

Information Retrieval (IN4325)

Syntax

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Admin

- NLP project proposal: due March 22
- Interviews are also on theory
- Remember office hours 9 -11.30 am on Fri, by appointment!
- P8: Hovy, Dirk, and Shannon L. Spruit. "The social impact of natural language processing." Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers). Vol. 2. 2016.

Last time ...

- The function of Natural Language Processing
- NLP applications
- Typical natural processing tasks
- Typical components/sub-tasks

Some terms

Normalization

Stemming

Lemmatization

Segmentation

Tokenization

Stopwords

Today you will learn about Syntax

Syntax - comes from the greek

sýntaxis ($\sigmaύνταξις$) (*coordination*)

$\sigmaύν$ *syn*, "together", and $\tauάξις$ *táxis*, "an ordering"

Refers to the way words are arranged together.

Ambiguity makes NLP hard: “Crash blossoms”

Teacher Strikes Idle Kids
Hospitals Are Sued by 7 Foot Doctors
Juvenile Court to Try Shooting Defendant

Applications: Sentiment Analysis



Great processor, but the memory **sucks**

This vacuum cleaner really **sucks**



Sentiment Analysis

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

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
 - Phrase, sentence, or entire document

Named Entity Recognition

In 1917, Einstein applied the general theory of relativity to model the large-scale structure of the universe. He was visiting the United States when Adolf Hitler came to power in 1933 and did not go back to Germany, where he had been a professor at the Berlin Academy of Sciences. He settled in the U.S., becoming an American citizen in 1940. On the eve of World War II, he endorsed a letter to President Franklin D. Roosevelt alerting him to the potential development of "extremely powerful bombs of a new type" and recommending that the U.S. begin similar research. This eventually led to what would become the Manhattan Project. Einstein supported defending the Allied forces, but largely denounced using the new discovery of nuclear fission as a weapon. Later, with the British philosopher Bertrand Russell, Einstein signed the Russell-Einstein Manifesto, which highlighted the danger of nuclear weapons. Einstein was affiliated with the Institute for Advanced Study in Princeton, New Jersey, until his death in 1955.

Tag colours:

LOCATION TIME PERSON ORGANIZATION MONEY PERCENT DATE

Syntax

- **Part-of-speech (POS) tagging**
 - Deep parsing
 - Shallow parsing
- **Language models**
 - Markov Chains: N-grams
 - Smoothing
 - Interpolation
 - Backoff
 - Web-Scale language models
- **Applications**
 - Named-entity recognition
 - Sentiment analysis

The Parts of Speech



Every name is called a **noun**,
As *field* and *fountain*, *street* and *town*.
In place of noun the **pronoun** stands,
As *he* and *she* can clap their hands.

The **adjective** describes a thing,
As *magic* wand or *bridal* ring.
The **verb** means action, something done,
To *read* and *write*, to *jump* and *run*.

How things are done the **adverbs** tell,
As *quickly*, *slowly*, *badly*, *well*.
The **preposition** shows relation,
As *in* the street or *at* the station.

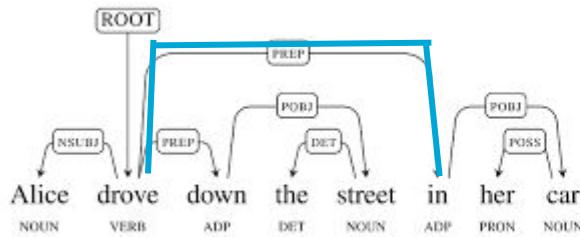
Conjunctions join, in many ways,
Sentences, words, *or* phrase *and* phrase.

The **interjection** cries out, "Hark!
I need an exclamation mark!"

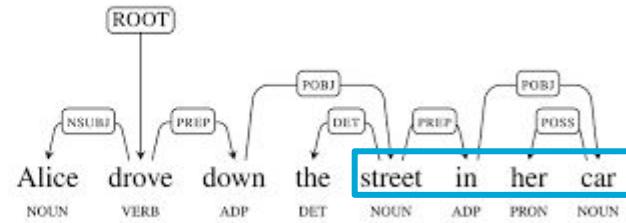
Through Poetry, we learn how each
of these make up **THE PARTS OF SPEECH**.



Part-of-speech tagging



Alice is driving in her car



Or the street is located in her car.

The ambiguity arises because the preposition *in* can either modify *drove* or *street*; this example is an instance of what is called *prepositional phrase attachment ambiguity*.

Part-of-speech tagging

Helps with

- Stemming
- Select particular information e.g., nouns, named entities
- Parsing
- Word sense disambiguation (e.g., **interest**)

Tagsets

- Penn Treebank (45)
- Brown corpus (87)
- Dutch training data in NLTK, e.g., CONLL 2002 (conll2002)

POS, word classes, morphological classes, or lexical tags

Part-of-speech tagging

The/**DT** grand/**JJ** jury/**NN** comment/**VBD** on/**IN** a/**DT** number/**NN** of/**IN** other/**JJ** topics/**NNS**.

Tag	Description	Example	Tag	Description	Example
CC	coordin. conjunction	<i>and, but, or</i>	SYM	symbol	+%, &
CD	cardinal number	<i>one, two, three</i>	TO	“to”	<i>to</i>
DT	determiner	<i>a, the</i>	UH	interjection	<i>ah, oops</i>
EX	existential ‘there’	<i>there</i>	VB	verb, base form	<i>eat</i>
FW	foreign word	<i>mea culpa</i>	VBD	verb, past tense	<i>ate</i>
IN	preposition/sub-conj	<i>of, in, by</i>	VBG	verb, gerund	<i>eating</i>
JJ	adjective	<i>yellow</i>	VBN	verb, past participle	<i>eaten</i>
JJR	adj., comparative	<i>bigger</i>	VBP	verb, non-3sg pres	<i>eat</i>
JJS	adj., superlative	<i>wildest</i>	VBZ	verb, 3sg pres	<i>eats</i>
LS	list item marker	<i>1, 2, One</i>	WDT	wh-determiner	<i>which, that</i>
MD	modal	<i>can, should</i>	WP	wh-pronoun	<i>what, who</i>
NN	noun, sing. or mass	<i>llama</i>	WP\$	possessive wh-	<i>whose</i>
NNS	noun, plural	<i>llamas</i>	WRB	wh-adverb	<i>how, where</i>
NNP	proper noun, singular	<i>IBM</i>	\$	dollar sign	\$
NNPS	proper noun, plural	<i>Carolinas</i>	#	pound sign	#
PDT	predeterminer	<i>all, both</i>	“	left quote	‘ or “
POS	possessive ending	<i>'s</i>	”	right quote	’ or ”
PRP	personal pronoun	<i>I, you, he</i>	(left parenthesis	[, (, {, <
PRP\$	possessive pronoun	<i>your, one's</i>)	right parenthesis],), }, >
RB	adverb	<i>quickly, never</i>	,	comma	,
RBR	adverb, comparative	<i>faster</i>	.	sentence-final punc	. ! ?
RBS	adverb, superlative	<i>fastest</i>	:	mid-sentence punc	: ; ... - -
RP	particle	<i>up, off</i>			

