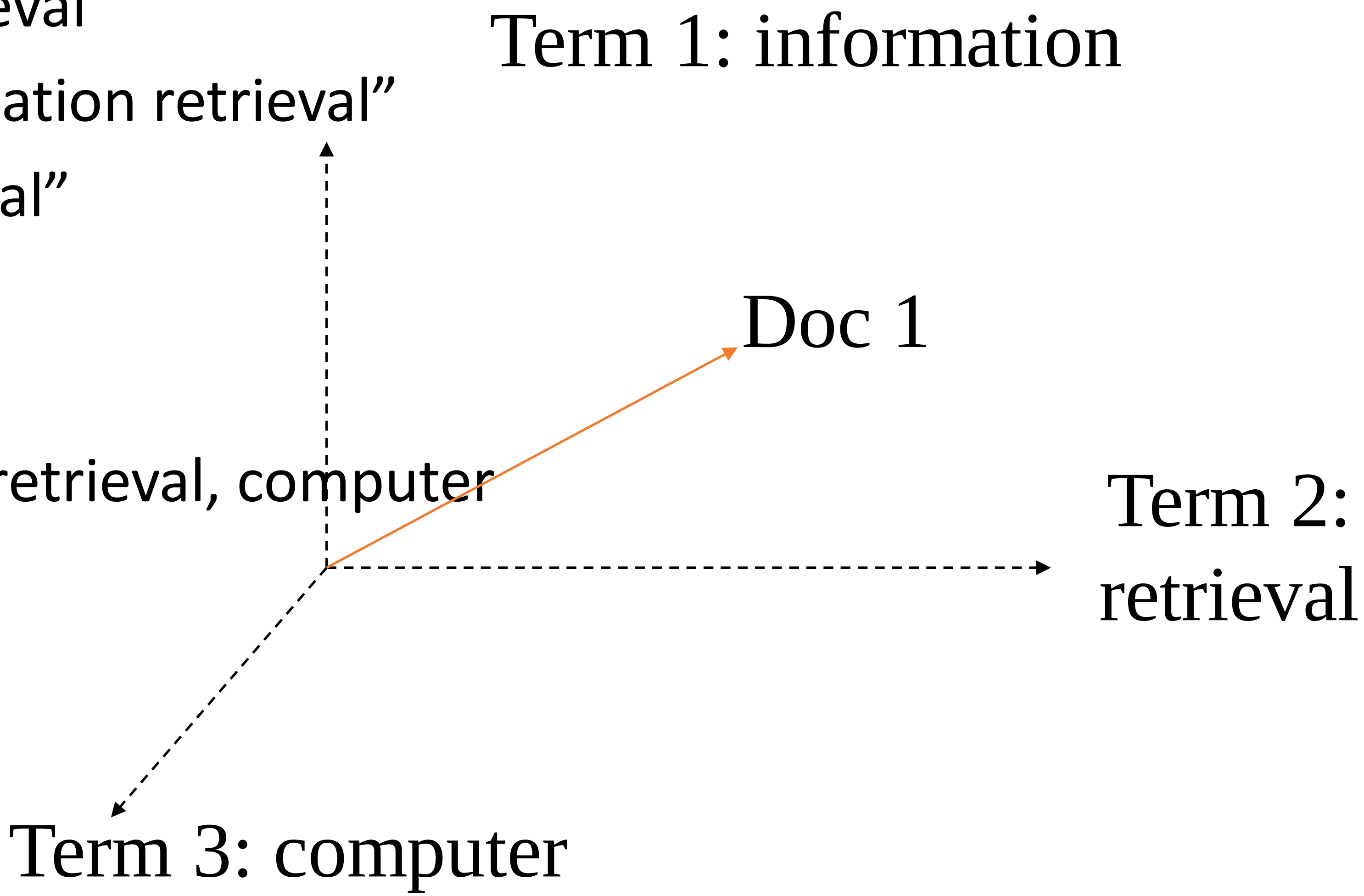
$$\begin{array}{cc} & \text{information, retrieval, computer} \\ D = & \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \end{array}$$

Question: Doc 4 = “retrieval information retrieval” ?

Documents in a Vector Space

- Doc 1= “information retrieval”
- Doc 2 = “computer information retrieval”
- Doc 3 = “computer retrieval”

- Vocabulary: information, retrieval, computer
- Doc 1 = <1, 1, 0>

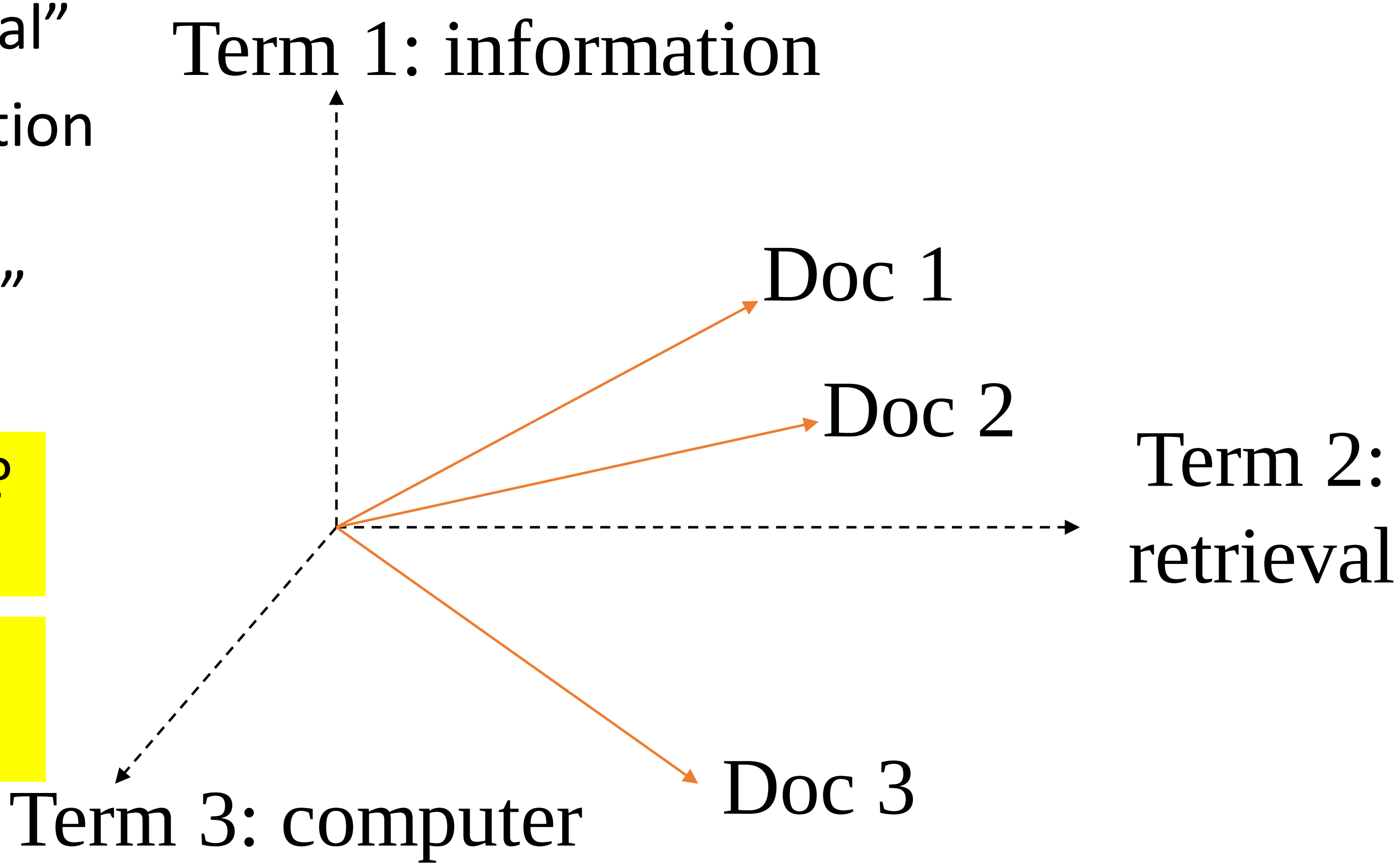


Relevance as Vector Similarity

- Doc 1= “information retrieval”
- Doc 2 = “computer information retrieval”
- Doc 3 = “computer retrieval”

Which document is closer to Doc 1? Doc 2 or Doc 3?

What if we have a query “retrieval”?



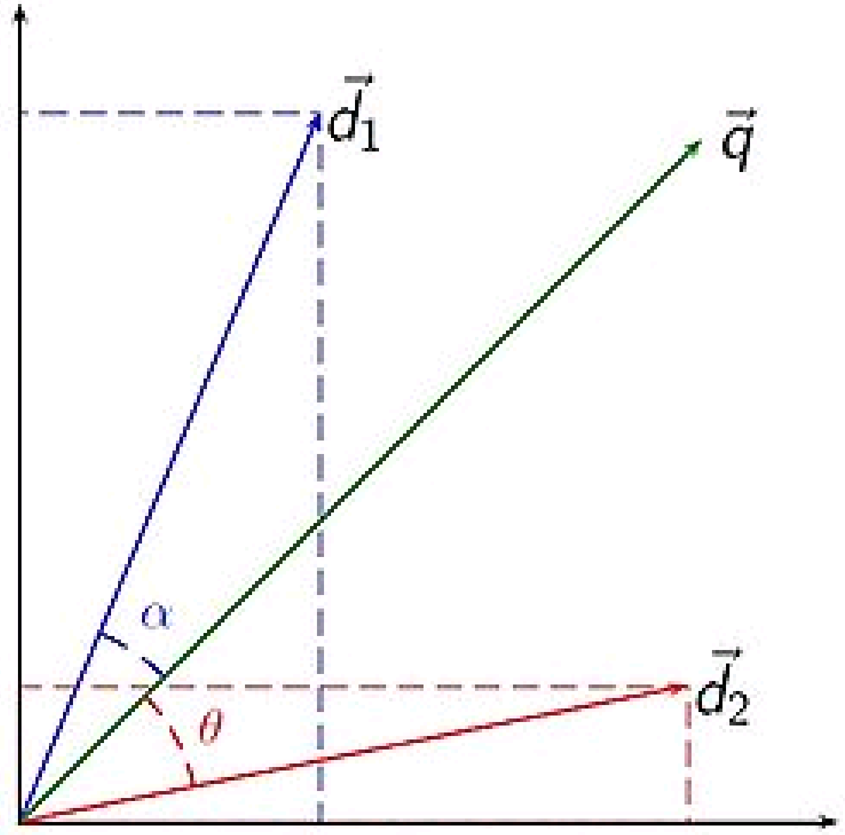
Distance/Similarity Calculation

- The similarity/relevance of two vectors can be calculated based on distance/similarity measures
- S: X, Y $\rightarrow$ (0, 1)
- X: $<x_1, x_2, \ldots, x_n>$
- Y: $<y_1, y_2, \ldots, y_n>$

- S(X, Y) = ?
  - The more dimensions in common, the larger the similarity
  - What about real values?
  - Normalization needed.

