

How does text become data?

Rob Speer

Luminoso

rob@luminoso.com

In this talk




- A whirlwind tour of data-driven NLP techniques
- Copious Python examples
- Don't worry, code is online:
<http://github.com/rspeer/text-as-data>
 - This is not what I do at my startup. This is about problems that can be solved in about 20 lines of Python code.



r bæði í landi
nilega ekki upp við velgengi
ekki. Margrét stundar nám við
u af frítíma sínum í fótboltaæfi
sé svona heillandi við fótbolta
er finnst svo gaman að spila fót
ð fer auðvitað mikill tími í æfin
vini mína. . . . Margrét sér fr
um. Hana langar að fara til
þröngdun eru

What can you do with text?

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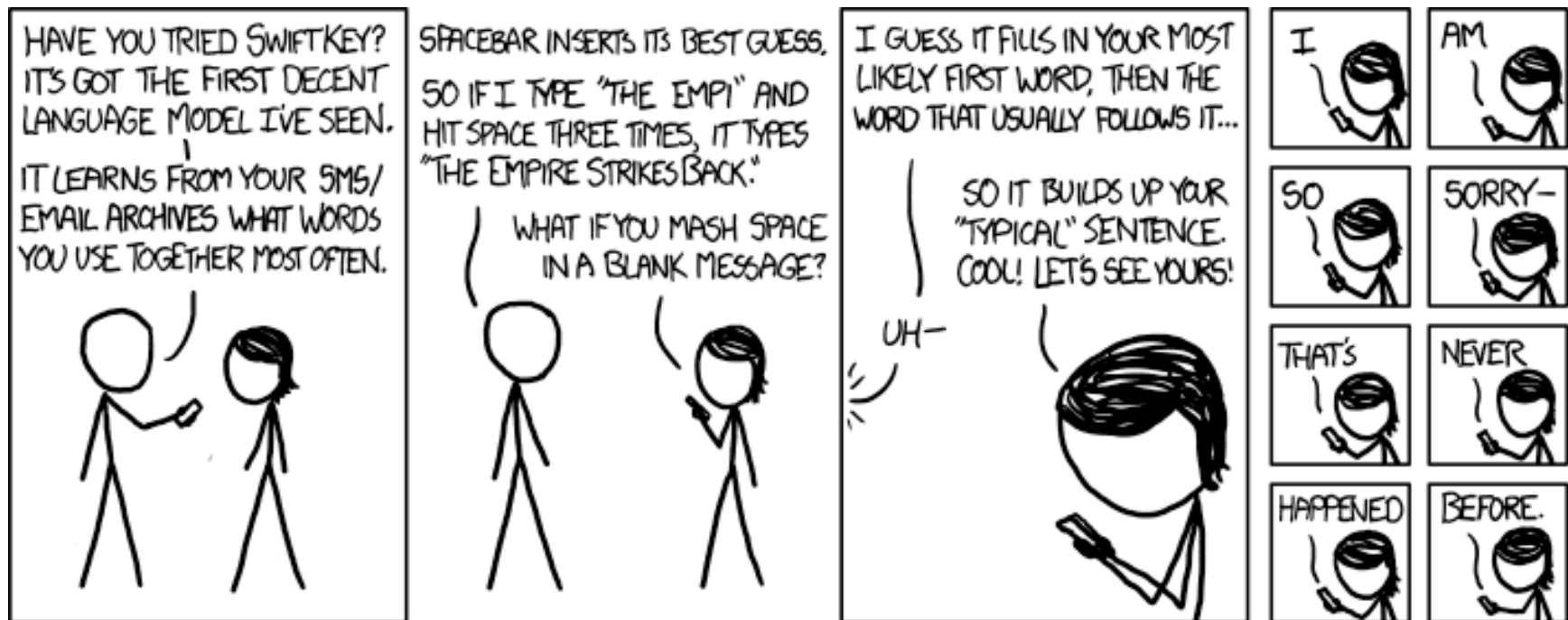
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Classify it

Delete all spam messages now (messages that have been in Spam more than 30 days will be automatically deleted)

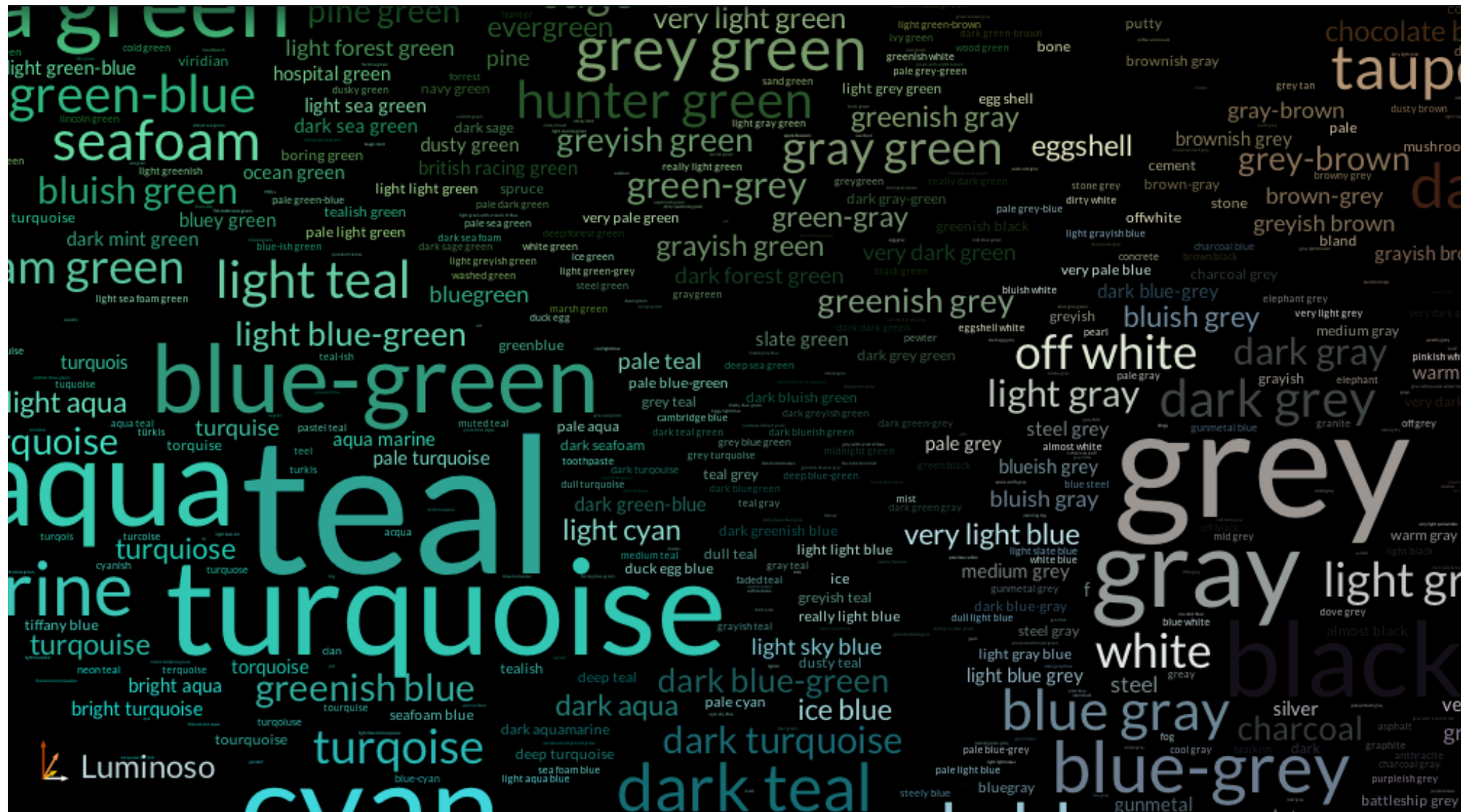
<input type="checkbox"/>			Regal Ecigs	Trial - Smoke Almost Anywhere! - Trial - Smoke Almost Anywhere!	
<input type="checkbox"/>			Loan Department	All Credit OK - Up to 1000 dollars - All Credit OK - Up to 1000 dollars	
<input type="checkbox"/>			Next Payday Advance	Need emergency cash? Let us help you. - Get the funds you need in 1 hour.	
<input type="checkbox"/>			Kohls Summer Savings Gif.	Are you tired of all the cold weather and ready for Summer? Complete ou	
<input type="checkbox"/>			da_30	FEEM2013—Submissions due: July 30th,2013 - 2013 International Confe	
<input type="checkbox"/>			Harp Mortgage	President Announced the HARP Program. Save Thousands a Year on Yc	
<input type="checkbox"/>			Jacuzzi Walk In Hot Tubs	Soak away life's aches and pains with a walk in hot tub - Soak away life's a	
<input type="checkbox"/>			Fingerhut Friends	Fingerhut: Best Gifts, Low Payments! Open Your Account Today!* - Finge	
<input type="checkbox"/>			The LASIK Vision Institu.	Looking for more freedom from your glasses? Get Lasik info - Looking for	
<input type="checkbox"/>			KaplanUniversity	KaplanUniversity online & campus degree programs available - KaplanUr	
<input type="checkbox"/>			Vistaprint Offers	Buy 250 Premium Business Cards get 250 More Free from Vistaprint! - Bu	
<input type="checkbox"/>			Lifestyle Lift	Look more beautiful with alot less risk - Look more beautiful with alot less ris	
<input type="checkbox"/>			MetLife Partner	Get \$250k in Term Life Insurance - as low as \$16/mo. - Get \$250k in Term L	
	<input type="checkbox"/>			NextPaydayAdvance	You Could Have 1,500 Cash Wired Into Your Account - Apply Now - You C