Part-of-speech tagging

Ambiguity:

Book/VB that/DT flight/NN./.

Book/NN that/DT flight/NN./.

Rule-based tagging

Statistical methods: Markov chains and n-grams

Transformation-base tagging and memory-tagging

Syntax

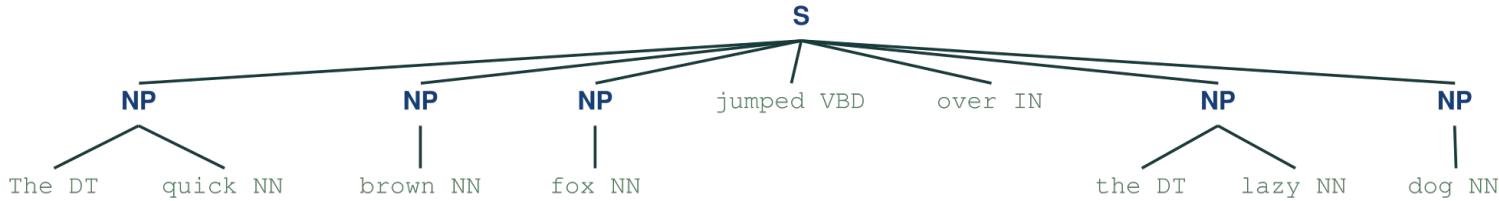
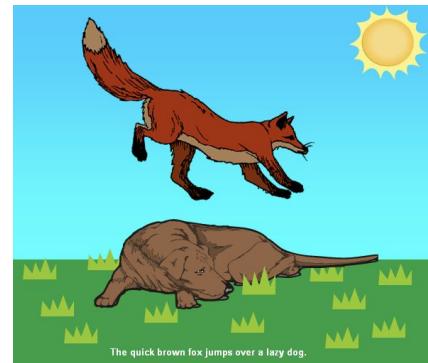
Part 1:

- Part-of-speech (POS)
- **Parsing**
- Language modeling

Part 2:

- Sentiment analysis
- Named-entity recognition

Parsing

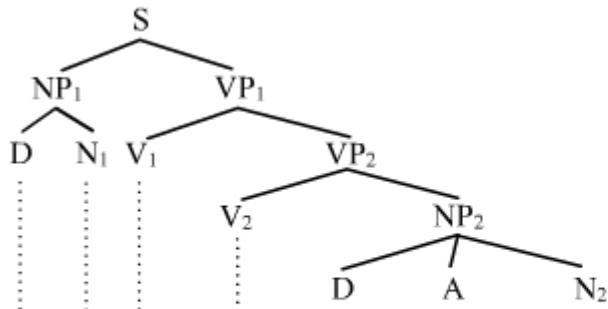


Parser

- **Input:** Text
- **Output:** Linguistic structure
- Can be for PoS tagging, disambiguation etc
- Dependency grammars versus phrase structure grammars
- Deep parsing versus shallow parsing

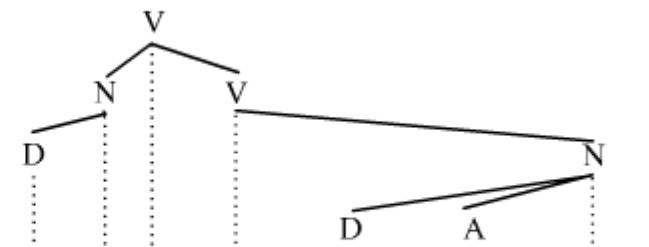
Grammars

- Dependency grammar
 - one-to-one correspondence element/constituent, less ambiguous
 - dependency grammars are word (or morph) grammars.
 - Dependency structures are more minimal, much fewer nodes.
- Phrase structure (context-free/constituency) grammars
 - Constituency is a one-to-one-or-more correspondence
 - More information



This tree is illustrating the constituency relation.

Constituency relation (PSG)



This tree is illustrating the dependency relation.

Dependency relation

Parsing versus Chunking

- Partial parse = shallow parse
- Identify segments that are likely to contain valuable information.

Chunking

- Identify major PoS types: nouns, verbs, adjectives, prepositional phrases
- Used e.g., for named entity recognition
- No hierarchical structure
- Type of **sequential classification**

Chunking example: IOB tagging

Beginning (**B**), internal (**I**), outside (**O**) of a chunk:

The morning flight from Denver has arrived.
B_NP **I_NP** **I_NP** **B_PP** **B_NP** **B_VP** **I_VP**

Only NP tags gives:

The morning flight from Denver has arrived.
B_NP **I_NP** **I_NP** **O** **B_NP** **O** **O**

Syntax

Part 1:

- Part-of-speech (POS)
- Parsing
- **Language modeling**

Part 2:

- Sentiment analysis
- Named-entity recognition

Why?

Probabilistic Language Models

Assign a probability to a sentence

- Machine Translation:
 - $P(\text{high winds tonite}) > P(\text{large winds tonite})$
- Spell Correction
 - The office is about fifteen **minutes** from my house
 - $P(\text{about fifteen minutes from}) > P(\text{about fifteen minutse from})$
- Speech Recognition
 - $P(\text{I saw a van}) \gg P(\text{eyes awe of an})$
- + Summarization, question-answering, etc., etc.!!