Document Similarity

- Used in information retrieval to determine which document (d_1 or d_2) is more similar to a given query q
- Documents and queries are represented in the same space
- Angle (or cosine) is a proxy for similarity between two vectors



Similarity Measures

- The Jaccard similarity (Similarity of Two Sets)

$$Jaccard(X, Y) = \frac{|X \cap Y|}{|X \cup Y|}$$

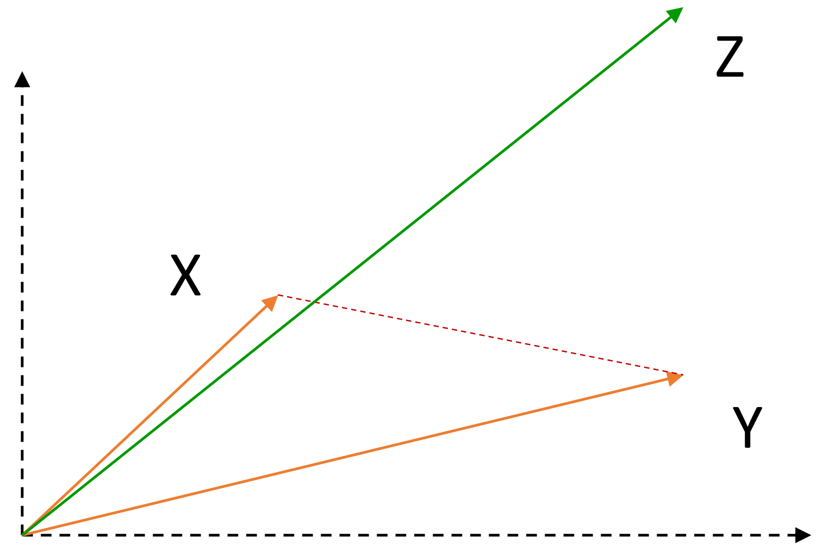
- D1 = “information retrieval class”
- D2 = “information retrieval algorithm”
- D3 = “processing information”
- What’s the Jaccard similarity of S(D1, D2)? S(D1, D3)?

- What about D3 = “information of information retrieval”

Similarity Measures

- Euclidean Distance – distance of two points

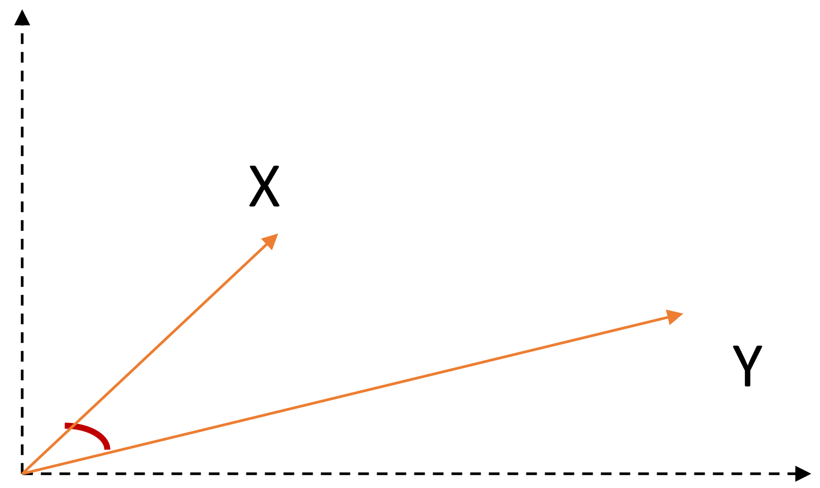
$$D(X,Y)=\sqrt{(x_1-y_1)^2+(x_2-y_2)^2+\ldots+(x_n-y_n)^2}=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}$$



Similarity Measures (Cont.)

- Cosine similarity: similarity of two vectors, normalized

$$\cos(X,Y) = \frac{x_1y_1 + x_2y_2 + \ldots + x_ny_n}{\sqrt{x_1^2 + \ldots + x_n^2} \times \sqrt{y_1^2 + \ldots + y_n^2}} = \frac{\sum_{i=1}^{n} x_iy_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \times \sqrt{\sum_{i=1}^{n} y_i^2}}$$



Which one do you think is suitable for retrieval? Jaccard? Euclidean? Cosine?

Example

- What is the cosine similarity between:
  - D= "cat,dog,dog" = $\langle 1,2,0 \rangle$
  - Q= "cat,dog,mouse,mouse" = $\langle 1,1,2 \rangle$
- Answer:

$$\sigma(D,Q) = \frac{1\times1+2\times1+0\times2}{\sqrt{1^2+2^2+0^2}\sqrt{1^2+1^2+2^2}} = \frac{3}{\sqrt{5}\sqrt{6}} \approx 0.55$$

- In comparison:

$$\sigma(D,D) = \frac{1\times1+2\times2+0\times0}{\sqrt{1^2+2^2+0^2}\sqrt{1^2+2^2+0^2}} = \frac{5}{\sqrt{5}\sqrt{5}} = 1$$

Quiz

- Given three documents

  $D_1 = <1,3>$

  $D_2 = <10,30>$

  $D_3 = <3,1>$

- Compute the cosine scores

  $\sigma(D_1,D_2)$

  $\sigma(D_1,D_3)$

- What do the numbers tell you?

Answers to the Quiz

$\sigma(D_1,D_2) = 1$

one of the two documents is a scaled version of the other

$\sigma(D_1,D_3) = 0.6$

swapping the two dimensions results in a lower similarity

Quiz

- What is the range of values that the cosine scores can take?

Answer to the Quiz

- Mathematically, the cosine function has a range of [-1,1]
- However, when the two vectors are both in the first quadrant (since all word counts are non-negative), the range is [0,1]
- For word embeddings, the range is [-1,1] (since the values don’t have to be non-negative)

Term-Document Matrix

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

Figure 6.2 The term-document matrix for four words in four Shakespeare plays. Each cell contains the number of times the (row) word occurs in the (column) document.

Term-Document Matrix

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

Figure 6.3 The term-document matrix for four words in four Shakespeare plays. The red boxes show that each document is represented as a column vector of length four.

Representing Documents as Vectors

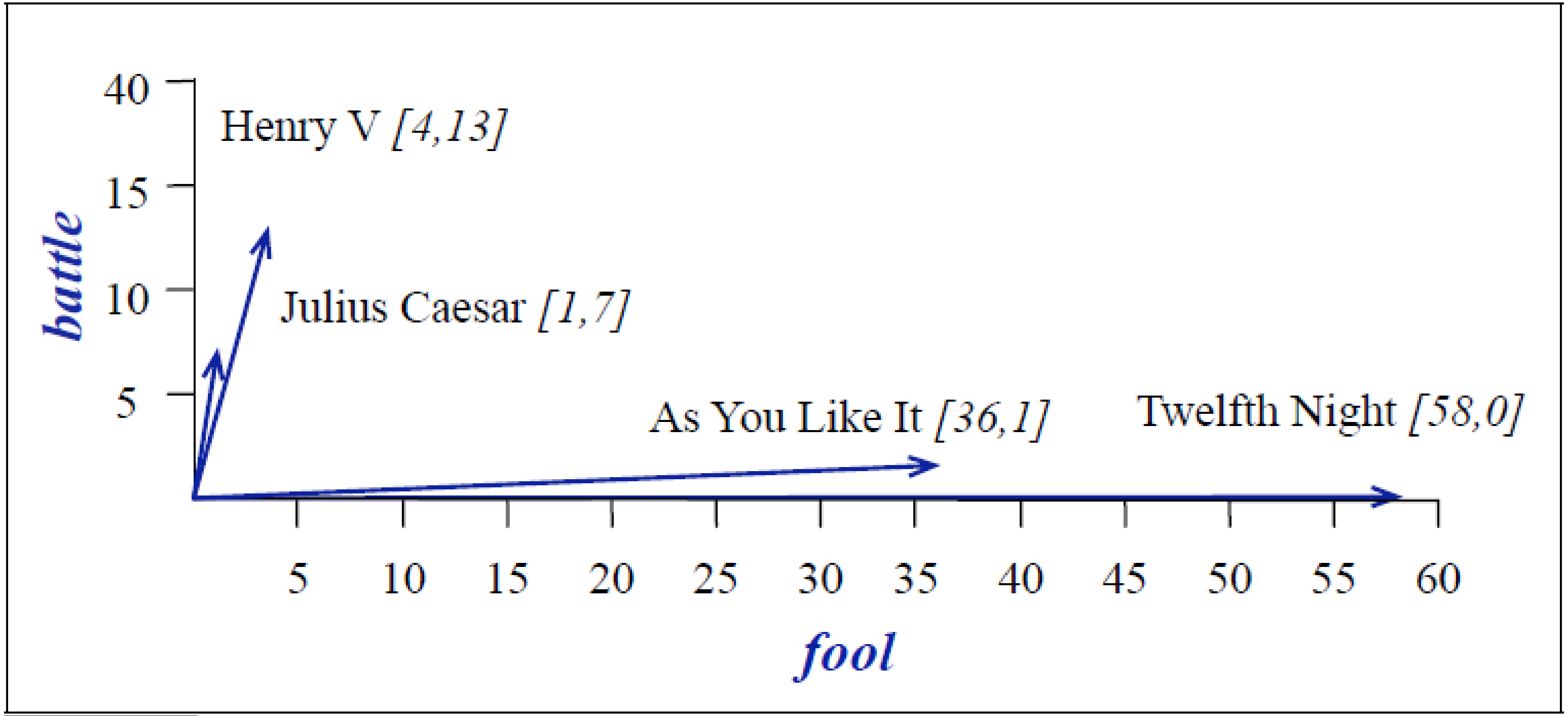


Figure 6.4 A spatial visualization of the document vectors for the four Shakespeare play documents, showing just two of the dimensions, corresponding to the words *battle* and *fool*. The comedies have high values for the *fool* dimension and low values for the *battle* dimension.