Predict it



"SwiftKey" from xkcd
<http://xkcd.com/1068/>

Visualize and explore it

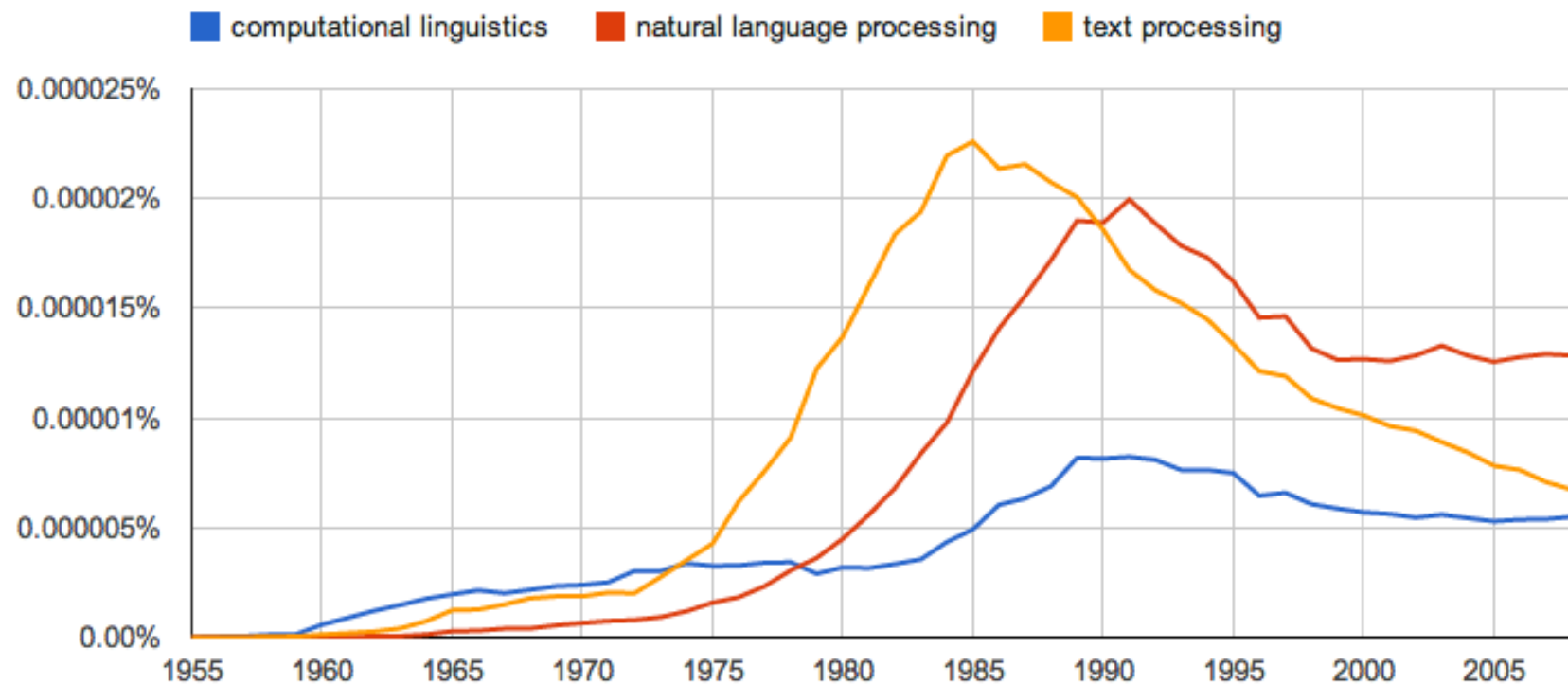


How is the text represented?

Simple word counts



N-gram models



Term-document matrices

	woe	betray	vengeance	death	alas
<i>Julius Caesar</i>	2	1	0	29	8
<i>Hamlet</i>	8	0	2	37	9
<i>Macbeth</i>	2	2	0	20	4