Probabilistic Language Modeling

- Goal: compute the probability of a sentence or sequence of words:
 - $P(W) = P(w_1, w_2, w_3, w_4, w_5 \dots w_n)$
- Related task: probability of an upcoming word:
 - $P(w_5 | w_1, w_2, w_3, w_4)$
- A model that computes either of these:
 - $P(W)$ or $P(w_n | w_1, w_2 \dots w_{n-1})$ is called a **language model**.
- Better: **the grammar**
- But **language model** or **LM** is standard

Maximum Likelihood Estimates

- The maximum likelihood estimate
 - of some parameter of a model M from a training set T
 - maximizes the likelihood of the training set T given the model M
- Suppose the word “banana” occurs 400 times in a corpus of a million words
- What is the probability that a random word from some other text will be “banana”?
- MLE estimate is $400/1,000,000 = .0004$
- This may be a bad estimate for some other corpus
 - But it is the **estimate** that makes it **most likely** that “banana” will occur 400 times in a million word corpus.



How to compute $P(W)$

- How to compute this joint probability:
 - $P(\text{its, water, is, so, transparent, that})$
- Intuition: let's rely on the Chain Rule of Probability

The Chain Rule

- Conditional probability: $P(B|A)$
- More variables:
 - $P(A,B,C,D) = P(A) P(B|A) P(C|A,B) P(D|A,B,C)$
- The Chain Rule in General
- $P(x_1, x_2, x_3, \dots, x_n) = P(x_1) P(x_2|x_1) P(x_3|x_1, x_2) \dots P(x_n|x_1, \dots, x_{n-1})$

The Chain Rule applied to compute joint probability of words in sentence

$$P(w_1 w_2 \dots w_n) = \prod_i P(w_i | w_1 w_2 \dots w_{i-1})$$

$P(\text{"its water is so transparent"}) =$

$P(\text{its}) \times P(\text{water}|\text{its}) \times P(\text{is}|\text{its water})$

$\times P(\text{so}|\text{its water is}) \times P(\text{transparent}|\text{its water is so})$

How to estimate these probabilities

- Could we just count and divide?

$$P(\text{the} \mid \text{its water is so transparent that}) =$$
$$\frac{\text{Count}(\text{its water is so transparent that the})}{\text{Count}(\text{its water is so transparent that})}$$

- No! Too many possible sentences!
- We'll never see enough data for estimating these



Andrei Markov

Markov Assumption

- Simplifying assumption:

$$P(\text{the} \mid \text{its water is so transparent that}) \approx P(\text{the} \mid \text{that})$$

- Or maybe

$$P(\text{the} \mid \text{its water is so transparent that}) \approx P(\text{the} \mid \text{transparent that})$$

Markov Assumption

$$P(w_1 w_2 \dots w_n) \approx \prod_i P(w_i | w_{i-k} \dots w_{i-1})$$

- In other words, we approximate each component in the product

$$P(w_i | w_1 w_2 \dots w_{i-1}) \approx P(w_i | w_{i-k} \dots w_{i-1})$$

Simplest case: Unigram model

$$P(w_1 w_2 \dots w_n) \approx \prod_i P(w_i)$$

Automatically generated sentences from a unigram model:

fifth, an, of, futures, the, an, incorporated, a, a,
the, inflation, most, dollars, quarter, in, is, mass

thrift, did, eighty, said, hard, 'm, july, bullish

that, or, limited, the

Bigram model

- Condition on the previous word:

$$P(w_i \mid w_1 w_2 \dots w_{i-1}) \approx P(w_i \mid w_{i-1})$$

texaco, rose, one, in, this, issue, is, pursuing,
growth, in, a, boiler, house, said, mr., gurria,
mexico, 's, motion, control, proposal, without,
permission, from, five, hundred, fifty, five, yen

outside, new, car, parking, lot, of, the,
agreement, reached

this, would, be, a, record, november

N-gram models

- We can extend to trigrams, 4-grams, 5-grams
- In general this is an insufficient model of language
 - because language has **long-distance dependencies**:

“The computer which I had just put into the machine room on the fifth floor crashed. ”

- However, we can often get away with N-gram models.
- Generativity of language is problem that affects deep-learning too!

Estimating bigram probabilities

The Maximum Likelihood Estimate

$$P(w_i \mid w_{i-1}) = \frac{\text{count}(w_{i-1}, w_i)}{\text{count}(w_{i-1})}$$

$$P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

An example

$$P(w_i | w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

< s > I am Sam < /s >

< s > Sam I am < /s >

< s > I do not like green eggs and ham < /s >

$$P(I | < s >) = \frac{2}{3} = .67$$

$$P(Sam | < s >) = \frac{1}{3} = .33$$

$$P(am | I) = \frac{2}{3} = .67$$

$$P(< /s > | Sam) = \frac{1}{2} = 0.5$$

$$P(Sam | am) = \frac{1}{2} = .5$$

$$P(do | I) = \frac{1}{3} = .33$$

Bigram estimates of sentence probabilities

$$P(<\text{s}> \text{ I want english food } </\text{s}>) =$$

$$P(\text{I}|<\text{s}>)$$

- × $P(\text{want}|\text{I})$
- × $P(\text{english}|\text{want})$
- × $P(\text{food}|\text{english})$
- × $P(</\text{s}>|\text{food})$

