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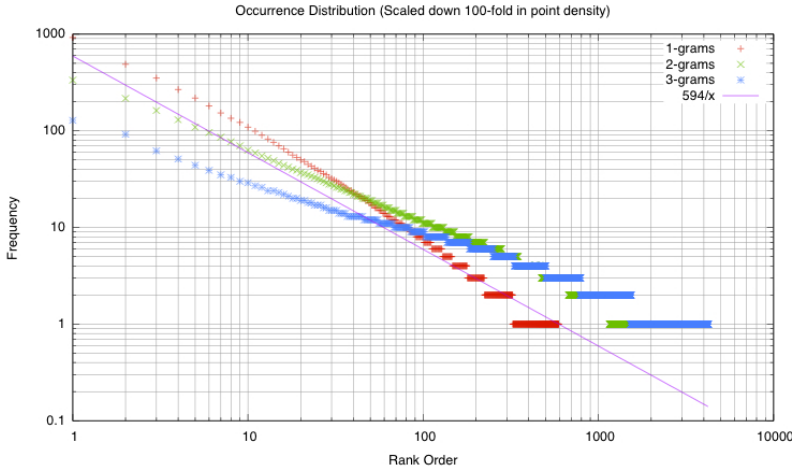
- Weights

A question for you

Remember Zipf's law?

$$freq \propto \frac{1}{rank}$$



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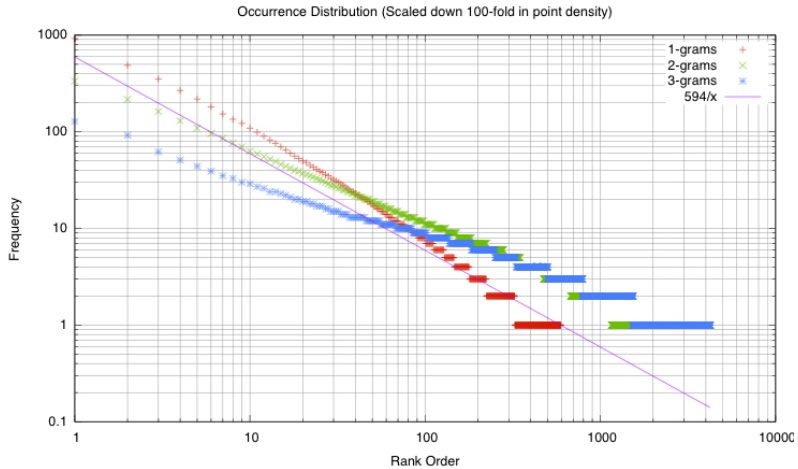

- Suppose you have a corpus with N word tokens
- K of these tokens appear exactly once.
  (These are called *hapax legomena*.)

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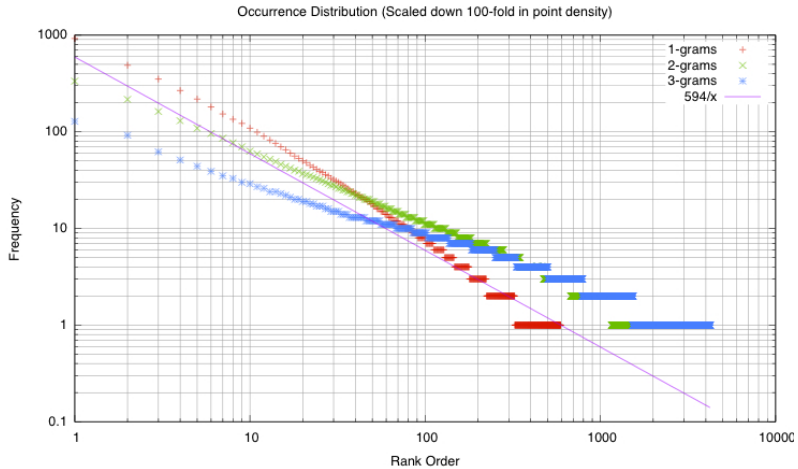

- Suppose you have a corpus with N word tokens
- K of these tokens appear exactly once.
  (These are called *hapax legomena*.)
- Now suppose you get $2N$ tokens from the same corpus.
  How many words appear exactly once in the new corpus?
  1. roughly $2K$
  2. more than K, but less than $2K$
  3. roughly K
  4. less than K but more than $\frac{K}{2}$
  5. roughly $\frac{K}{2}$

IPython Notebook

- `http://ipython.org/notebook.html`
- Browser-based IDE for Python
- Integrates code, text, LaTeX, ...