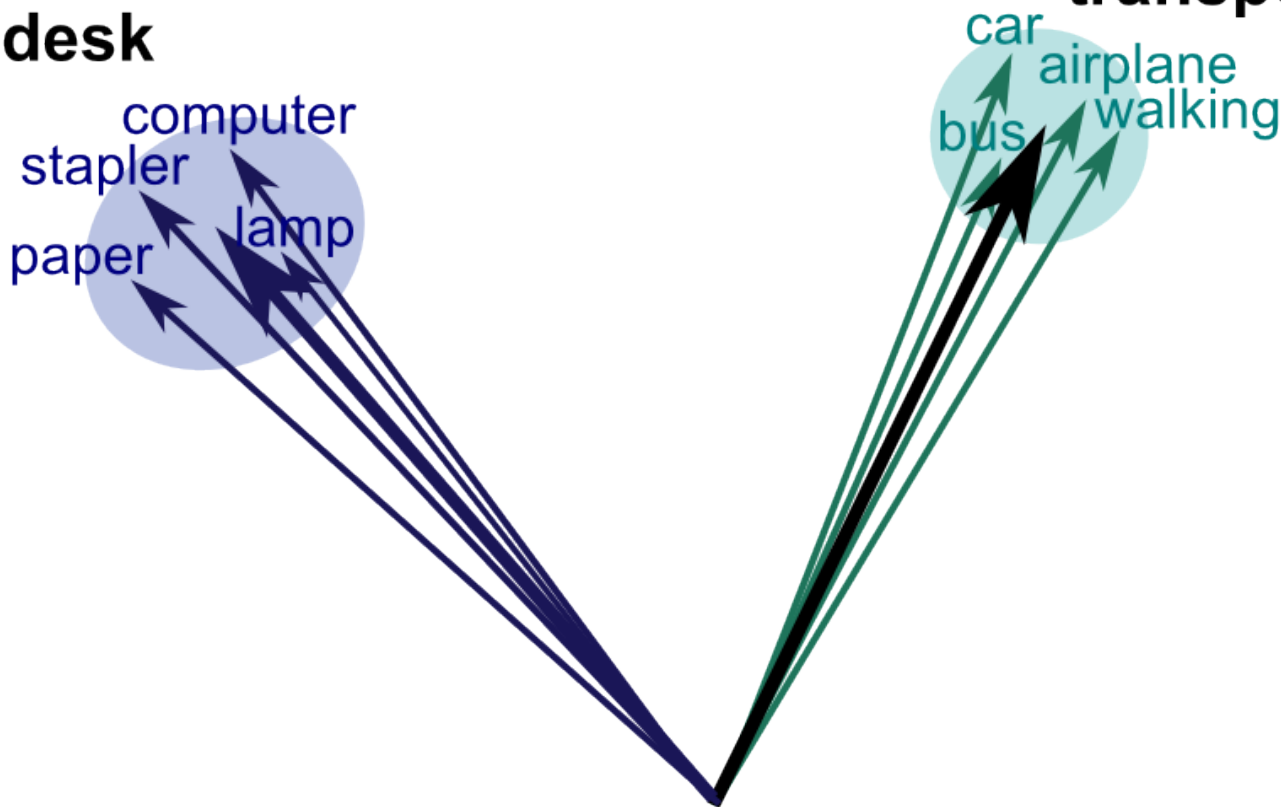
Vector space models

**things on
my desk**

computer
stapler
paper
lamp

**modes of
transportation**

car
airplane
bus
walking



Python example: word splitting and normalizing

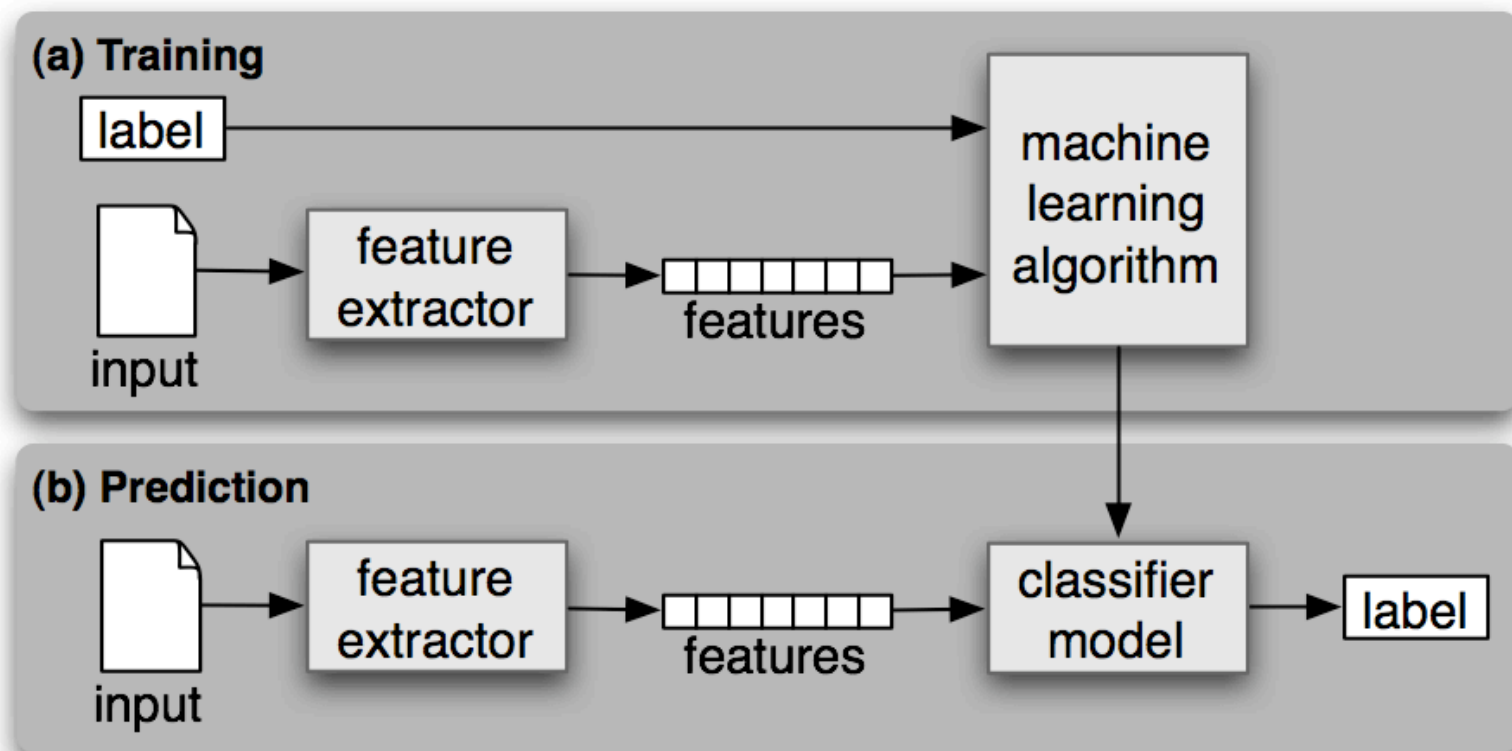
Which N-grams are interesting?

Consider this contingency table:

$p(\mathbf{vice},$ $\mathbf{president})$	$p(\mathbf{vice},$ $\sim\mathbf{president})$
$p(\sim\mathbf{vice},$ $\mathbf{president})$	$p(\sim\mathbf{vice},$ $\sim\mathbf{president})$