$$= .000031$$

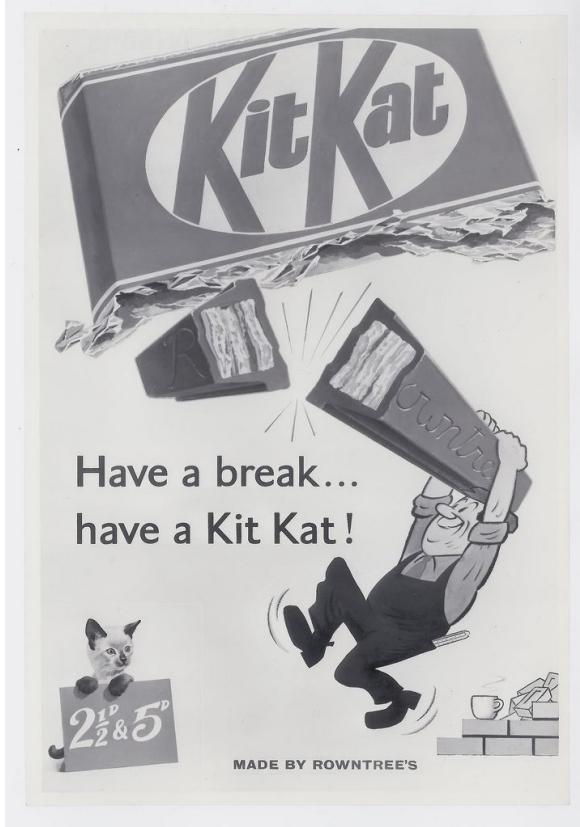
Practical Issues

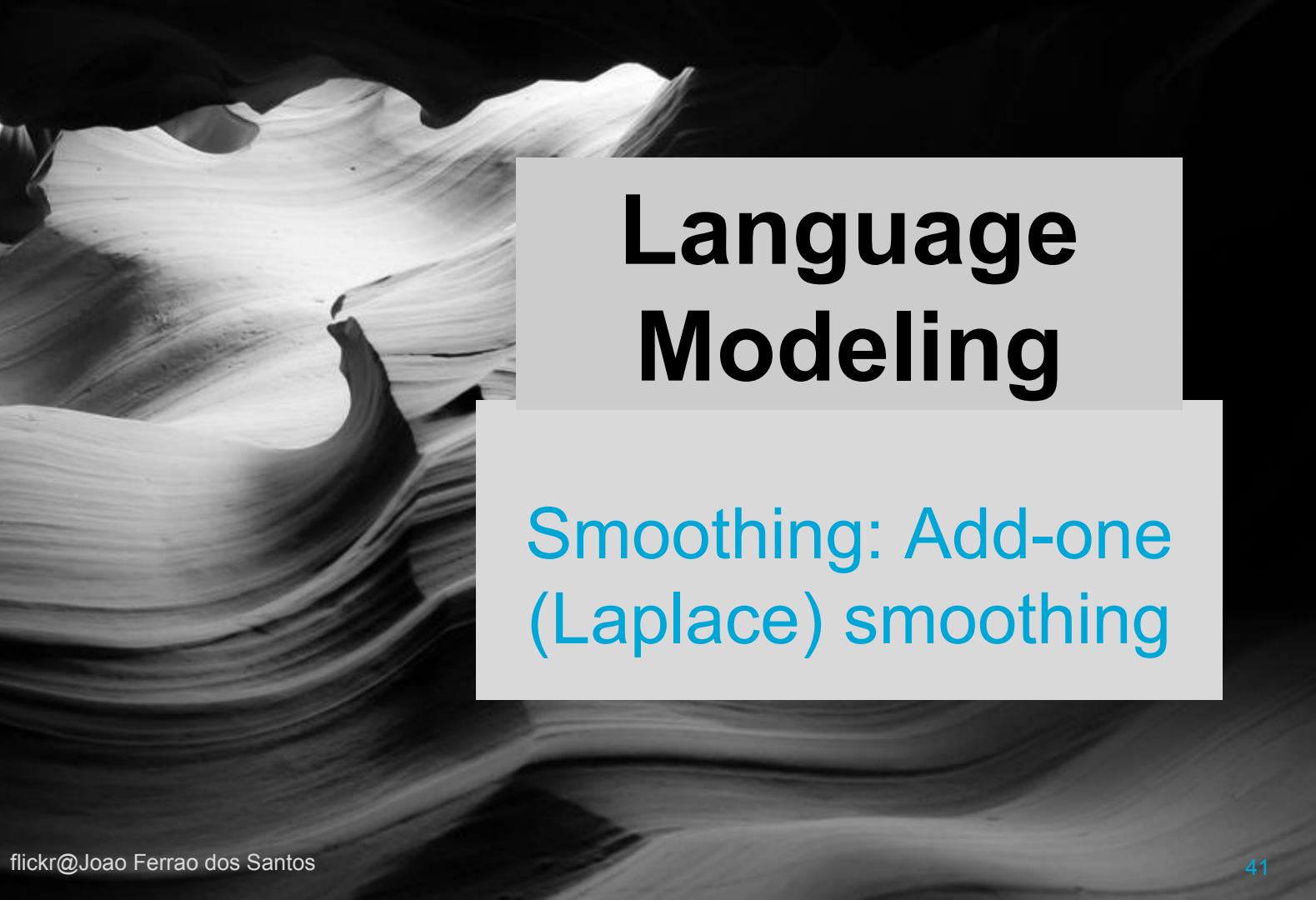
We do everything in log space

- Avoid underflow
- (also adding is faster than multiplying)

$$\log(p_1 \times p_2 \times p_3 \times p_4) = \log p_1 + \log p_2 + \log p_3 + \log p_4$$

Questions?





Language Modeling

Smoothing: Add-one
(Laplace) smoothing

The intuition of smoothing (from Dan Klein)

When we have sparse statistics:

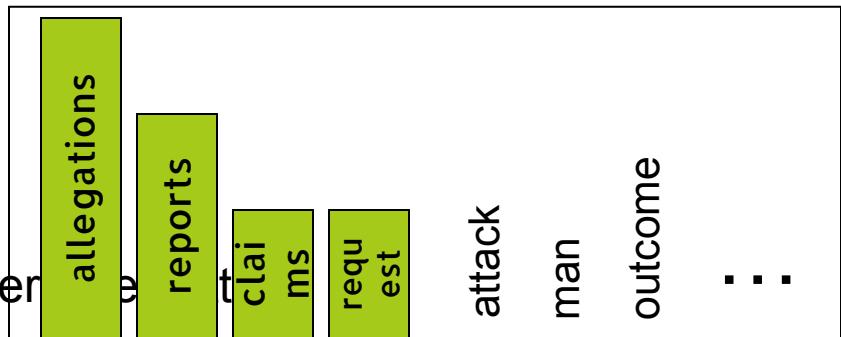
$P(w | \text{denied the})$

3 allegations

2 reports

1 claims

'Steal' probability mass to generate
1 request
7 total



$P(w | \text{denied the})$

2.5 allegations

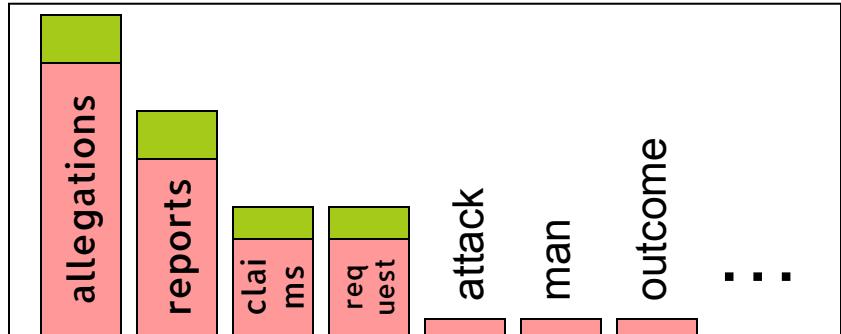
1.5 reports

0.5 claims

0.5 request

2 other

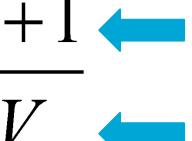
7 total



Add-one estimation

- Also called Laplace smoothing
- Pretend we saw each word one more time than we did
- Just add one to all the counts!