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Feature functions

Suppose $y \in \mathcal{Y} = \{\text{pos}, \text{neg} \quad\}$. Then,

$$\mathbf{f}(\mathbf{x}, y = \text{pos}) = [\mathbf{x}^\top \quad , \mathbf{0}^\top \quad]^\top$$
$$\mathbf{f}(\mathbf{x}, y = \text{neg}) = [\mathbf{0}^\top, \mathbf{x}^\top \quad]^\top$$

Feature functions

Suppose $y \in \mathcal{Y} = \{\text{pos}, \text{neg}, \text{neut}\}$. Then,

$$\begin{aligned}
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\end{aligned}$$

The feature vector is composed of individual feature functions, e.g.:

$$\begin{aligned}
f_{176}(\mathbf{x}, y) &:= x_{176} \times \delta(y = \text{pos}) \\
&= \delta(\text{great} \in \mathbf{w} \wedge y = \text{pos}) \\
f_{177}(\mathbf{x}, y) &:= x_{177} \times \delta(y = \text{pos}) \\
f_{10176}(\mathbf{x}, y) &:= x_{176} \times \delta(y = \text{neg}) \ldots
\end{aligned}$$

Feature functions

Suppose $y \in \mathcal{Y} = \{\text{pos}, \text{neg}, \text{neut}\}$. Then,

$$\begin{aligned}
\mathbf{f}(\mathbf{x}, y = \text{pos}) &= [\mathbf{x}^\mathsf{T}, 1, \mathbf{0}^\mathsf{T}, \mathbf{0}^\mathsf{T}]^\mathsf{T} \\
\mathbf{f}(\mathbf{x}, y = \text{neg}) &= [\mathbf{0}^\mathsf{T}, \mathbf{x}^\mathsf{T}, 1, \mathbf{0}^\mathsf{T}]^\mathsf{T} \\
\mathbf{f}(\mathbf{x}, y = \text{neut}) &= [\mathbf{0}^\mathsf{T}, \mathbf{0}^\mathsf{T}, \mathbf{x}^\mathsf{T}, 1]^\mathsf{T}
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We usually add an "offset" feature at the end of each vector.

Weights: Naive Bayes

$$\begin{aligned}\boldsymbol{\theta}^{\mathsf{T}}\mathbf{f}(\mathbf{x}, y) &:= \log P(\mathbf{x}, y; \phi, \mu) \\ &= \log P(\mathbf{x}|y; \phi)P(y; \mu) \\ &= \log P(\mathbf{x}|y; \phi) + \log P(y; \mu)\end{aligned}$$

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&\propto \sum_n x_n \log \phi_{y,n} + \log \mu_y \\
&= \boldsymbol{\theta}^{\mathsf{T}}\mathbf{f}(\mathbf{x}, y)
\end{aligned}
$$

where

$$
\begin{aligned}
\boldsymbol{\theta} &= [\log \boldsymbol{\phi}_1^{\mathsf{T}}, \log \mu_1, \log \boldsymbol{\phi}_2^{\mathsf{T}}, \log \mu_2, \ldots]^{\mathsf{T}} \\
\mathbf{f}(\mathbf{x}, y) &= [\mathbf{0}, \ldots, \mathbf{0}, \mathbf{x}^{\mathsf{T}}, 1, \mathbf{0}, \ldots, \mathbf{0}]^{\mathsf{T}}
\end{aligned}
$$

Today

Naive Bayes

- Recap maximum likelihood estimation
- Smoothing, and bias-variance tradeoff
- Practical details of machine learning
- Features, and the naivety of Naive Bayes

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- Averaged perceptron
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Word sense disambiguation

- Definition of word senses
- Formulation as a classification problem

Word senses

Remember these headlines?

- Iraqi head seeks arms
- Prostitutes appeal to Pope
- Drunk gets nine years in violin case

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They are ambiguous because words have multiple senses.