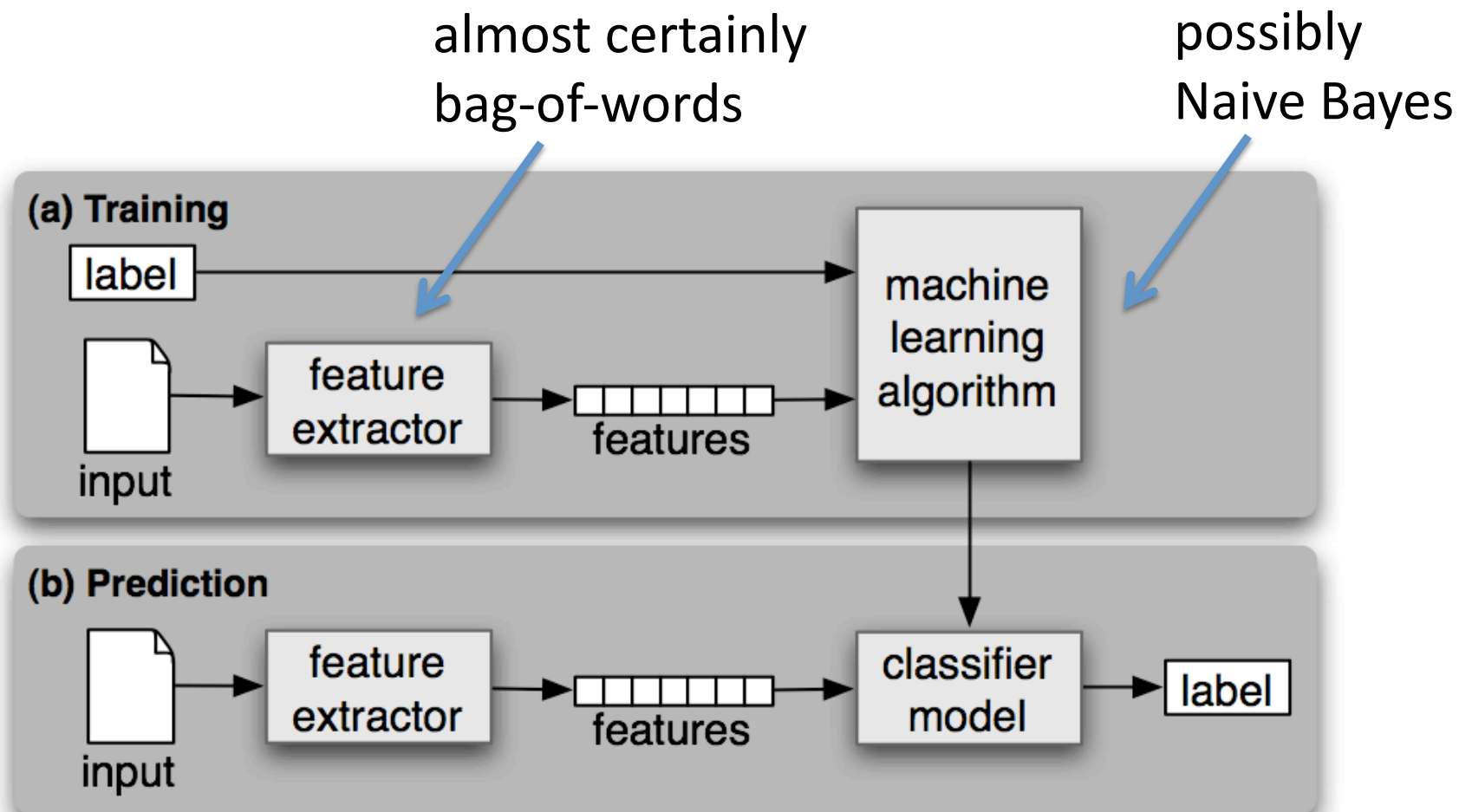
Python example: interesting N-grams

Text classification



from "Natural Language Processing with Python",
by Steven Bird, Ewan Klein, and Edward Loper (O'Reilly, 2009)

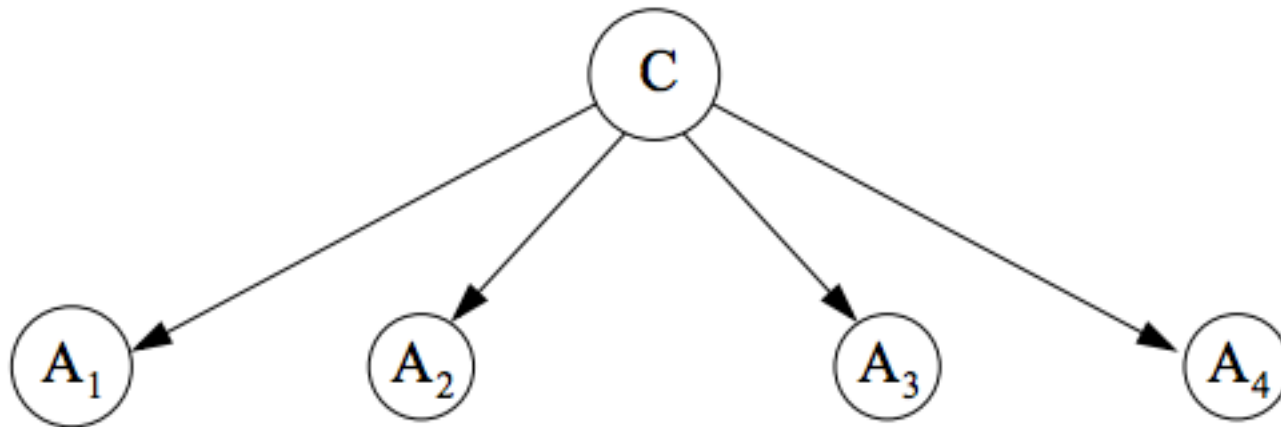
Text classification



from "Natural Language Processing with Python",
by Steven Bird, Ewan Klein, and Edward Loper (O'Reilly, 2009)

Overview of Naïve Bayes classification

- The probability that a document is in class C depends on its features, A_n
- Assume all features are statistically independent



Python example: Classification with NLTK and scikit-learn

What about stopwords?

- Shouldn't we remove common words such as "the" and "of"?
- It could help
- It could be premature optimization

Text similarity

- Bags of words can tell us how similar documents are

	woe	betray	vengeance	death	alas
<i>Julius Caesar</i>	2	1	0	29	8
<i>Hamlet</i>	8	0	2	37	9
<i>Macbeth</i>	2	2	0	20	4

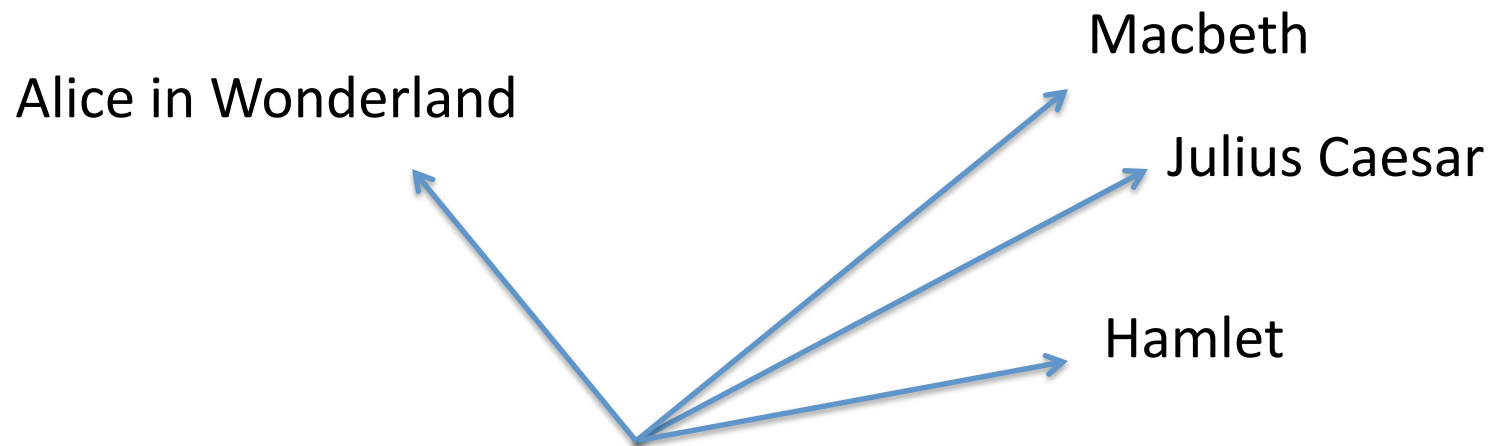
Text similarity

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<i>Julius Caesar</i>	2	1	0	29	8
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<i>Macbeth</i>	2	2	0	20	4
<i>Alice in Wonderland</i>	0	0	0	1	4