Example (Cont'd)

	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	
strawberry	0	...	0	0	1	60	19	
digital	0	...	1670	1683	85	5	4	
information	0	...	3325	3982	378	5	13	

Figure 6.5 Co-occurrence vectors for four words in the Wikipedia corpus, showing six of the dimensions (hand-picked for pedagogical purposes). The vector for *digital* is outlined in red. Note that a real vector would have vastly more dimensions and thus be much sparser.

Example (Cont'd)

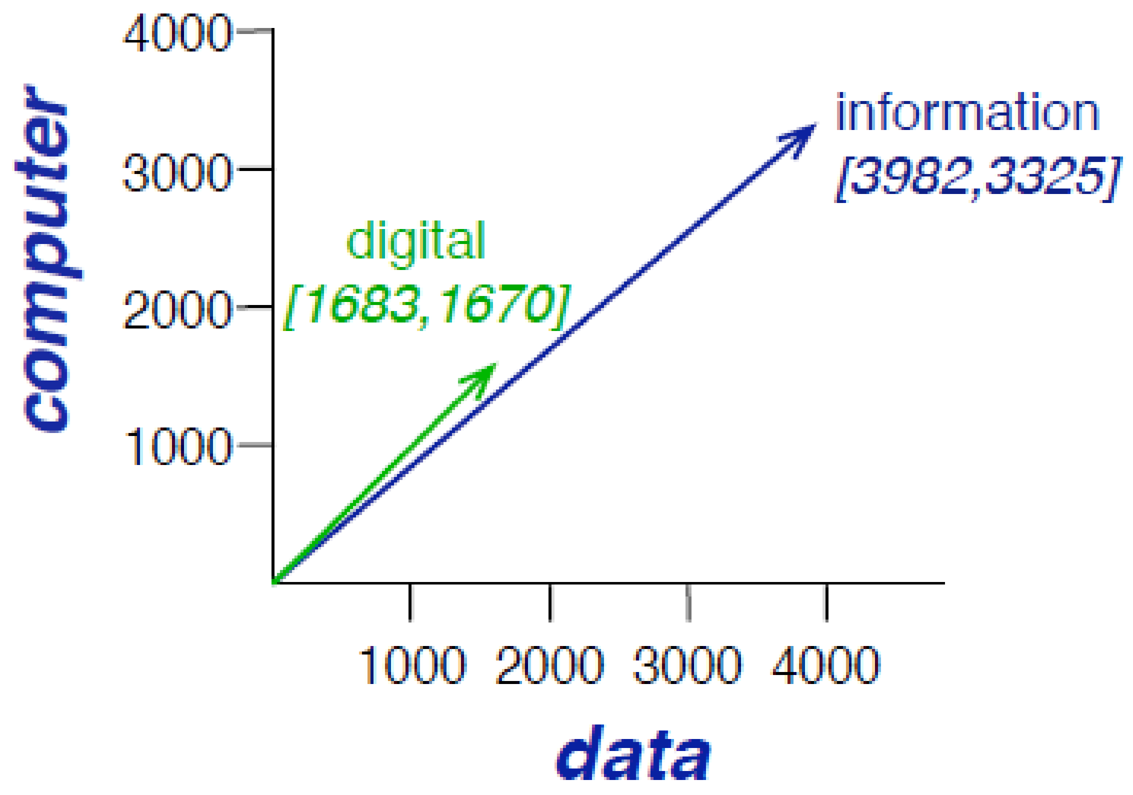


Figure 6.6 A spatial visualization of word vectors for *digital* and *information*, showing just two of the dimensions, corresponding to the words *data* and *computer*.

Example (Cont'd)

	pie	data	computer
cherry	442	8	2
digital	5	1683	1670
information	5	3982	3325

$$\cos(\text{cherry}, \text{information}) = \frac{442 * 5 + 8 * 3982 + 2 * 3325}{\sqrt{442^2 + 8^2 + 2^2}\sqrt{5^2 + 3982^2 + 3325^2}} = .017$$

$$\cos(\text{digital}, \text{information}) = \frac{5 * 5 + 1683 * 3982 + 1670 * 3325}{\sqrt{5^2 + 1683^2 + 1670^2}\sqrt{5^2 + 3982^2 + 3325^2}} = .996$$

Example (Cont'd)

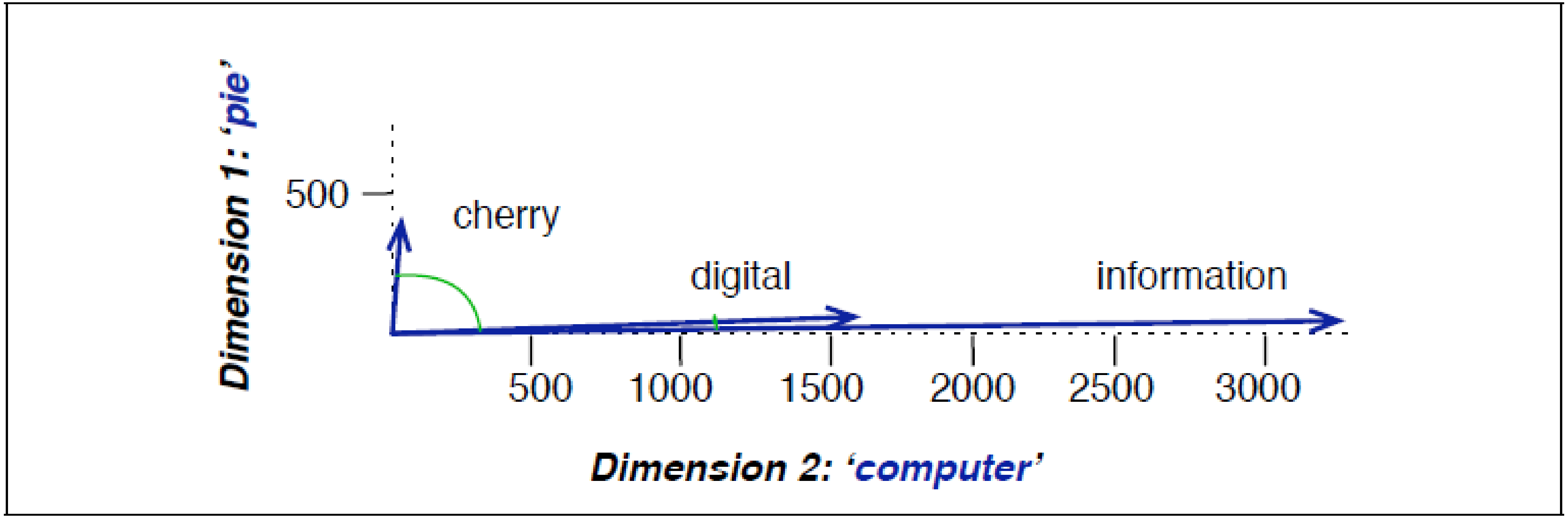


Figure 6.7 A (rough) graphical demonstration of cosine similarity, showing vectors for three words (*cherry*, *digital*, and *information*) in the two dimensional space defined by counts of the words *computer* and *pie* nearby. Note that the angle between *digital* and *information* is smaller than the angle between *cherry* and *information.* When two vectors are more similar, the cosine is larger but the angle is smaller; the cosine has its maximum (1) when the angle between two vectors is smallest (0°); the cosine of all other angles is less than 1.

Term Frequency and Inverse Document Frequency

	Collection Frequency	Document Frequency
Romeo	113	1
action	113	31

$$\text{idf}_t = \log_{10}\left(\frac{N}{\text{df}_t}\right)$$

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	0.074	0	0.22	0.28
good	0	0	0	0
fool	0.019	0.021	0.0036	0.0083
wit	0.049	0.044	0.018	0.022

Figure 6.8 A tf-idf weighted term-document matrix for four words in four Shakespeare plays, using the counts in Fig. 6.2. For example the 0.049 value for *wit* in *As You Like It* is the product of $\text{tf} = \log_{10}(20+1) = 1.322$ and $\text{idf} = .037$. Note that the idf weighting has eliminated the importance of the ubiquitous word *good* and vastly reduced the impact of the almost-ubiquitous word *fool*.