- head: BODY-PART,LEADER
- arms: BODY-PART,WEAPON

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Can you see what is ambiguous about the other examples?

Word sense disambiguation

Word Sense Disambiguation (WSD) is the problem of identifying the intended sense of each word token.

- Part of a larger field of research called **lexical semantics**
- Part-of-speech ambiguity (i'm heading out of town) is usually considered to be a different problem.
- For WSD, words include their POS tag (e.g., heading/V)
- Technically, we want to differentiate senses of each *lemma*. A *lemma* is a linguistic term for a group of inflected forms: arm, arms; serve, served, serves, serving.

How many word senses?

Words (lemmas) may have *many* more than two senses.
For example, serve:

- [FUNCTION]: The tree stump served as a table
- [ENABLE]: His evasive replies only served to heighten suspicion
- [DISH]: We serve only the rawest fish here
- [ENLIST]: She served her country in the marines
- [JAIL]: He served six years in Alcatraz
- [TENNIS]: Nobody can return his double-reverse spin serve
- [LEGAL]: They were served with subpoenas
- more?

How many word senses?

How can we test that these senses are really different?
We can construct a **zeugma**, which combines antagonistic senses in an uncomfortable way:

- Which flight serves breakfast?
- Which flights serve Tuscon?

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We can construct a **zeugma**, which combines antagonistic senses in an uncomfortable way:

- Which flight serves breakfast?
- Which flights serve Tuscon?
- *Which flights serve breakfast and Tuscon?

The asterisk is a linguistic notation for utterances which would not be judged to be grammatical by fluent speakers of a language.

The WSD task: Output

- What should the output of WSD be? What are the possible senses for each word?
- We could just look in the dictionary.

¹plunge *verb* \ˈplənj\

plunged | **plung·ing**

Definition of PLUNGE

transitive verb

1 : to cause to penetrate or enter quickly and forcibly into something <*plunged* the dagger>

2 : to cause to enter a state or course of action usually suddenly, unexpectedly, or violently <*plunged* the nation into economic depression>

intransitive verb

1 : to thrust or cast oneself into or as if into water

2 **a** : to become pitched or thrown headlong or violently forward and downward; *also* : to move oneself in such a manner <*plunged* off the embankment>

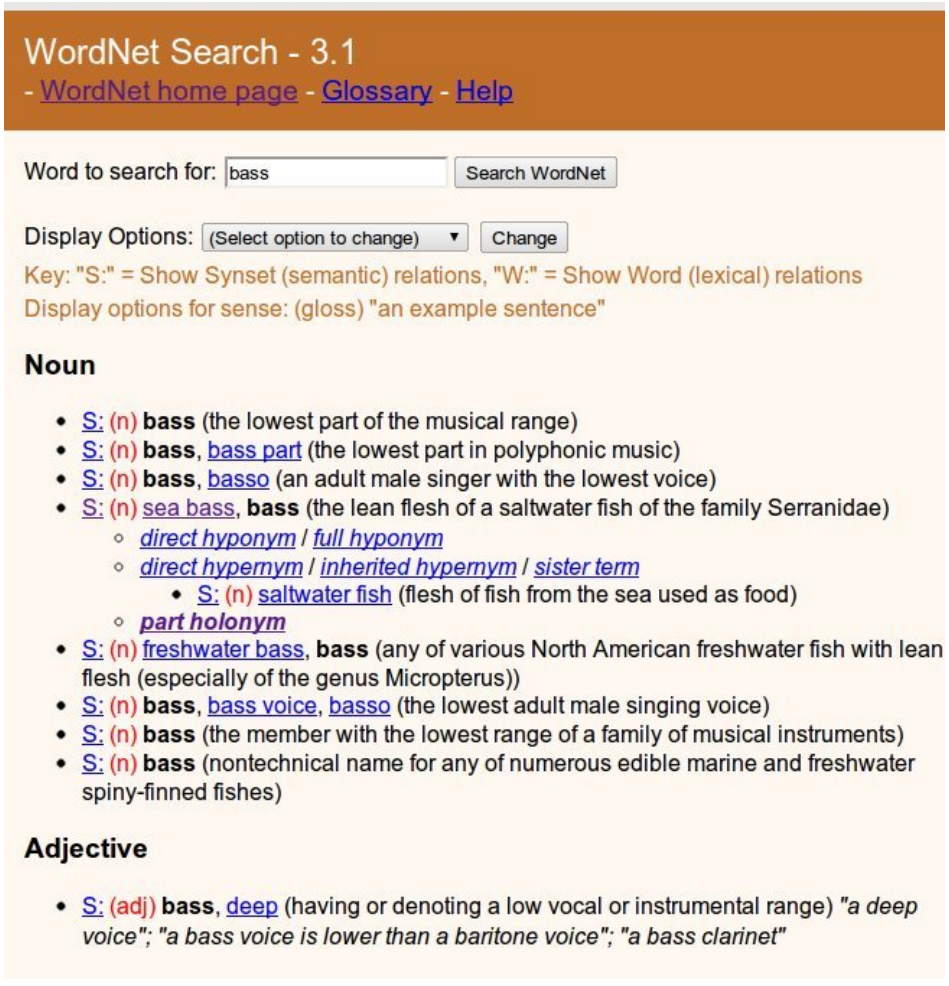
b : to act with reckless haste : enter suddenly or unexpectedly <*plunges* into project after project>