Vector-space similarity

- Similar texts have a small angle between them

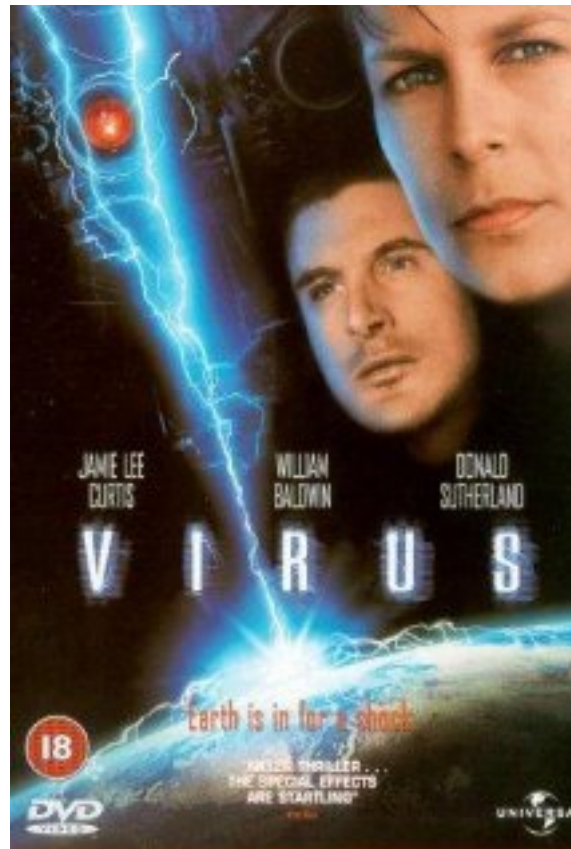


Dimensionality reduction

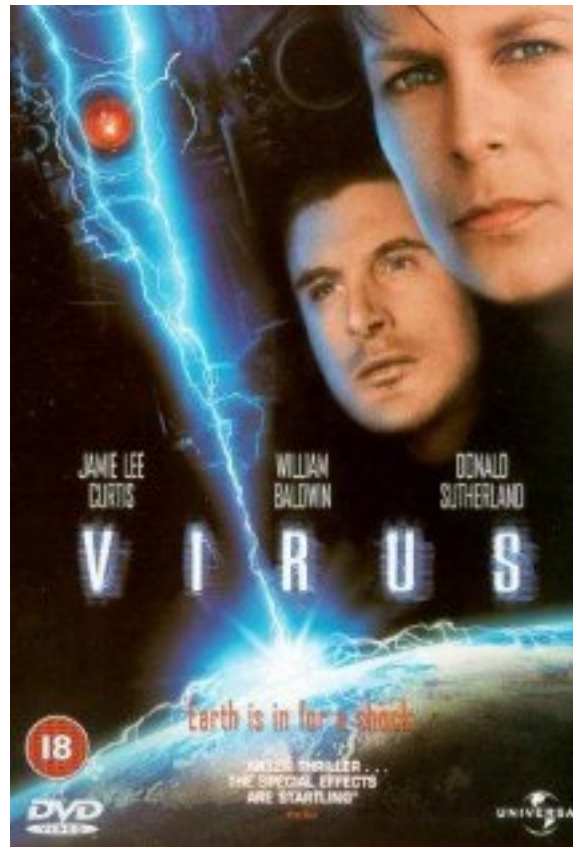
- Put terms and documents in a lower-dimensional space where we can easily compare them
- In NLP, this is called Latent Semantic Analysis or Latent Semantic Inference

Python example: Unsupervised text similarity using gensim

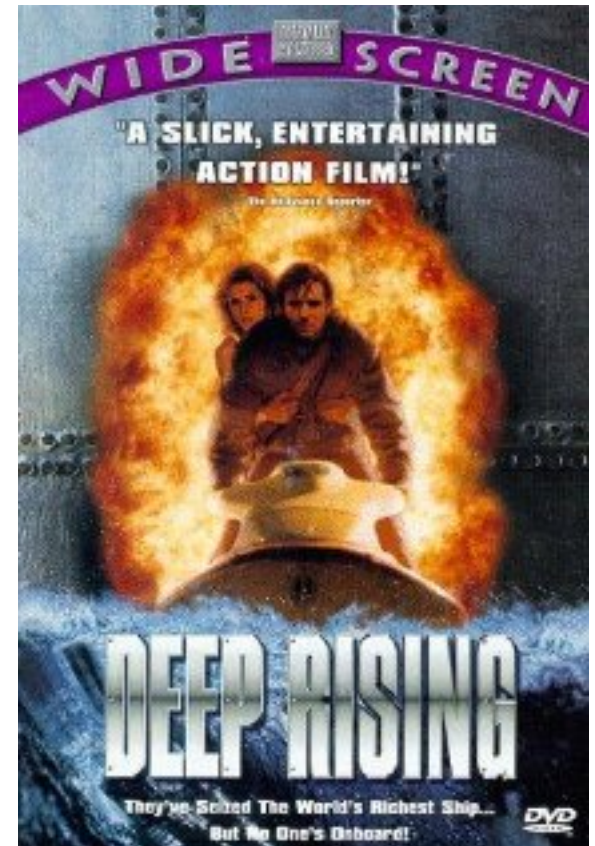
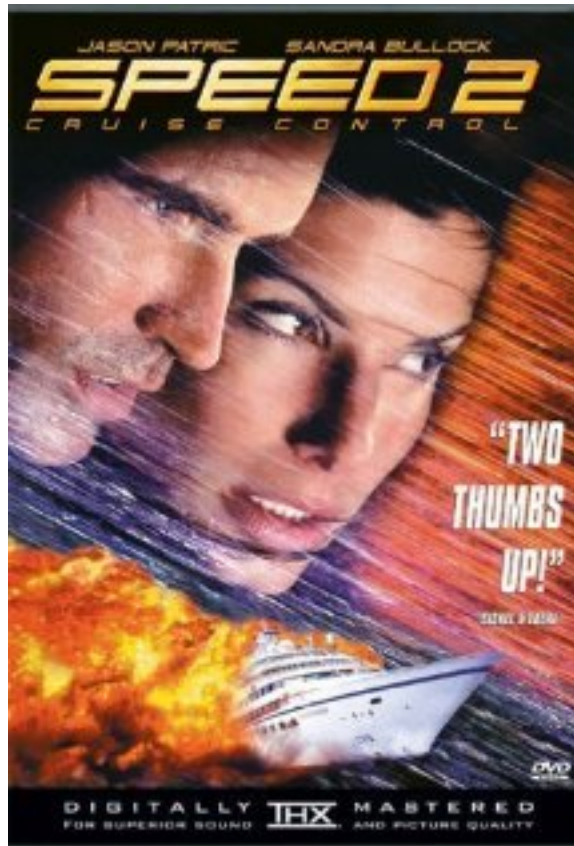
Similarity of movie reviews