Word	df	idf
Romeo	1	1.57
salad	2	1.27
Falstaff	4	0.967
forest	12	0.489
battle	21	0.246
wit	34	0.037
fool	36	0.012
good	37	0
sweet	37	0

Review: Mutual Information

$$I(x,y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

$$\mathrm{PMI}(w,c) = \log_2 \frac{P(w,c)}{P(w)P(c)}$$

$$\mathrm{PPMI}(w,c) = \max(\log_2 \frac{P(w,c)}{P(w)P(c)}, 0)$$

Mutual Information: Example

$$p_{ij} = \frac{f_{ij}}{\sum_{i=1}^{W}\sum_{j=1}^{C} f_{ij}} \quad p_{i*} = \frac{\sum_{j=1}^{C} f_{ij}}{\sum_{i=1}^{W}\sum_{j=1}^{C} f_{ij}} \quad p_{*j} = \frac{\sum_{i=1}^{W} f_{ij}}{\sum_{i=1}^{W}\sum_{j=1}^{C} f_{ij}}$$

$$\text{PPMI}_{ij} = \max(\log_2 \frac{p_{ij}}{p_{i*}p_{*j}}, 0)$$

	computer	data	result	pie	sugar	count(w)
cherry	2	8	9	442	25	486
strawberry	0	0	1	60	19	80
digital	1670	1683	85	5	4	3447
information	3325	3982	378	5	13	7703
count(context)	4997	5673	473	512	61	11716

Figure 6.9 Co-occurrence counts for four words in 5 contexts in the Wikipedia corpus, together with the marginals, pretending for the purpose of this calculation that no other words/contexts matter

Example (Cont'd)

$$
\begin{aligned}
P(\text{w=information,c=data}) &= \frac{3982}{11716} = .3399 \\
P(\text{w=information}) &= \frac{7703}{11716} = .6575 \\
P(\text{c=data}) &= \frac{5673}{11716} = .4842 \\
\text{ppmi(information,data)} &= \log 2(.3399/(.6575 * .4842)) = .0944
\end{aligned}
$$

Example (Cont'd)

	p(w,context)					p(w)
	computer	**data**	**result**	**pie**	**sugar**	**p(w)**
cherry	0.0002	0.0007	0.0008	0.0377	0.0021	0.0415
strawberry	0.0000	0.0000	0.0001	0.0051	0.0016	0.0068
digital	0.1425	0.1436	0.0073	0.0004	0.0003	0.2942
information	0.2838	0.3399	0.0323	0.0004	0.0011	0.6575
p(context)	0.4265	0.4842	0.0404	0.0437	0.0052	

Figure 6.10 Replacing the counts in Fig. 6.5 with joint probabilities, showing the marginals around the outside.

Example (Cont'd)

	computer	data	result	pie	sugar
cherry	0	0	0	4.38	3.30
strawberry	0	0	0	4.10	5.51
digital	0.18	0.01	0	0	0
information	0.02	0.09	0.28	0	0

Figure 6.11 The PPMI matrix showing the association between words and context words, computed from the counts in Fig. 6.10. Note that most of the 0 PPMI values are ones that had a negative PMI; for example PMI(*cherry,computer*) = -6.7, meaning that *cherry* and *computer* co-occur on Wikipedia less often than we would expect by chance, and with PPMI we replace negative values by zero.

NLP

Text Similarity

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Vector Semantics

What does “acerola” mean?

- *acerola* is a significant source of vitamin C.
- the pulp of the *acerola* is very soft
- *acerola* are now found growing in most sub-tropical regions of the world.
- *acerola* can be eaten fresh or used to make jams or jellies.

Distributional similarity

- Two words that appear in similar contexts are likely to be semantically related, e.g.,
  - schedule a test ***drive*** and investigate **Honda**'s financing options
  - **Volkswagen** debuted a new version of its front-wheel-***drive*** Golf
  - the **Jeep** reminded me of a recent ***drive***
  - Our test ***drive*** took place at the wheel of loaded **Ford** EL model
- "You will know a word by the company that it keeps." (J.R. Firth 1957)

Basic Ideas

- Represent words as vectors
  - For example, based on nearby words
- Similar words (synonyms) should have similar representations
- Different senses of the same word should have different representations
- Relations should be preserved
  - For example, “cat”-”kitten” should be similar to “dog”-”puppy”

Context Features

- The context features can be any of the following:
  - The word before the target word
  - The word after the target word
  - Any word within *n* words of the target word
  - Any word within a specific syntactic relationship with the target word (e.g., the head of the dependency or the subject of the sentence)
  - Any word within the same sentence
  - Any word within the same document

Example

- S1: schedule a test ***drive*** and investigate **Honda**'s financing options
- S2: **Volkswagen** debuted a new version of its front-wheel-***drive*** Golf
- S3: the **Jeep** reminded me of a recent ***drive***
- S4: Our test ***drive*** took place at the wheel of loaded **Ford** EL model

	schedule	test	drive	version	front	recent	model
Honda	1	1	**1**				
Vokswagen			**1**	1	1		
Jeep			**1**			1	
Ford		1	**1**				1

t-SNE Projection

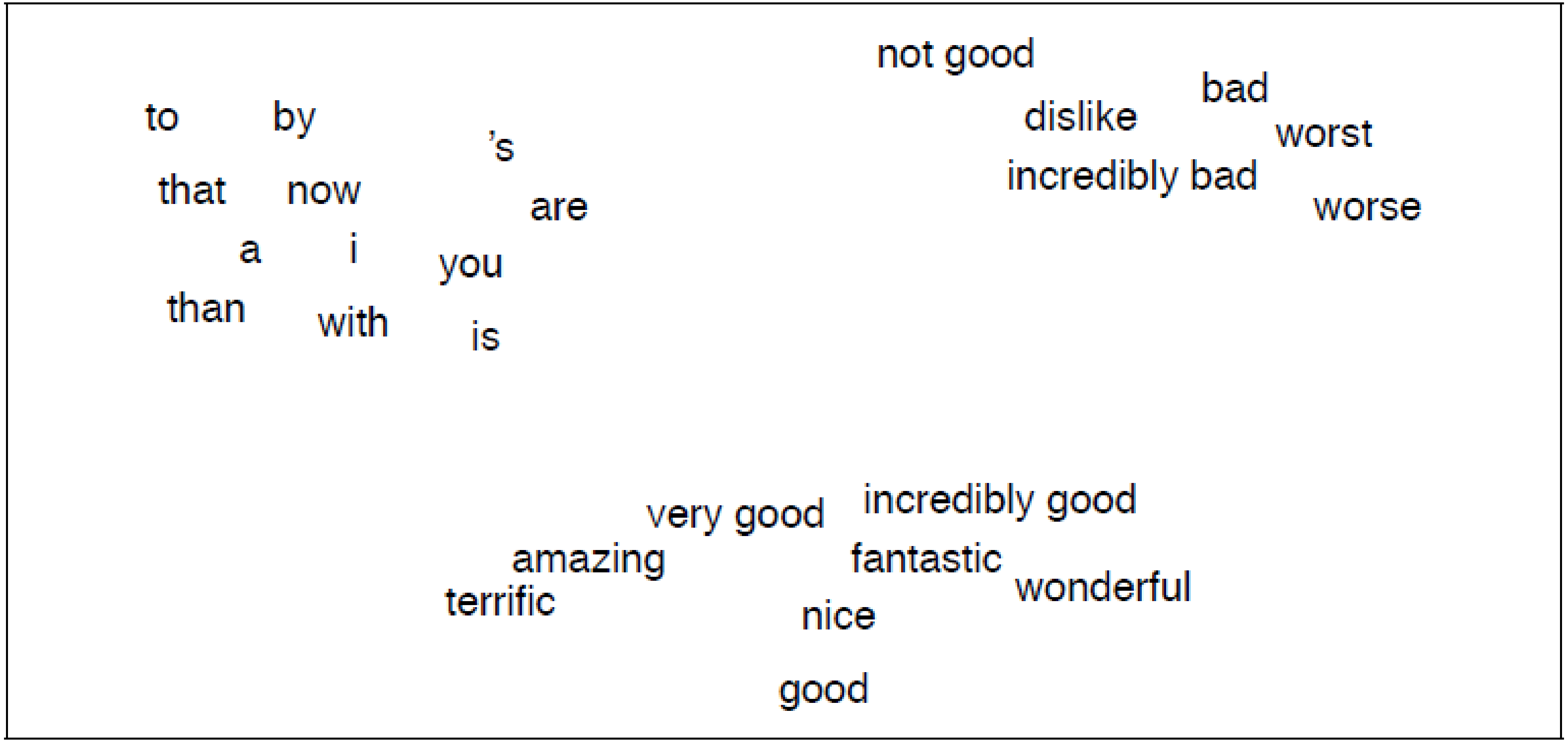

Figure 6.1 A two-dimensional (t-SNE) projection of embeddings for some words and phrases, showing that words with similar meanings are nearby in space. The original 60-dimensional embeddings were trained for sentiment analysis. Simplified from Li et al. (2015).

NLP

Text Similarity

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Dimensionality Reduction

Issues with Vector Similarity

- Polysemy (sim < cos)
  - bar, bank, jaguar, hot
- Synonymy (sim > cos)
  - building/edifice, large/big, spicy/hot
- Relatedness (people are really good at figuring this)
  - doctor/patient/nurse/treatment

Semantic Matching

Query = “natural language processing”

Document 1 = “linguistics semantics viterbi learning”

Document 2 = “welcome to new haven”

- Which one should we rank higher?
- Query vocabulary & doc vocabulary mismatch!
- If only we can represent documents/queries as concepts!
- That’s where dimensionality reduction helps

Semantic Concepts

	election	vote	president	tomato	salad
NEWS1	4	4	4	0	0
NEWS2	3	3	3	0	0
NEWS3	1	1	1	0	0
NEWS4	5	5	5	0	0
RECIPE1	0	0	0	1	1
RECIPE2	0	0	0	4	4
RECIPE3	0	0	0	1	1

Semantic Concepts

	election	vote	president	tomato	salad
NEWS1	4	4	4	0	0
NEWS2	3	3	3	0	0
NEWS3	1	1	1	0	0
NEWS4	5	5	5	0	0
RECIPE1	0	0	0	1	1
RECIPE2	0	0	0	4	4
RECIPE3	0	0	0	1	1

Concept Space = Dimension Reduction

- Number of concepts (K) is smaller than the number of words (N) or number of documents (M).
- If we represent a document as a N-dimensional vector; and the corpus as an M*N matrix…
  - The goal is to reduce the dimensionality from N to K.
  - But how can we do that?