- MLE estimate:
- $$P_{MLE}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$
- Add-1 estimate:

$$P_{Add-1}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i) + 1}{c(w_{i-1}) + V}$$


Berkeley Restaurant Corpus:

- Bigram counts for 8 words ($V=1446$)
- 9332 sentences
- **Zeros in blue**

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

Berkeley Restaurant Corpus: Laplace smoothed bigram counts

	i	want	to	eat	chinese	food	lunch	spend
i	6	828	1	10	1	1	1	3
want	3	1	609	2	7	7	6	2
to	3	1	5	687	3	1	7	212
eat	1	1	3	1	17	3	43	1
chinese	2	1	1	1	1	83	2	1
food	16	1	16	1	2	5	1	1
lunch	3	1	1	1	1	2	1	1
spend	2	1	2	1	1	1	1	1

Laplace-smoothed bigrams

$$P^*(w_n|w_{n-1}) = \frac{C(w_{n-1}w_n) + 1}{C(w_{n-1}) + V}$$

	i	want	to	eat	chinese	food	lunch	spend
i	0.0015	0.21	0.00025	0.0025	0.00025	0.00025	0.00025	0.00075
want	0.0013	0.00042	0.26	0.00084	0.0029	0.0029	0.0025	0.00084
to	0.00078	0.00026	0.0013	0.18	0.00078	0.00026	0.0018	0.055
eat	0.00046	0.00046	0.0014	0.00046	0.0078	0.0014	0.02	0.00046
chinese	0.0012	0.00062	0.00062	0.00062	0.00062	0.052	0.0012	0.00062
food	0.0063	0.00039	0.0063	0.00039	0.00079	0.002	0.00039	0.00039
lunch	0.0017	0.00056	0.00056	0.00056	0.00056	0.0011	0.00056	0.00056
spend	0.0012	0.00058	0.0012	0.00058	0.00058	0.00058	0.00058	0.00058

Reconstituted counts

Multiply probability with original count for comparison

$$c^*(w_{n-1}w_n) = \frac{[C(w_{n-1}w_n) + 1] \times C(w_{n-1})}{C(w_{n-1}) + V}$$

	i	want	to	eat	chinese	food	lunch	spend
i	3.8	527	0.64	6.4	0.64	0.64	0.64	1.9
want	1.2	0.39	238	0.78	2.7	2.7	2.3	0.78
to	1.9	0.63	3.1	430	1.9	0.63	4.4	133
eat	0.34	0.34	1	0.34	5.8	1	15	0.34
chinese	0.2	0.098	0.098	0.098	0.098	8.2	0.2	0.098
food	6.9	0.43	6.9	0.43	0.86	2.2	0.43	0.43
lunch	0.57	0.19	0.19	0.19	0.19	0.38	0.19	0.19
spend	0.32	0.16	0.32	0.16	0.16	0.16	0.16	0.16

Compare with raw bigram counts

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

	i	want	to	eat	chinese	food	lunch	spend
i	3.8	527	0.64	6.4	0.64	0.64	0.64	1.9
want	1.2	0.39	238	0.78	2.7	2.7	2.3	0.78
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eat	0.34	0.34	1	0.34	5.8	1	15	0.34
chinese	0.2	0.098	0.098	0.098	0.098	8.2	0.2	0.098
food	6.9	0.43	6.9	0.43	0.86	2.2	0.43	0.43
lunch	0.57	0.19	0.19	0.19	0.19	0.38	0.19	0.19
spend	0.32	0.16	0.32	0.16	0.16	0.16	0.16	0.16

Language Modeling

Interpolation, Backoff,
and Web-Scale LMs

Backoff and Interpolation

- Sometimes it helps to use **less** context
 - Condition on less context for contexts you haven't learned much about
- **Backoff:**
 - use trigram if you have good evidence,
 - otherwise bigram, otherwise unigram
- **Interpolation:**
 - mix unigram, bigram, trigram
- Interpolation works better

Linear Interpolation

- Simple interpolation

$$\begin{aligned}\hat{P}(w_n | w_{n-1} w_{n-2}) = & \lambda_1 P(w_n | w_{n-1} w_{n-2}) \\ & + \lambda_2 P(w_n | w_{n-1}) \\ & + \lambda_3 P(w_n)\end{aligned}$$

$$\sum_i \lambda_i = 1$$

- Lambdas conditional on context:

$$\begin{aligned}\hat{P}(w_n | w_{n-2} w_{n-1}) = & \lambda_1(w_{n-2}^{n-1}) P(w_n | w_{n-2} w_{n-1}) \\ & + \lambda_2(w_{n-2}^{n-1}) P(w_n | w_{n-1}) \\ & + \lambda_3(w_{n-2}^{n-1}) P(w_n)\end{aligned}$$

How to set the lambdas?