Similarity of movie reviews



Similarity of movie reviews



Word associations

Word associations

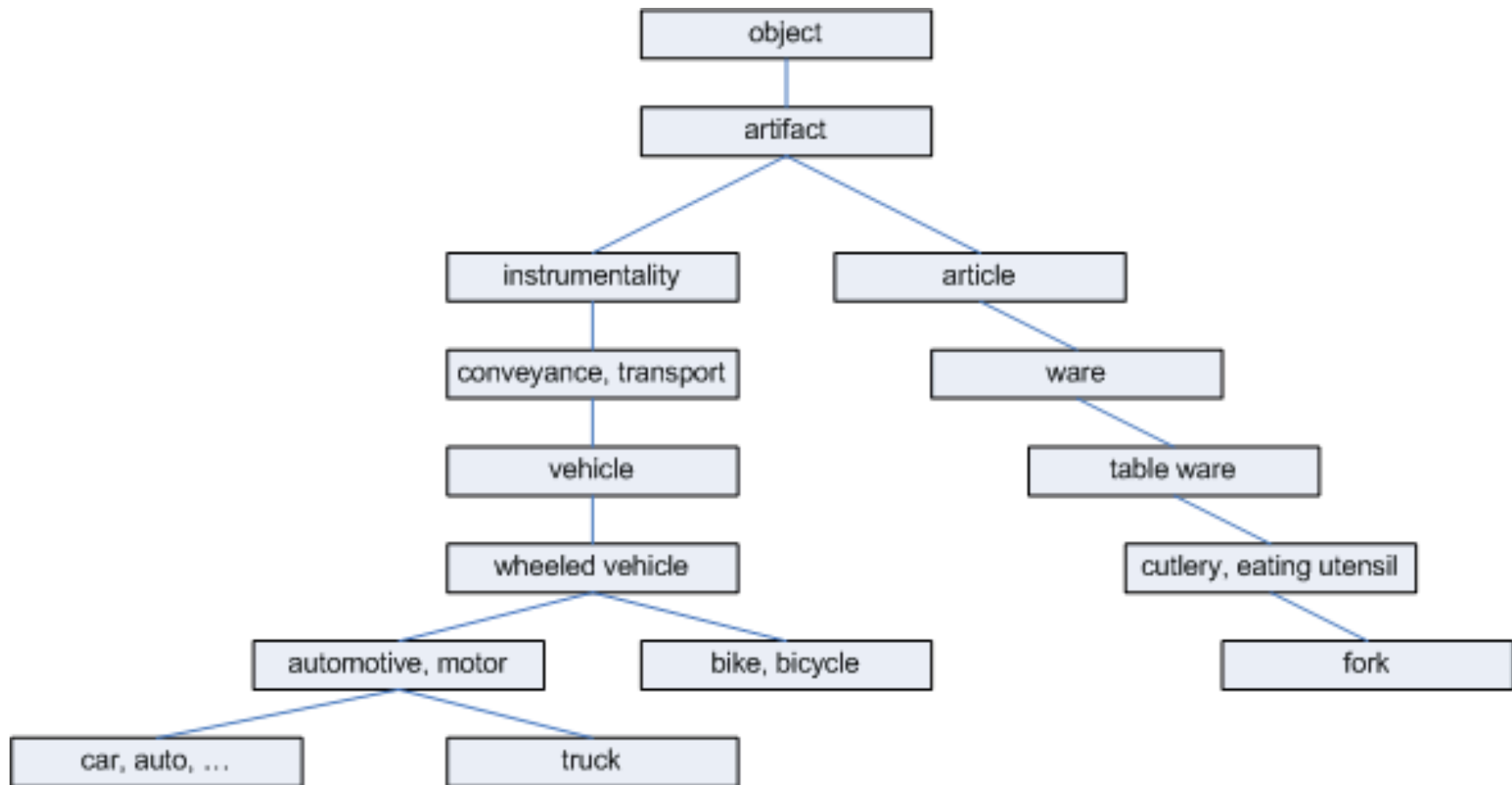
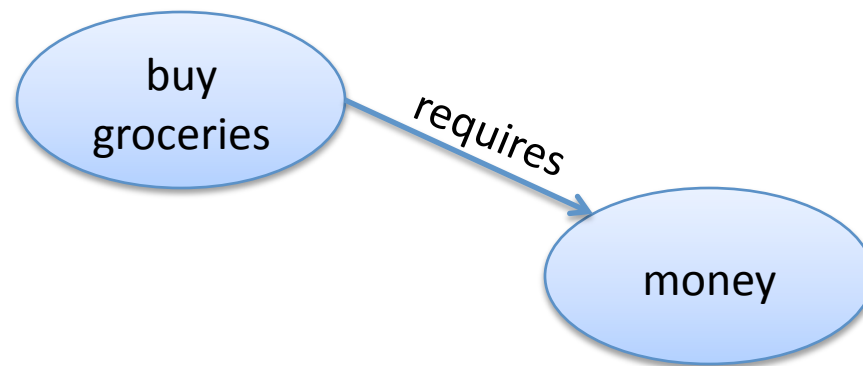
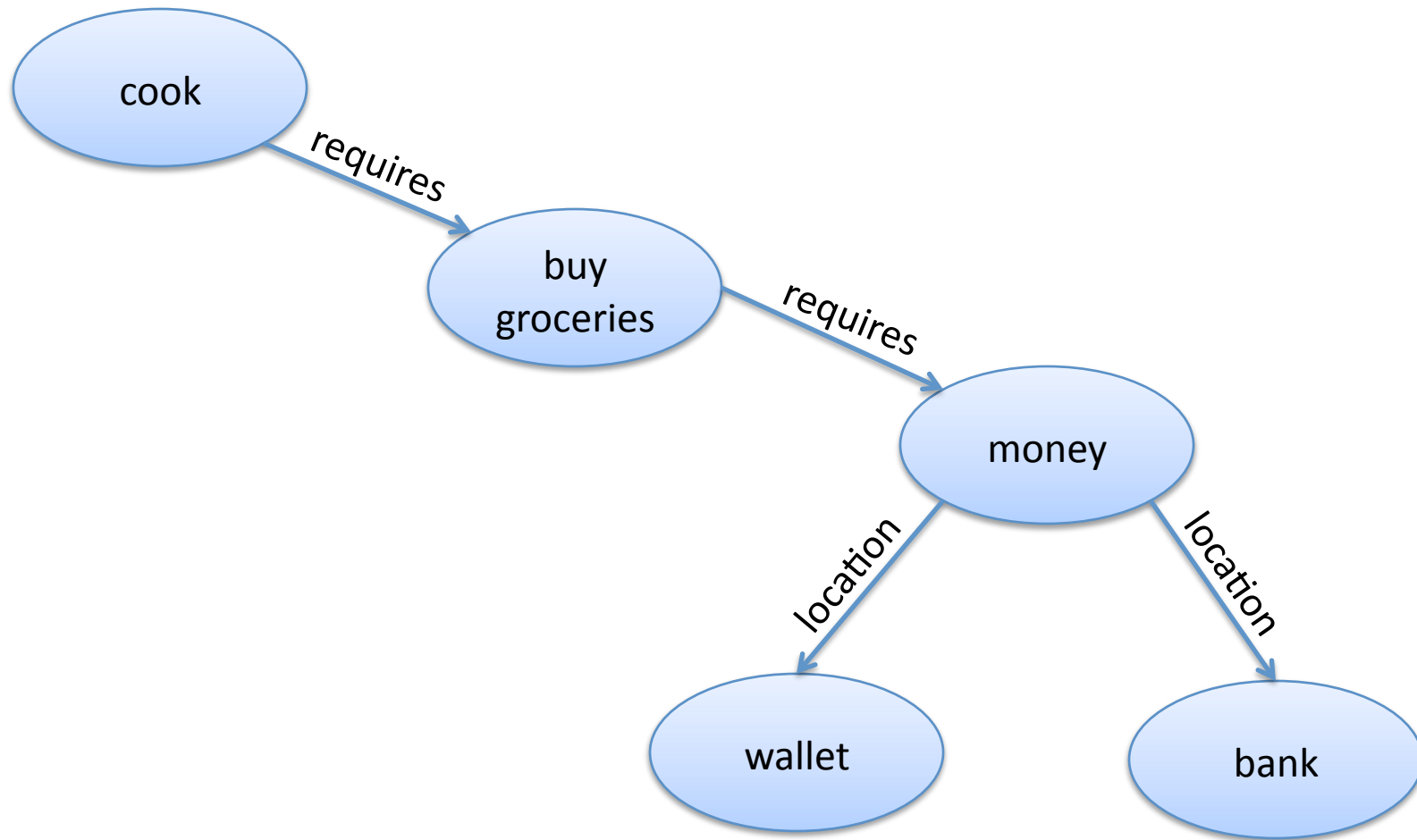
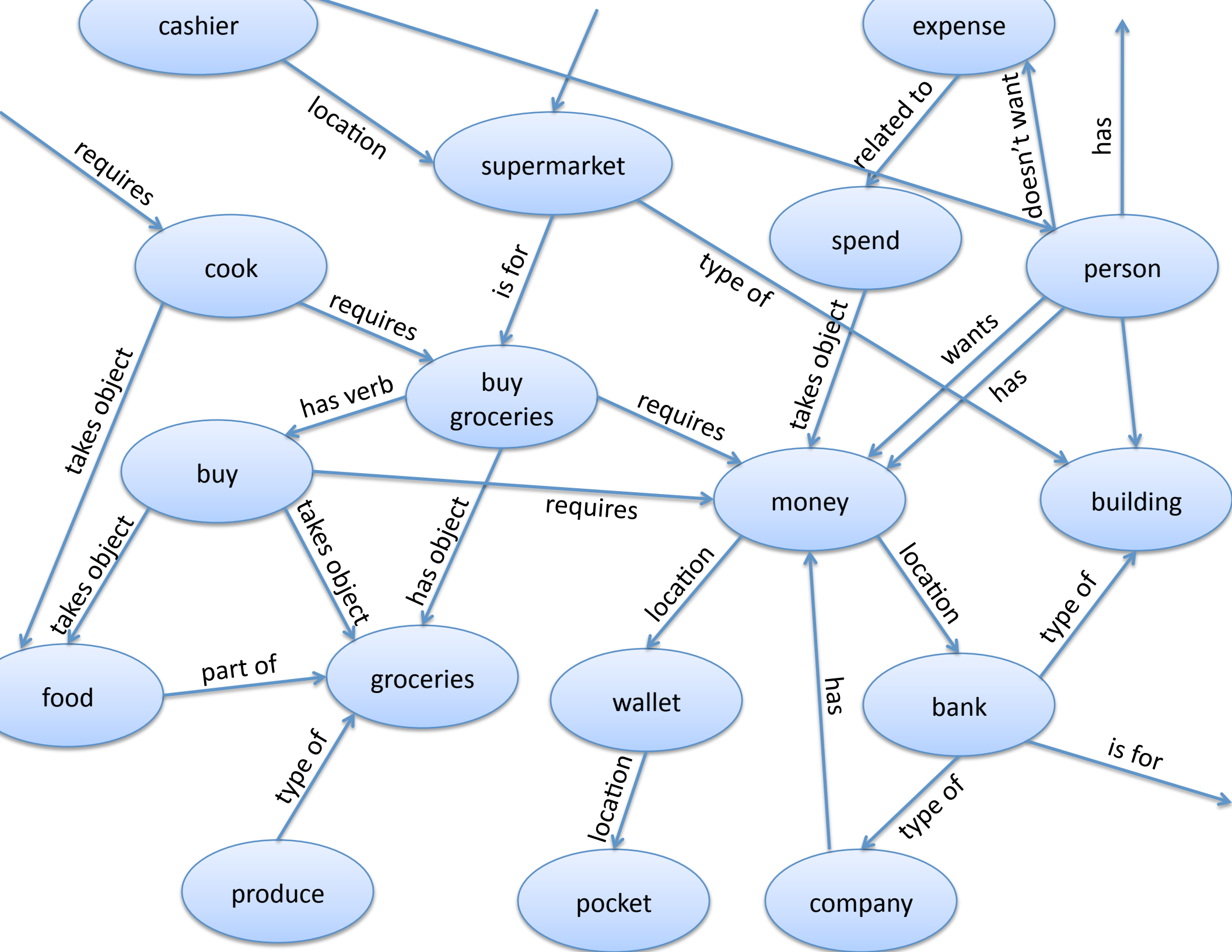