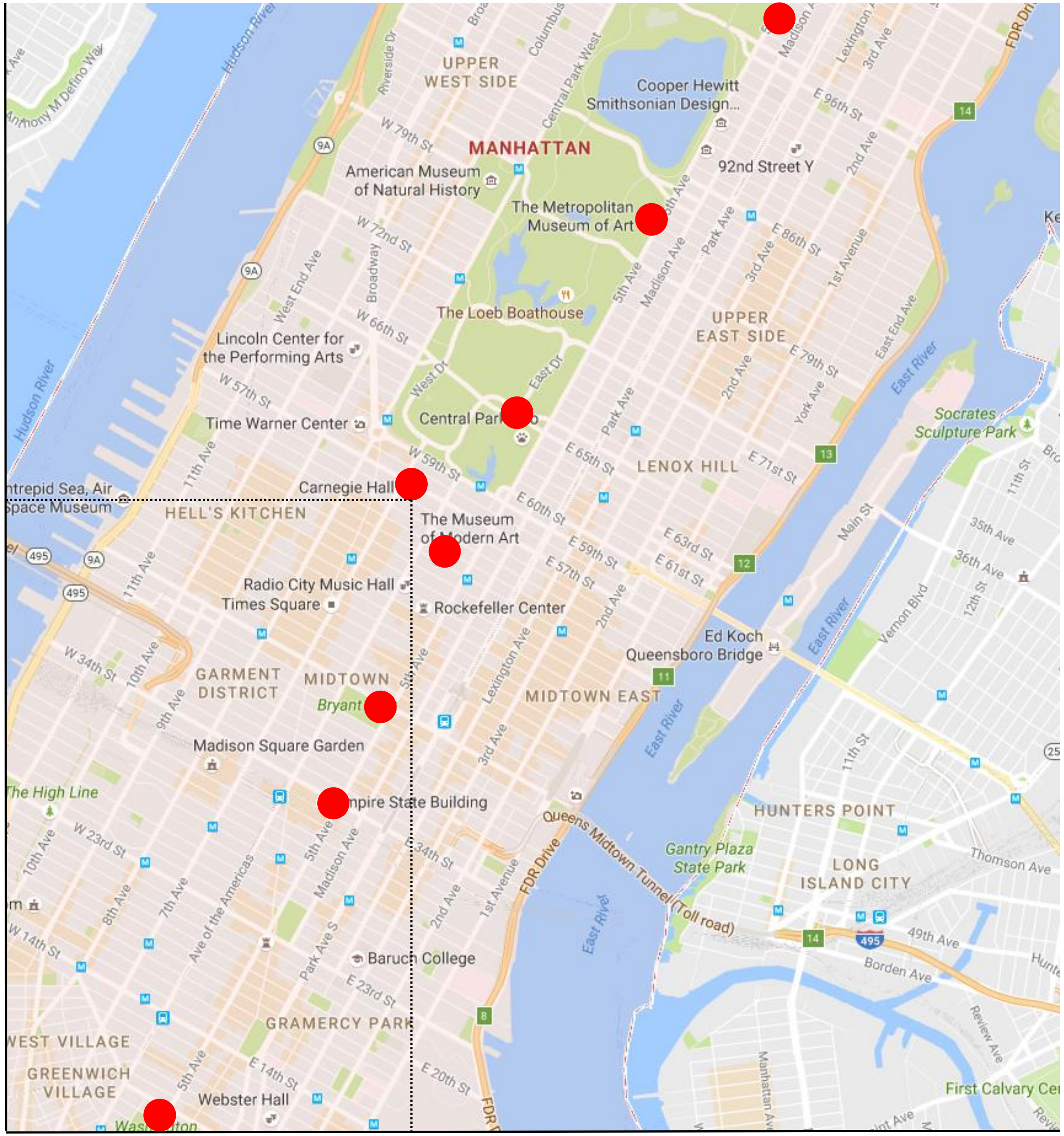
TOEFL Synonyms and SAT Analogies

- Word similarity vs. analogies

Stem:		levied
Choices:	(a)	imposed
	(b)	believed
	(c)	requested
	(d)	correlated
Solution:	(a)	imposed

Stem:	mason:stone
Choices:	(a) teacher:chalk
	(b) carpenter:wood
	(c) soldier:gun
	(d) photograph:camera
	(e) book:word
Solution:	(b) carpenter:wood

Example from Peter Turney



MANHATTAN
UPPER WEST SIDE
Cooper Hewitt Smithsonian Design...
92nd Street Y
American Museum of Natural History
The Metropolitan Museum of Art
The Loeb Boathouse
UPPER EAST SIDE
Lincoln Center for the Performing Arts
Time Warner Center
LENOX HILL
Socrates Sculpture Park
Carnegie Hall
HELL'S KITCHEN
The Museum of Modern Art
Radio City Music Hall
Times Square
Rockefeller Center
Ed Koch Queensboro Bridge
GARMENT DISTRICT
MIDTOWN
MIDTOWN EAST
Madison Square Garden
The High Line
HUNTERS POINT
Gantry Plaza State Park
LONG ISLAND CITY
Baruch College
GRAMERCY PARK
WEST VILLAGE
GREENWICH VILLAGE
Webster Hall
Hudson River
East River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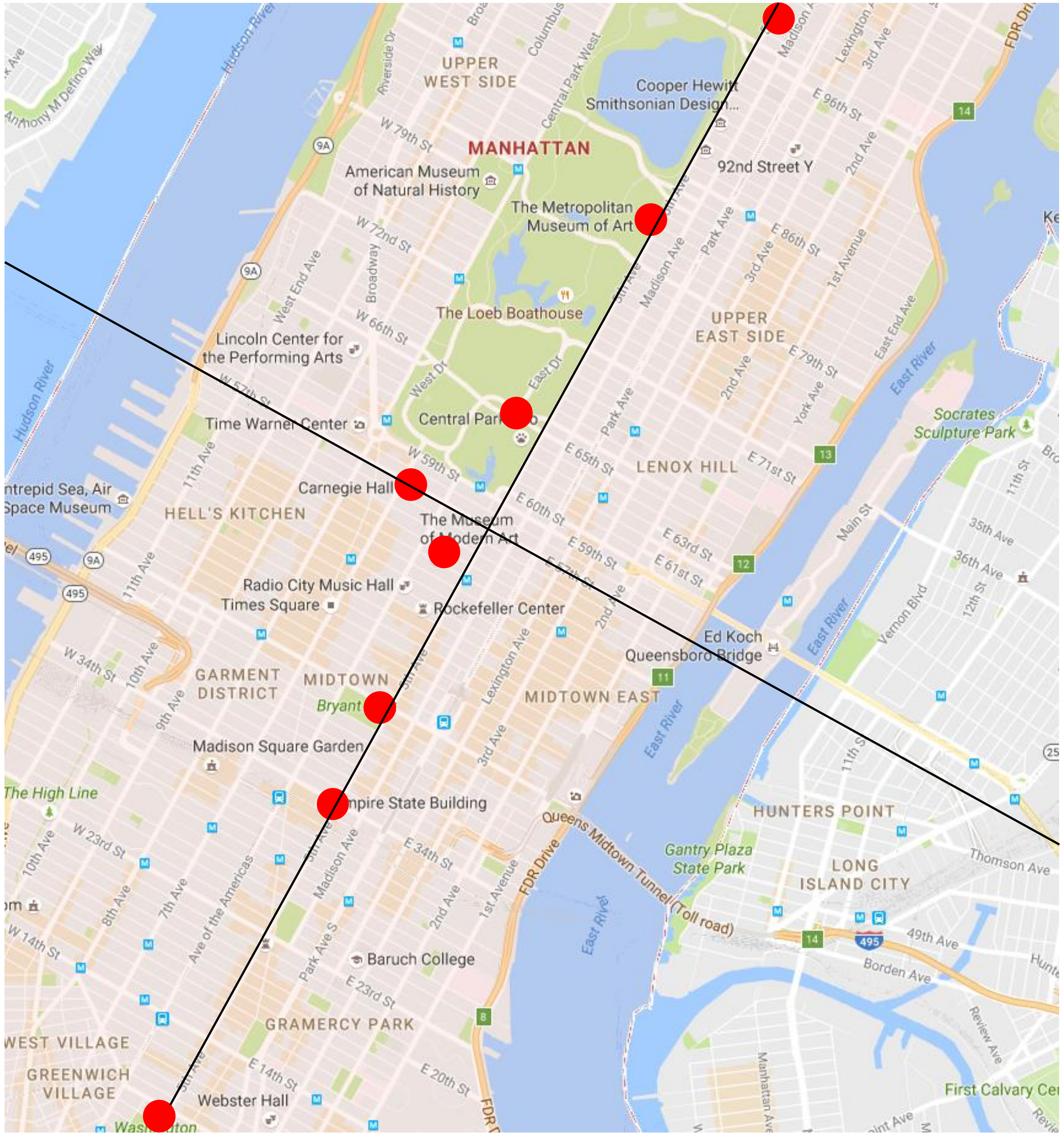
Madison Square Garden
Baruch College
Webster Hall
Socrates Sculpture Park
Gantry Plaza State Park
The High Line
Hudson River
East River
Queens Midtown Tunnel (Toll road)

29 degrees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Baruch College
GRAMERCY PARK
WEST VILLAGE
GREENWICH VILLAGE
Webster Hall
Socrates Sculpture Park
Hudson River
East River

29 degrees

Vectors and Matrices

- A matrix is an m x n table of objects (in our case, numbers)
- Each row (or column) is a vector.
- Matrices of compatible dimensions can be multiplied together.
- What is the result of the multiplication below?

$$\begin{bmatrix} 1 & 2 & 4 \\ 2 & 5 & 7 \\ 4 & 9 & 14 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} \\ \\ \\ \end{bmatrix}$$

Answer to the Quiz

$$\begin{bmatrix} 1 & 2 & 4 \\ 2 & 5 & 7 \\ 4 & 9 & 14 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 1 \times 2 + 2 \times 1 + 4 \times (-1) \\ 2 \times 2 + 5 \times 1 + 7 \times (-1) \\ 4 \times 2 + 9 \times 1 + 14 \times (-1) \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \\ 3 \end{bmatrix}$$

Eigenvectors and Eigenvalues

- An eigenvector is an implicit “direction” for a matrix A

$$A\vec{v} = \lambda\vec{v}$$

  - *v* (the eigenvector) is non-zero
  - *λ* (the eigenvalue) can be any complex number, in principle.