- Use a **held-out** corpus

Training Data

Held-Out
Data

Test
Data

- Choose λ s to maximize the probability of held-out data:
 - Fix the N-gram probabilities (on the training data)
 - Then search for λ s that give largest probability to held-out set:

$$\log P(w_1 \dots w_n \mid M(\lambda_1 \dots \lambda_k)) = \sum_i \log P_{M(\lambda_1 \dots \lambda_k)}(w_i \mid w_{i-1})$$

Unknown words: Open versus closed vocabulary tasks

- If we know all the words in advanced
 - Vocabulary V is fixed; **Closed vocabulary task**
- Often we don't know this
 - **Out Of Vocabulary** = OOV words; **Open vocabulary task**
- Instead: create an unknown word token **<UNK>**
 - **Training** of **<UNK>** probabilities
 - Create a fixed lexicon L of size V
 - At text normalization phase, any training word not in L changed to **<UNK>**
 - Now we train its probabilities like a normal word
 - At **decoding** time
 - If text input: Use UNK probabilities for any word not in training

Language Modeling

Web-Scale LMs

Huge web-scale n-grams

Pruning

- Only store N-grams with count > threshold.
 - Remove singletons of higher-order n-grams
- Entropy-based pruning
 - select N-grams for pruning such that gap between two models is minimized

$$D(p||p') = - \sum_{w_i, h_j} p(w_i, h_j) [\log p'(w_i|h_j) - \log p(w_i|h_j)]$$

Huge web-scale n-grams

Efficiency

- Efficient data structures like **tries** (prefix tree)
- **Bloom filters:** hashing for approximate language models
- Store words as **indexes**, not strings
 - Use **Huffman coding** (based on word frequency) to fit large numbers of words into two bytes
- Quantize probabilities (4-8 bits instead of 8-byte float)

Smoothing for Web-scale N-grams

- “Stupid backoff” (Brants *et al.* 2007)
- Use relative frequencies
- First look for the word at the n-gram level
 - if there is no n-gram of that size it will recurse to the (n-1)-gram and multiply its score with 0.4.
 - The recursion stops at unigrams.

$$S(w_i | w_{i-k+1}^{i-1}) = \begin{cases} \frac{\text{count}(w_{i-k+1}^i)}{\text{count}(w_{i-k+1}^{i-1})} & \text{if } \text{count}(w_{i-k+1}^i) > 0 \\ 0.4S(w_i | w_{i-k+2}^{i-1}) & \text{otherwise} \end{cases}$$

$$S(w_i) = \frac{\text{count}(w_i)}{N}$$

Syntax

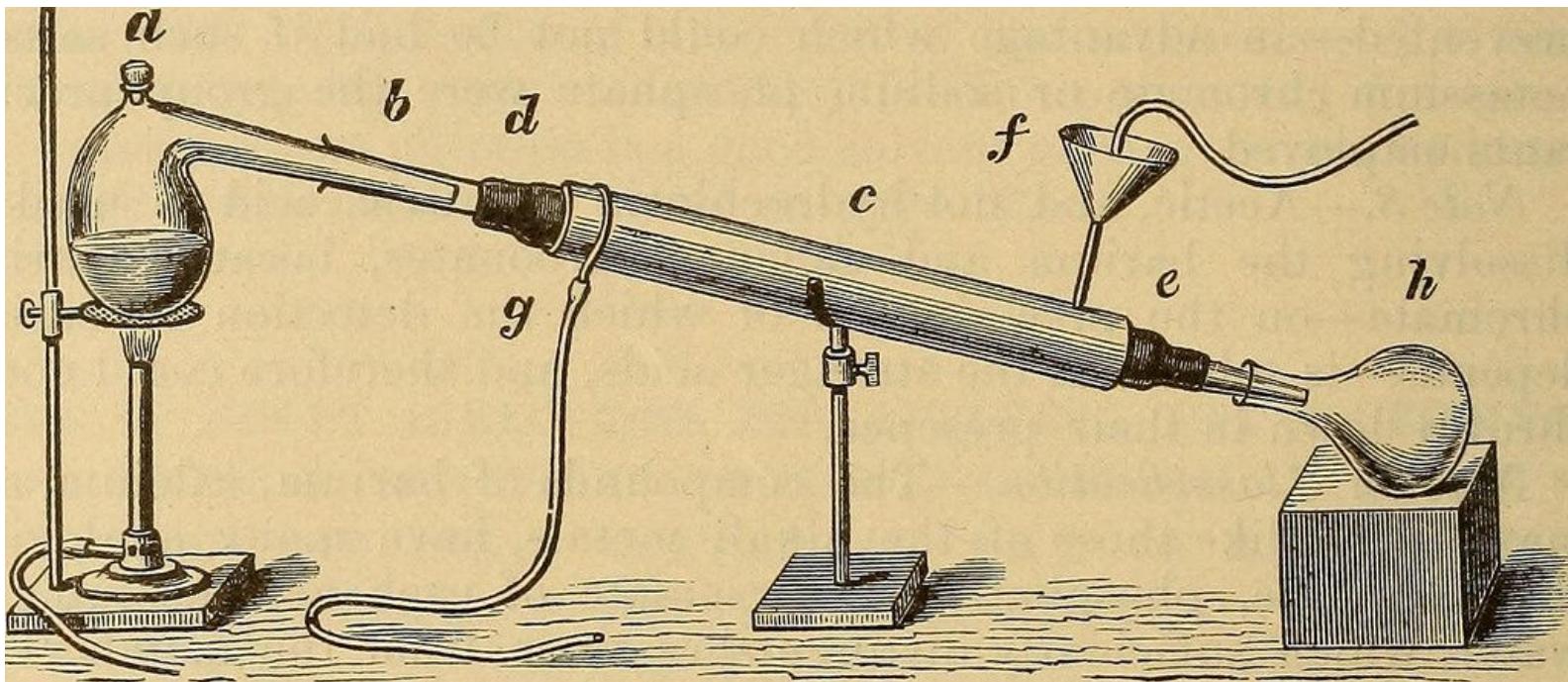
Part 1:

- Part-of-speech (POS)
- Parsing
- Language modeling

Part 2:

- Sentiment analysis
- Named-entity recognition

Applications



Sentiment analysis



Sentiment analysis

Lexicon based approaches

- Fun, good (+1)
- Terrible, destroy (-1)

Not, never are sentiment shifters (or valence shifters)

The image shows a screenshot of an Amazon product page. At the top, there are two screenshots of reviews. The left one is a 4-star review by Reid hamlin from February 3, 2018, which reads: "A fun way to ruin a weekend and blow 100 bucks. We took this ball to the beach and after close to 2 hours to pump it up, we pushed it around for about 10 fun filled minutes. That was when the wind picked it up and sent it huddling down the beach at about 40 knots. It destroyed everything in its path. Children screamed in terror at the giant inflatable monster that crushed their sand castles. Grown men were knocked down trying to save their families. The faster we chased it, the faster it rolled. It was like it was mocking us. Eventually, we had to stop running after it because its path of injury and destruction was going to cost us a fortune in legal fees. Rumor has it that it can still be seen stalking innocent families on the Florida panhandle. We lost it in South Carolina, so there is something to be said about its durability." The right screenshot shows the product listing for "Sol Coastal The Beach Behemoth Giant Inflatable 12-Foot Pole-to-Pole Beach Ball by Sol Coastal". It features a large, multi-colored beach ball (yellow, blue, red) and a small figure of a man standing next to it. The price is listed as \$95.96.