Image source: “WordNet-based semantic similarity measurement”
by Troy Simpson and Thanh Dao, on codeproject.com

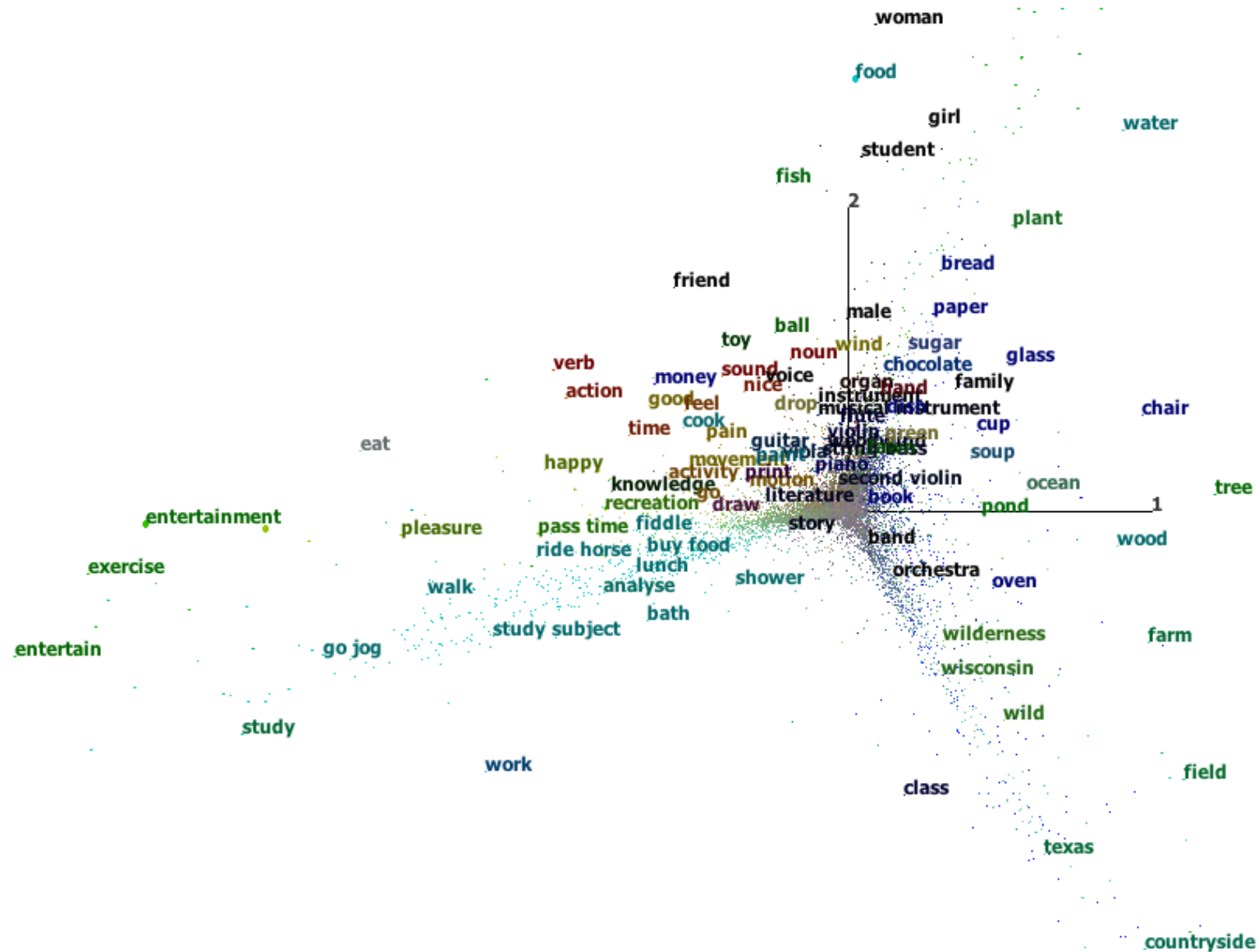
Python example: Querying WordNet







ConceptNet as a vector space



Python example: Querying ConceptNet

- See API documentation at:

<http://conceptnet5.media.mit.edu>

Many incompatible systems

- Supervised text classification
- Unsupervised document similarity
- Domain-general word associations

Many incompatible systems

- Supervised text classification
 - Unsupervised document similarity
 - Domain-general word associations
-
- It would be nice if one model could do all of these.



NLP with “batteries included”

- **nltk** (the basics)
- **scikit-learn** (classification)
- **gensim** (text similarity)
- Interfaces to **WordNet** and **ConceptNet**
(word associations)

What is Python missing?

- A good search index.

What is Python missing?

- A good search index.
- Recommendation: use Lucene, or something that uses Lucene.