- Computing eigenvalues:

$$\det(A - \lambda I) = 0$$

Eigenvectors and Eigenvalues

Example:

$$A = \begin{pmatrix} -1 & 3 \\ 2 & 0 \end{pmatrix} \qquad A - \lambda I = \begin{pmatrix} -1-\lambda & 3 \\ 2 & -\lambda \end{pmatrix}$$

det $(A-\lambda I) = (-1-\lambda)*(-\lambda)-3*2=0$

Then: $\lambda+\lambda^2-6=0$; $\lambda_1=2$; $\lambda_2=-3$

For $\lambda_1=2$:

$$\begin{pmatrix} -3 & 3 \\ 2 & -2 \end{pmatrix}\begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = 0$$

Solutions: $v_1=v_2$

Matrix decomposition

- If Σ is a square matrix, it can be decomposed into $U\Lambda U^{-1}$, where

  U = matrix of eigenvectors

  Λ = diagonal matrix of eigenvalues

$\Sigma U = U\Lambda$

$U^{-1}\Sigma U = \Lambda$

$\Sigma = U\Lambda U^{-1}$

Example

$$S = \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}, \lambda_1 = 1, \lambda_2 = 3$$

$$U = \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix}$$

$$U^{-1} = \begin{pmatrix} 1/2 & -1/2 \\ 1/2 & 1/2 \end{pmatrix}$$

$$S = U \Lambda U^{-1} = \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 3 \end{pmatrix} \begin{pmatrix} 1/2 & -1/2 \\ 1/2 & 1/2 \end{pmatrix}$$

SVD: Singular Value Decomposition

- $A=U\Sigma V^T$
  - U is the matrix of orthogonal eigenvectors of AA^T
  - V is the matrix of orthogonal eigenvectors of A^TA (co-variance matrix)
  - The components of Σ are the eigenvalues of A^TA
- Properties
  - This decomposition exists for all matrices and is unique
  - U, V are column orthonormal
  - $U^T U = I$; $V^T V = I$
  - Σ is diagonal and sorted by absolute value of the singular values (large to small)
  - Each column (row) of Σ corresponds to a principal component
  - If A has 5 columns and 3 rows, then U will be 5x5 and V will be 3x3

Example (Berry and Browne)

T1: baby
T2: child
T3: guide
T4: health
T5: home
T6: infant
T7: proofing
T8: safety
T9: toddler

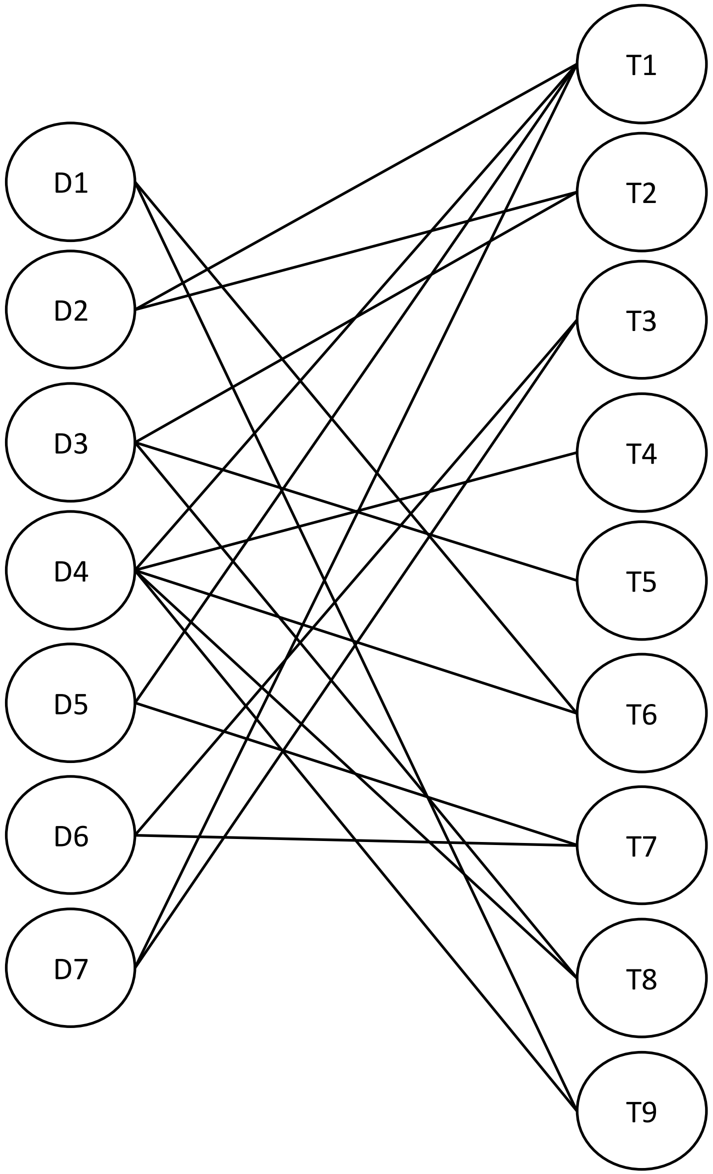
D1: <u>infant</u> & <u>toddler</u> first aid
D2: <u>babies</u> & <u>children</u>’s room (for your home)
D3: <u>child</u> <u>safety</u> at <u>home</u>
D4: your <u>baby</u>’s <u>health</u> and <u>safety</u>: from <u>infant</u> to <u>toddler</u>
D5: <u>baby</u> <u>proofing</u> basics
D6: your <u>guide</u> to easy rust <u>proofing</u>
D7: beanie <u>babies</u> collector’s <u>guide</u>

Example

D1: T6, T9
D2: T1, T2
D3: T2, T5, T8
D4: T1, T4, T6, T8, T9
D5: T1, T7
D6: T3, T7
D7: T1, T3

Example

D1: T6, T9
D2: T1, T2
D3: T2, T5, T8
D4: T1, T4, T6, T8, T9
D5: T1, T7
D6: T3, T7
D7: T1, T3



Document-Term Matrix

raw

normalized

$$A = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$A^{(n)} = \begin{bmatrix} 0 & 0.58 & 0 & 0.45 & 0.71 & 0 & 0.71 \\ 0 & 0.58 & 0.58 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.71 & 0.71 \\ 0 & 0 & 0 & 0.45 & 0 & 0 & 0 \\ 0 & 0.58 & 0.58 & 0 & 0 & 0 & 0 \\ 0.71 & 0 & 0 & 0.45 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.71 & 0.71 & 0 \\ 0 & 0 & 0.58 & 0.45 & 0 & 0 & 0 \\ 0.71 & 0 & 0 & 0.45 & 0 & 0 & 0 \end{bmatrix}$$

Dimensionality Reduction

- Low rank matrix approximation

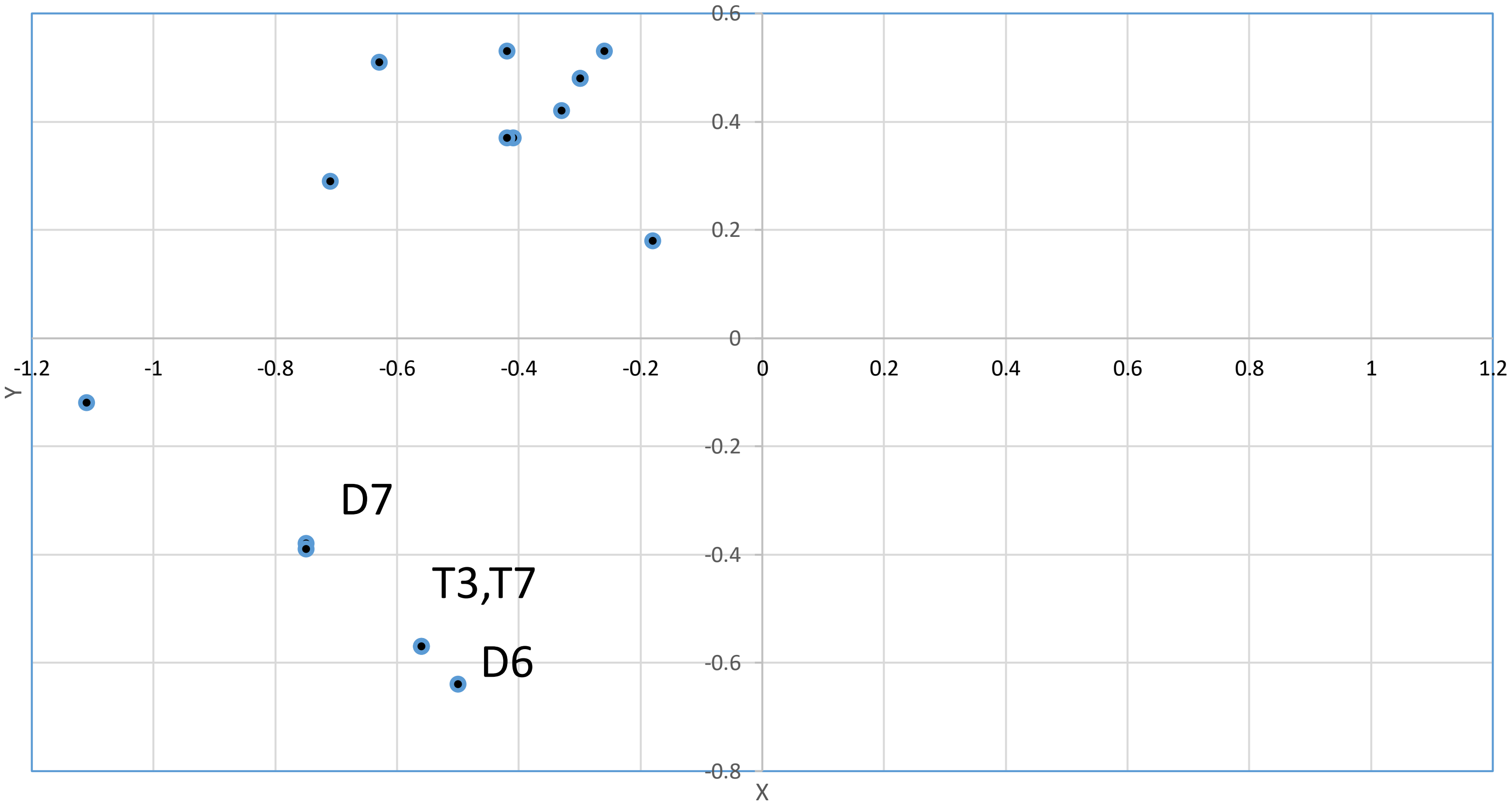
  $A_{[m*n]} = U_{[m*m]}\Sigma_{[m*n]}V^{T}_{[n*n]}$