Sentiment analysis

Syntactic pattern as a sequence of POS tags (Turney, 2002)

Penn treebank tags: JJ= adjective, NN= noun, VB=verb, RB=adverb

https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html

Rule	First word	Second word	Third word (not extracted)
1	JJ	NN or NNS	anything
2	RB, RBR, or RBS	JJ	Not NN nor NNS
3	JJ	JJ	Not NN nor NNS
4	NN or NNS	JJ	Not NN nor NNS
5	RB, RBR, or RBS	VB, VBD, VBN, or VBG	anything

Sentiment analysis

- 1) Syntactic pattern as a sequence of POS tags (Turney, 2002)

“This piano produces beautiful sounds” ← 1) JJ+NN/NNS

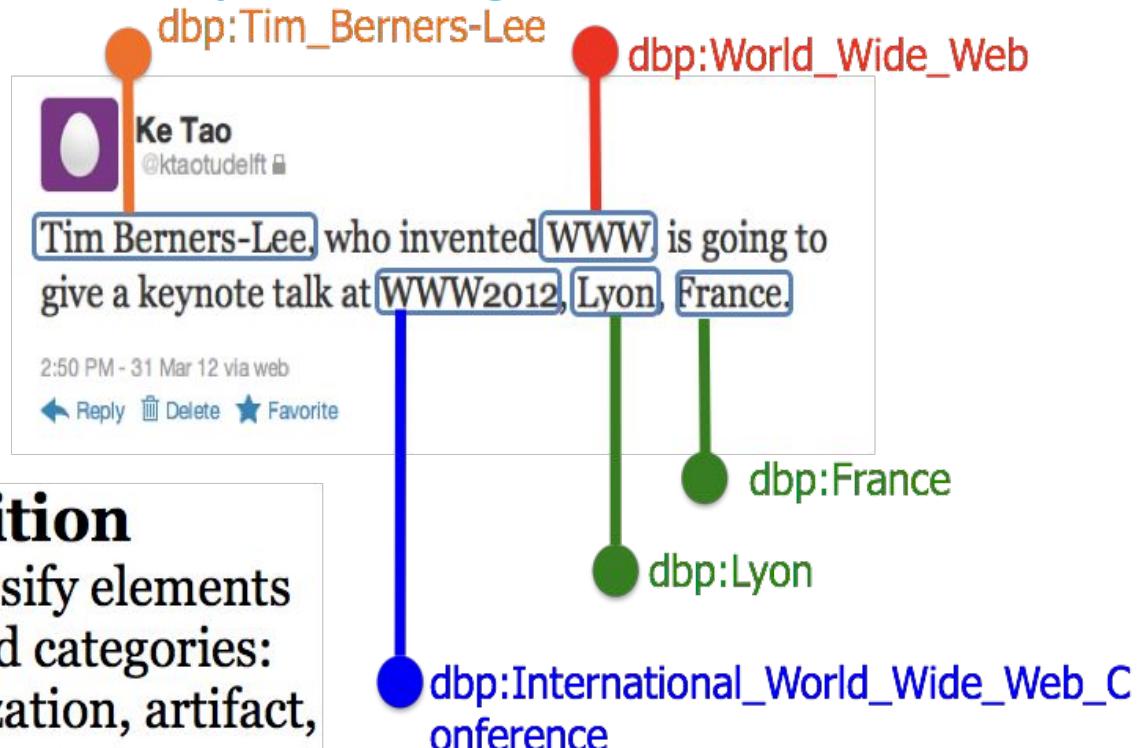
- 2) Sentiment orientation (SO) using Pointwise Mutual Information Measure (PMI)

$$\text{pmi}(x; y) \equiv \log \frac{p(x, y)}{p(x)p(y)} = \log \frac{p(x|y)}{p(x)} = \log \frac{p(y|x)}{p(y)}.$$

SO(phrase)= PMI(phrase, “excellent”) - PMI(phrase, “poor”)

- 3) Average SO score for all phrases gives sentiment to e.g., a review.

Named entity recognition



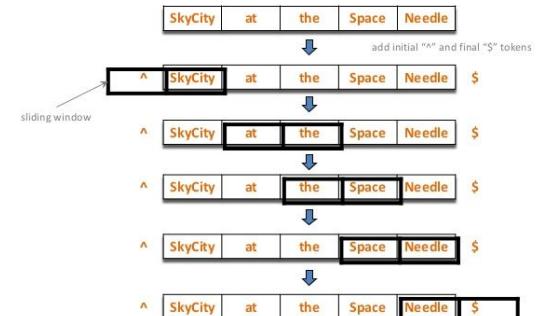
Named entity recognition

- Detect and classify all **proper names** in a text.
- **Application specific:** commercial products, names of genes, works of art
- **Generic:** names of people, places, and organizations mentioned in news

NER as sequence labeling

- Task similar to POS tagging and syntactic chunking
- Classifier trained to label tokens with tags.
- Features to predict
 - NER type (label)
 - Boundary

Sliding Window (bi-grams)



NER as sequence labeling

- **Shape** feature
 - Lower case, upper case, expressions that make use of numbers (A9), punctuation (Yahoo!), and typical case alternations (eBay)
- **Gazetter** or **name list**
 - Extensive lists
 - Place names = gazetters, millions of entries
 - Difficult to create and maintain
 - Usefulness varies considerably
 - Gazetters (places) mostly effective
 - Name lists for persons and organizations not nearly as beneficial!