That's all

Code and slides:

<http://github.com/rspeer/text-as-data>

Cool things I work on:

<http://conceptnet5.media.mit.edu>

<http://luminoso.com>

Extra slides

TF-IDF normalization

- Some documents are longer than others
- Some words appear more than others

	woe	betray	vengeance	death	alas
<i>Julius Caesar</i>	55.0	32.9	0	0	219.9
<i>Hamlet</i>	38.0	0	73.1	0	171.0
<i>Macbeth</i>	61.4	73.5	0	0	122.7
<i>Alice in Wonderland</i>	0	0	0	0	83.2

(TF-IDF values from NLTK's Project Gutenberg corpus,
in micro-bits per word)

TF-IDF normalization

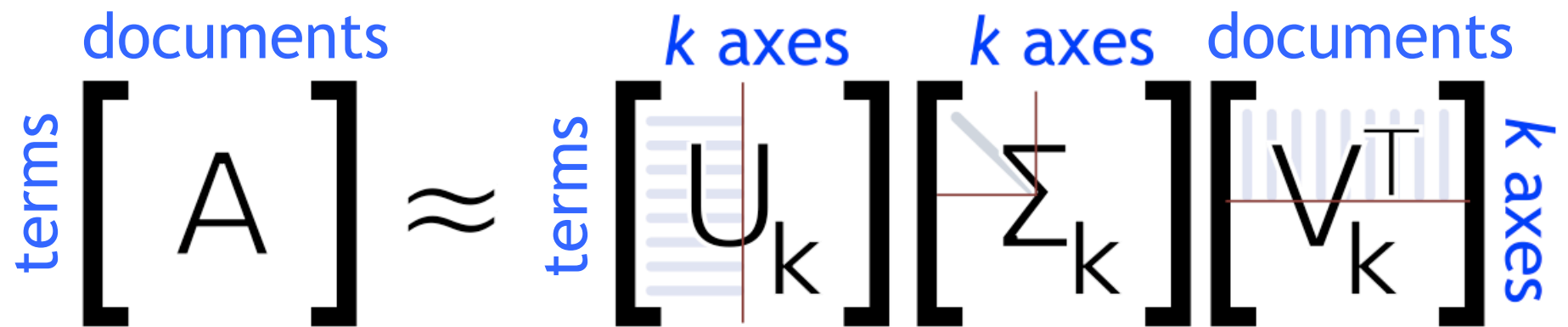
- TF replaces term counts with term frequencies
- IDF tells us how much information we get when a word appears
- In Project Gutenberg:
 - $\text{IDF}(\text{the}) = 0$ bits
 - $\text{IDF}(\text{vengeance}) = 1.36$ bits
 - $\text{IDF}(\text{whale}) = 2.17$ bits
 - $\text{IDF}(\text{Ishmael}) = 3.17$ bits

Dimensionality reduction

$$\begin{array}{c} \text{documents} \\ \text{terms} \end{array} \begin{bmatrix} A \end{bmatrix} = \begin{array}{c} \text{terms} \\ \text{axes} \end{array} \begin{bmatrix} U \end{bmatrix} \begin{array}{c} \text{axes} \\ \text{axes} \end{array} \begin{bmatrix} \Sigma \end{bmatrix} \begin{array}{c} \text{documents} \\ \text{axes} \end{array} \begin{bmatrix} V^T \end{bmatrix}$$

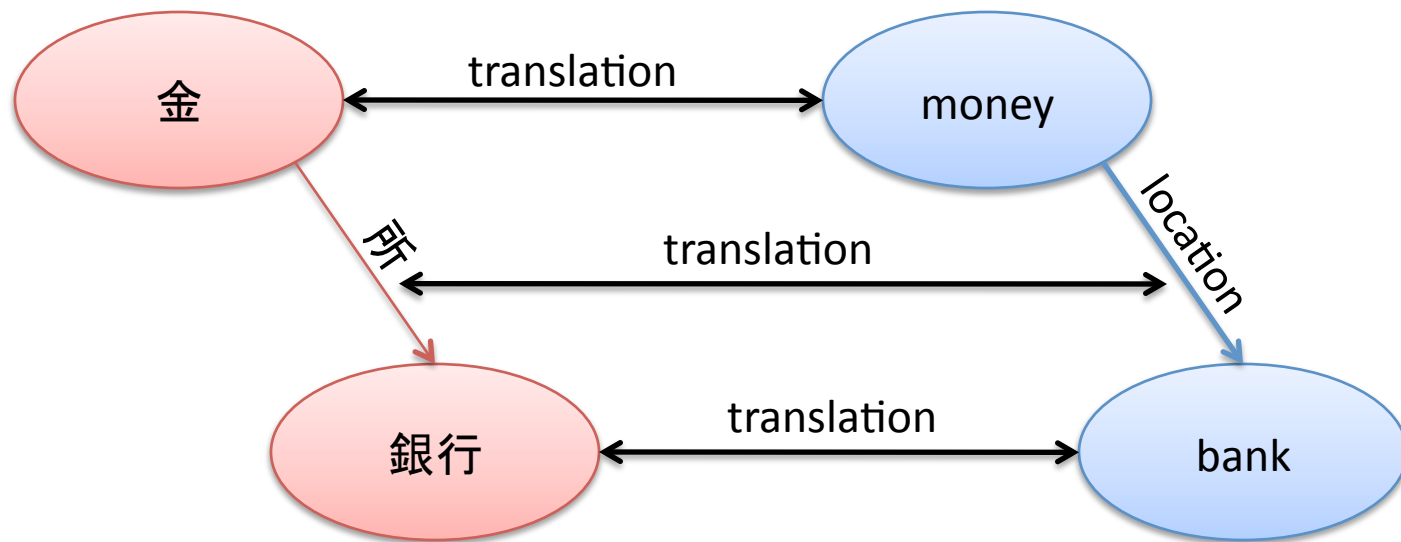
The diagram illustrates the Singular Value Decomposition (SVD) of a matrix A . The matrix A is labeled with 'documents' above and 'terms' to the left. It is equal to the product of three matrices: U , Σ , and V^T . Matrix U is labeled with 'terms' to the left and 'axes' above. Matrix Σ is labeled with 'axes' above and 'axes' to the right. Matrix V^T is labeled with 'documents' above and 'axes' to the right. The matrix U is represented by horizontal blue lines, Σ by a diagonal line, and V^T by vertical blue lines.

Dimensionality reduction



The diagram illustrates the process of dimensionality reduction using matrix factorization. It shows the approximation of a matrix A as the product of three matrices: U_k , Σ_k , and V_k^T . The matrix A is labeled with "terms" on the left and "documents" on top. The matrix U_k is labeled with "terms" on the left and "k axes" on top. The matrix Σ_k is labeled with "k axes" on top. The matrix V_k^T is labeled with "documents" on top and "k axes" on the right. The approximation is indicated by the symbol \approx . The matrices U_k and V_k^T are represented by light blue shaded rectangles with a vertical red line, indicating they are $k \times n$ matrices. The matrix Σ_k is represented by a light blue shaded rectangle with a diagonal red line, indicating it is a $k \times k$ diagonal matrix. A small grey arrow points from the top-right corner of U_k towards the bottom-left corner of Σ_k .

$$\begin{array}{c} \text{terms} \end{array} \begin{array}{c} \text{documents} \\ [A] \end{array} \approx \begin{array}{c} \text{terms} \end{array} \begin{array}{c} k \text{ axes} \\ [U_k] \end{array} \begin{array}{c} k \text{ axes} \\ [\Sigma_k] \end{array} \begin{array}{c} \text{documents} \\ [V_k^T] \end{array} \begin{array}{c} k \text{ axes} \end{array}$$



But Naïve Bayes is so naïve!

- Sure, its fundamental assumption is wrong
- Often, it works anyway
- On NLP tasks, NB is blazingly fast and surprisingly effective

(See “The Optimality of Naive Bayes”, Harry Zhang, AAAI 2004)