- Σ is a diagonal matrix of eigenvalues
- If we only keep the largest *r* eigenvalues

  $A \approx U_{[m*r]}\Sigma_{[r*r]}V^{T}_{[n*r]}$

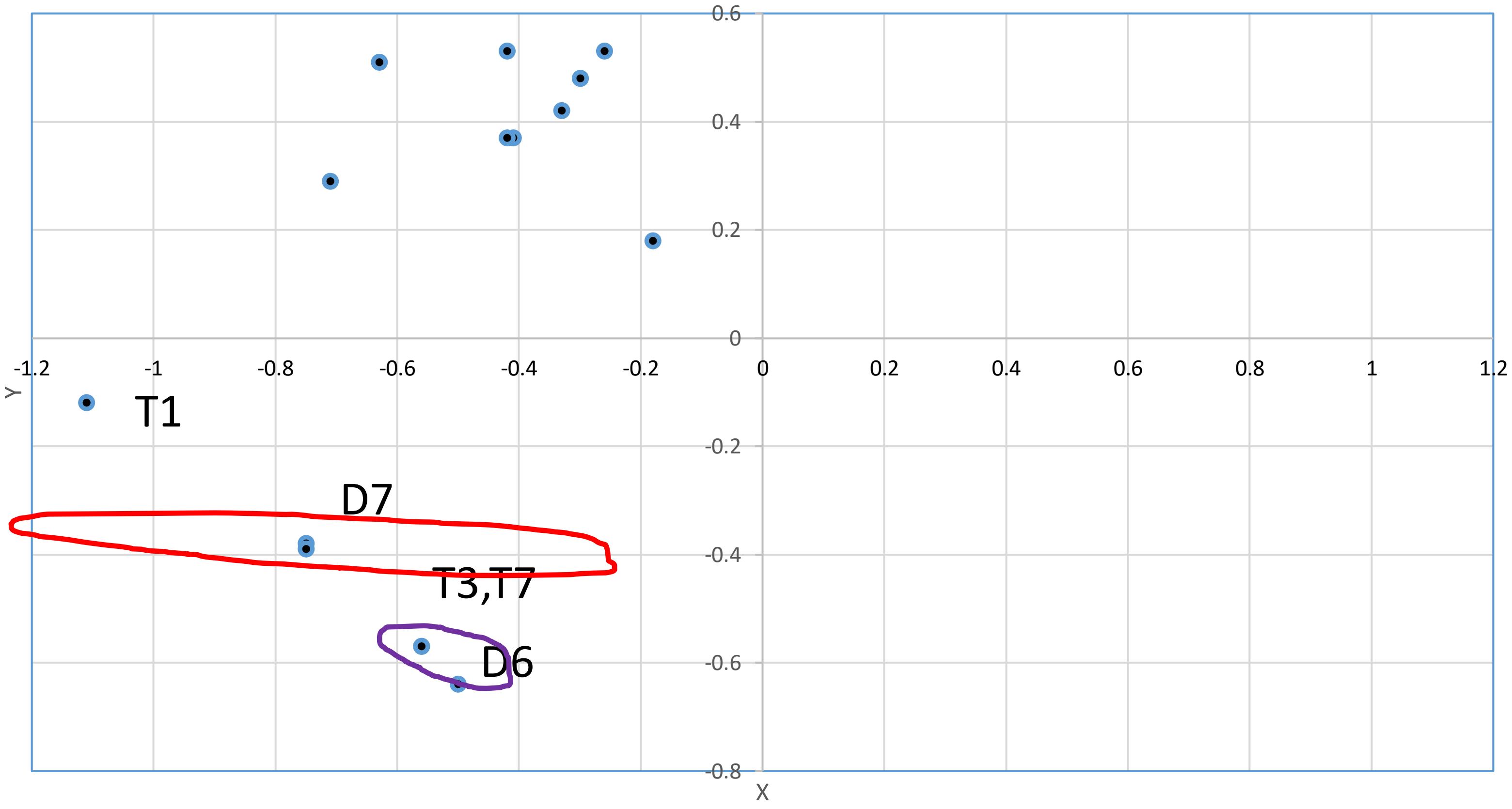
D1	D2	D3	D4	D5	D6	D7
-0.26	-0.71	-0.42	-0.62	-0.74	-0.50	-0.74
0.53	0.29	0.54	0.51	-0.38	-0.64	-0.38

T1	T2	T3	T4	T5	T6	T7	T8	T9
-1.10	-0.41	-0.56	-0.18	-0.41	-0.30	-0.56	-0.33	-0.30
-0.12	0.38	-0.57	0.18	0.38	0.47	-0.57	0.42	0.47



D1	D2	D3	D4	D5	D6	D7
-0.26	-0.71	-0.42	-0.62	-0.74	-0.50	-0.74
0.53	0.29	0.54	0.51	-0.38	-0.64	-0.38

T1	T2	T3	T4	T5	T6	T7	T8	T9
-1.10	-0.41	-0.56	-0.18	-0.41	-0.30	-0.56	-0.33	-0.30
-0.12	0.38	-0.57	0.18	0.38	0.47	-0.57	0.42	0.47



Semantic Concepts

	election	vote	president	tomato	salad
NEWS1	4	4	4	0	0
NEWS2	3	3	3	0	0
NEWS3	1	1	1	0	0
NEWS4	5	5	5	0	0
RECIPE1	0	0	0	1	1
RECIPE2	0	0	0	4	4
RECIPE3	0	0	0	1	1

Semantic Concepts

	election	vote	president	tomato	salad
NEWS1	4	4	4	0	0
NEWS2	3	3	3	0	0
NEWS3	1	1	1	0	0
NEWS4	5	5	5	0	0
RECIPE1	0	0	0	1	1
RECIPE2	0	0	0	4	4
RECIPE3	0	0	0	1	1

Adding Noise

	election	vote	president	tomato	salad
NEWS1	4	4	4	0	0
NEWS2	3	**0**	3	0	**2**
NEWS3	1	1	1	**1**	0
NEWS4	5	5	**3**	0	0
RECIPE1	0	0	0	1	1
RECIPE2	0	**1**	0	4	4
RECIPE3	0	0	0	**0**	1

Quiz

- Let A be a document x term matrix.
- What is A*A'?
- What about A'*A?

Interpretation of SVD

- Best direction to project on
  - The principal eigenvector is the dimension that explains most of the variance
- Finding hidden concepts
  - Mapping documents, terms to a lower-dimensional space
- Turning the matrix into block-diagonal form
  - (same as finding bi-partite cores)
- In the NLP/IR literature, SVD is called LSA (LSI)
  - Latent Semantic Analysis (Indexing)
- Keep as many dimensions as necessary to explain 80-90% of the data (energy)
  - In practice, use 300 dimensions or so

Problem #5 (20 points). In a series of experiments run in Carnegie Mellon University (Pittsburgh, USA) in 2010, volunteers were first shown some English words, while activity was being registered in different locations of their brains. Then the volunteers were asked to think of some other words from a preselected list of 60 words, while the researchers were measuring their brain activity again. Using the obtained data, the researchers were able to determine the words the volunteers were thinking of quite successfully.

Below you can find some data on the activity levels for four brain locations depending on which word the volunteers were thinking of.

Word	Translation	Location A	Location B	Location C	Location D
airplane	airplane	high	low	low	high
apartment	apartment	high	low	low	high
arm	arm	low	high	low	low
corn	corn	low	low	high	low
cup	cup	low	low	high	low
igloo	igloo	high	low	low	low
key	key	high	high	low	low
lettuce	lettuce	low	low	high	high
screwdriver	screwdriver	low	high	low	high

The same information is given below on six more words the volunteers were thinking of: ***bed*** 'bed', ***butterfly*** 'butterfly', ***cat*** 'cat', ***cow*** 'cow', ***refrigerator*** 'refrigerator', ***spoon*** 'spoon'.

Word	Location A	Location B	Location C	Location D
1	low	low	high	high
2	low	low	high	low
3	high	low	low	low
4	low	low	low	high
5	low	high	high	low
6	low	low	low	low

Determine the correct correspondences.

—*Boris Iomdin*

Problem #5. Location A is activated by the idea of shelter. Location B is activated by the idea of manipulation. Location C is activated by the idea of eating. Location D is activated by long words. The researchers claim that the first three factors have high ecological validity (i. e., the results of the experiment conform to the data on human behaviour in real life) and survival value, and that Location D is responsible for a low-level visual representation of the printed word.