NER as sequence labeling

Training features:

- Shape feature
- Gazetteer or name list
- **Lexical items**
 - Stemmed lexical items
- **Character affixes:** of the target and surrounding words
- **Part of speech of the word**
- **Syntactic chunk labels:** base-phrase chunk label
- **BoW/Bag of n-grams:** words or n-grams occurring in the surrounding context

Techniques

- **Hidden-markov models (HMM)**
 - Generative model: **joint** probability distribution
 - **observation** likelihood and **the prior**
 - Uses Bayes rule to model most probably PoS tag sequence
- **Maximal entropy markov model (MEMM)**
 - Discriminative model: **conditional** probability
 - "*the probability of state given observation*".
 - Compute the posterior of each state, conditioned on the previous state and current observation

Named entity recognition

- Multi-way classification task

In 1917, Einstein applied the general theory of relativity to model the large-scale structure of the universe. He was visiting the United States when Adolf Hitler came to power in 1933 and did not go back to Germany, where he had been a professor at the Berlin Academy of Sciences. He settled in the U.S., becoming an American citizen in 1940. On the eve of World War II, he endorsed a letter to President Franklin D. Roosevelt alerting him to the potential development of "extremely powerful bombs of a new type" and recommending that the U.S. begin similar research. This eventually led to what would become the Manhattan Project. Einstein supported defending the Allied forces, but largely denounced using the new discovery of nuclear fission as a weapon. Later, with the British philosopher Bertrand Russell, Einstein signed the Russell-Einstein Manifesto, which highlighted the danger of nuclear weapons. Einstein was affiliated with the Institute for Advanced Study in Princeton, New Jersey, until his death in 1955.

Tag colours:

LOCATION TIME PERSON ORGANIZATION MONEY PERCENT DATE

Summary

- Part-of-speech (POS) tagging
- Language modeling

Applications in...

- Sentiment analysis
- Named-entity recognition

Questions?



Next deadlines:

- Review P8: handed out March 15, due March 22.
Hovy, Dirk, and Shannon L. Spruit. "The social impact of natural language processing." Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers). Vol. 2. 2016.
- NLP project proposal: **due March 22.**

Possible project 1: Rbutr



NATURAL NEWS Natural Health News & Scientific Discoveries

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Vaccinated children have up to 500% more diseases than unvaccinated children

Tuesday, June 19, 2012 by: PF Louis
Tags: [vaccinated children](#), [disease](#), [allergies](#)

46K 1,628 97 141
[f Share](#) [Tweet](#) [g+1](#) [Save](#)
[Print this Article](#) [Email to a Friend](#) [Share](#)

(NaturalNews) Suspicions have been growing among those wary of vaccinating their children. Now a large study corroborates other independent surveys comparing unvaccinated children to vaccinated children.

Direct rbutls

[Rachael's Ramblings - Pro-Science Rant](#)
bratty-jedi.livejournal.com/222088.html
"Shows how the study this article is about is heavily biased and flawed"
[Link by Shane](#) 27 Nov
[Vaccination](#) [Health](#) [Science](#)

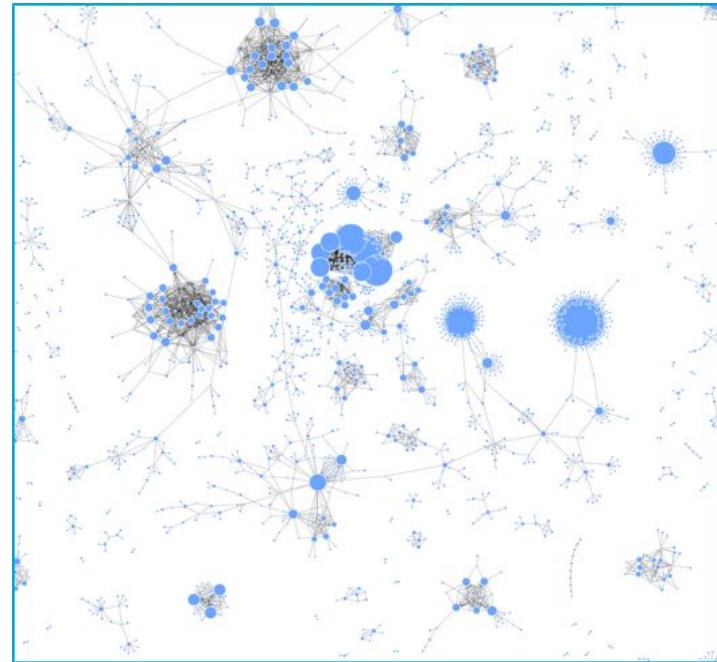
[Vaccinated children have 500% more diseases than unvaccinated children.](#)
sguforums.com/index.php?topic=42209.0
"This is not a study. It is a web survey."
[Link by Shane](#) 02 Mar
[Vaccination](#) [Health](#)

[A survey administered by a German anti-vaccine homeopath backfires spectacularly – Respectful Insolence](#)
scienceblogs.com/insolence/2011/08/31/an-anti-vaccine-administered-survey-backfires/
"The study this article is based on doesn't show anything of the sort."
[Link by Shane](#) 27 Nov
[Vaccination](#) [Health](#) [Science](#)

Possible project 1: Rbutr

- Created 2012
- 2K active users per week
- 60K total users
- 28K edges, 40K nodes

Summarization of articles that “agree”.



Possible project 2: Explaining Recommendations

Ratings for a group

Anna	10	1	5	
Bob	1	5	10	
Chris	1	10	5	

Aggregation strategy

E.g., Fairness,
users take turns
in picking:

- 1)
- 2)
- 3)

Explanation

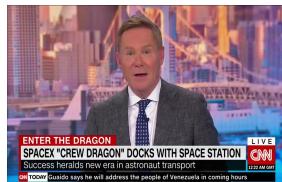
E.g., The
electrical
guitar song
is Bob's
choice, and
it is his turn
to pick!

Possible project 3:

Summarizing emotions

How do we combine different emotion or sentiment?

SpaceX nails historic docking at International Space Station



After the first test launch for SpaceX's Crew Dragon capsule, the spacecraft **pulled off** a **risky** and **crucial** test when it docked with the International Space Station.

Possible project 4:

Comparison of Speech-to-Text approaches for different purposes

SpaceX nails historic docking at International Space Station



Which transcription provides a better suited summarization of the video?



Transcript
Option 1



Transcript
Option 1



Transcript
Option 1

Next week...

- **Semantics**
 - Word sense disambiguation
 - Other features for sentiment analysis