Word	Translation	Location A (shelter)	Location B (manipulation)	Location C (eating)	Location D (long words)
refrigerator	'refrigerator'	low	low	high	high
cow	'cow'	low	low	high	low
bed	'bed'	high	low	low	low
butterfly	'butterfly'	low	low	low	high
spoon	'spoon'	low	high	high	low
cat	'cat'	low	low	low	low

fMRI example

- fMRI
  - functional MRI (magnetic resonance imaging)
  - Used to measure activity in different parts of the brain when exposed to various stimuli
- Factor analysis
- Paper
  - Just, M. A., Cherkassky, V. L., Aryal, S., & Mitchell, T. M. (2010). A neurosemantic theory of concrete noun representation based on the underlying brain codes. PLoS ONE, 5, e8622

Table 1. 60 stimulus words grouped into 12 semantic categories.

Category	Exemplar 1	Exemplar 2	Exemplar 3	Exemplar 4	Exemplar 5
body parts	leg	arm	eye	foot	hand
furniture	chair	table	bed	desk	dresser
vehicles	car	airplane	train	truck	bicycle
animals	horse	dog	bear	cow	cat
kitchen utensils	glass	knife	bottle	cup	spoon
tools	chisel	hammer	screwdriver	pliers	saw
buildings	apartment	barn	house	church	igloo
building parts	window	door	chimney	closet	arch
clothing	coat	dress	shirt	skirt	pants
insects	fly	ant	bee	butterfly	beetle
vegetables	lettuce	tomato	carrot	corn	celery
man-made objects	refrigerator	key	telephone	watch	bell

doi:10.1371/journal.pone.0008622.t001

[Just et al. 2010]

Table 2. Ten words with highest factor scores (in descending order) for each of the 4 factors.

Shelter	*Manipulation*	*Eating*	*Word length*
apartment	pliers	carrot	butterfly
church	saw	lettuce	screwdriver
train	screwdriver	tomato	telephone
house	hammer	celery	refrigerator
airplane	key	cow	bicycle
key	knife	saw	apartment
truck	bicycle	corn	dresser
door	chisel	bee	lettuce
car	spoon	glass	chimney
closet	arm	cup	airplane

doi:10.1371/journal.pone.0008622.t002

[Just et al. 2010]

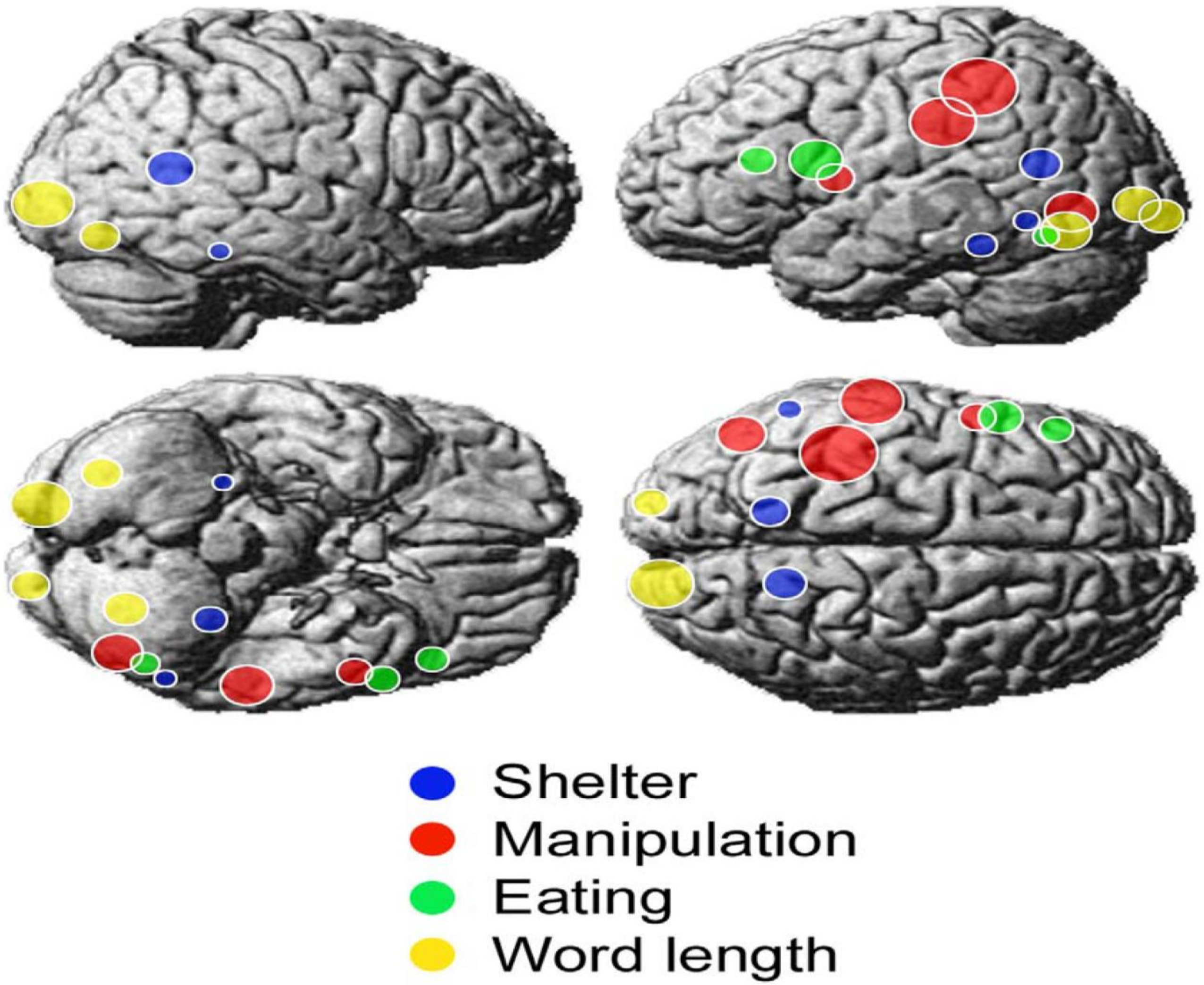


Figure 1. Locations of the voxel clusters (spheres) associated with the four factors. The spheres (shown as surface projections) are centered at the cluster centroid, with a radius equal to the mean radial dispersion of the cluster voxels.
doi:10.1371/journal.pone.0008622.g001

[Just et al. 2010]

Table 3. Locations (MNI centroid coordinates) and sizes of the voxel clusters associated with the four factors.

Factor	Cluster location	x	y	z	No. of voxels	Radius (mm)
shelter	L Fusiform Gyrus/Parahippocampal Gyrus (PPA)	−32	−42	−18	26	6
	R Fusiform Gyrus/Parahippocampal Gyrus (PPA)	26	−38	−20	6	4
	L Precuneus	−12	−60	16	40	8
	R Precuneus	16	−54	14	36	8
	L Inf Temporal Gyrus	−56	−56	−8	12	4
manipulation	L Supramarginal Gyrus	−60	−30	34	51	10
	L Postcentral/Supramarginal Gyri	−38	−40	48	21	12
	L Precentral Gyrus	−54	4	10	18	6
	L Inf Temporal Gyrus	−46	−70	−4	34	8
eating	L Inf Frontal Gyrus	−54	10	18	26	8
	L Mid/Inf Frontal Gyri	−48	28	18	10	6
	L Inf Temporal Gyrus	−52	−62	−14	7	4
word length	L Occipital Pole	−18	−98	−6	24	6
	R Occipital Pole	16	−94	0	47	10
	L Lingual/Fusiform Gyri	−28	−68	−12	20	8
	R Lingual/Fusiform Gyri	30	−76	−14	14	6

doi:10.1371/journal.pone.0008622.t003

[Just et al. 2010]

External pointers

- http://lsa.colorado.edu
- http://www.cs.utk.edu/~lsi

Example of LSI

$$A \quad = \quad U \quad \Lambda \quad V^T$$

CS-concept

MD-concept

Strength of CS-concept

Dim. Reduction

$$
\begin{array}{c} \\ \text{CS} \\ \\ \\ \\ \text{MD} \\ \\ \end{array}
\begin{array}{c}
\begin{array}{ccccc} \textbf{data} & \textbf{inf} & \textbf{retrieval} & \textbf{brain} & \textbf{lung} \end{array} \\
\begin{bmatrix}
1 & 1 & 1 & 0 & 0 \\
2 & 2 & 2 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 \\
0 & 0 & 0 & 3 & 3 \\
0 & 0 & 0 & 1 & 1
\end{bmatrix}
\end{array}
=
\begin{bmatrix}
0.18 & 0 \\
0.36 & 0 \\
0.18 & 0 \\
0.90 & 0 \\
0 & 0.53 \\
0 & 0.80 \\
0 & 0.27
\end{bmatrix}
\times
\begin{bmatrix}
9.64 & 0 \\
0 & 5.29
\end{bmatrix}
\times
\begin{bmatrix}
0.58 & 0.58 & 0.58 & 0 & 0 \\
0 & 0 & 0 & 0.71 & 0.71
\end{bmatrix}
$$

Term rep of concept

[Example modified from Christos Faloutsos]

Mapping Queries and Docs to the Same Space

$q^T_{concept} = q^T V$

$d^T_{concept} = d^T V$

CS-concept

Similarity with CS-concept

$$q^T = \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \\ \hline \end{array}$$

$$q^T = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0.58 & 0 \\ 0.58 & 0 \\ 0.58 & 0 \\ 0 & 0.71 \\ 0 & 0.71 \end{bmatrix} = \begin{bmatrix} 0.58 & 0 \end{bmatrix}$$

$$d^T = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 1.16 & 0 \end{bmatrix}$$

[Example modified from Christos Faloutsos]

NLP