c : to bet or gamble heavily and recklessly

3 : to descend or dip suddenly <the stock's value *plunged*>

WordNet

WSD research is dominated by a computational resource called WordNet. (`http://wordnet.princeton.edu`)



WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: bass Search WordNet

Display Options: (Select option to change) Change

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations
Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **bass** (the lowest part of the musical range)
- S: (n) **bass**, bass part (the lowest part in polyphonic music)
- S: (n) **bass**, basso (an adult male singer with the lowest voice)
- S: (n) sea bass, **bass** (the lean flesh of a saltwater fish of the family Serranidae)
  - *direct hyponym* / *full hyponym*
  - *direct hypernym* / *inherited hypernym* / *sister term*
    - S: (n) saltwater fish (flesh of fish from the sea used as food)
  - ***part holonym***
- S: (n) freshwater bass, **bass** (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
- S: (n) **bass**, bass voice, basso (the lowest adult male singing voice)
- S: (n) **bass** (the member with the lowest range of a family of musical instruments)
- S: (n) **bass** (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

Adjective

- S: (adj) **bass**, deep (having or denoting a low vocal or instrumental range) *"a deep voice"; "a bass voice is lower than a baritone voice"; "a bass clarinet"*

WordNet

- WordNet consists of roughly 100K *synsets*,
  groups of words or phrases with an identical meaning.
  (e.g., $\{\text{CHUMP}^1, \text{FOOL}^2, \text{SUCKER}^1, \text{MARK}^9\}$)
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  A lemma is polysemous if it participates in multiple synsets.
- WordNet also describes many other lexical relationships:
  - antonymy (x means the opposite of y)
  - hyponymy (x is a hyponym of y if x is-a y)
  - ...

WordNet

Some statistics of English Wordnet 3:

POS	polysemy
NOUN	1.24
VERB	2.17
ADJECTIVE	1.40
ADVERB	1.25

WordNet Senses: Pros and cons

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  The premise that word senses can be differentiated in a task-neutral way has been criticized as linguistically naïve [Kil97].
- WordNets are heavyweight.
  - expensive to develop for new languages
  - become outdated as language changes
    (consider: I'm dead tired, sick as a positive adjective, etc)
  - Would WordNet have good coverage for Twitter?

Translation Sets as Word Senses

- An alternative is to use translation to differentiate word senses.
- E.g., since bill is translated as pico or cuenta in spanish, there are clearly two senses.
- But if there is no language with different spellings of the purported senses, then they are not meaningfully different.
- Most WSD research has focused on WordNet, so we will too.

WSD Tasks

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WSD Tasks

- **Synthetic** data: different words are conflated (banana-phone), the system must identify the original word.
- **Lexical sample**: disambiguate a few target words (e.g., "plant" etc). First large-scale WSD evaluation, SENSEVAL-1 (1998).
- **All-words** WSD: a sense must be identified for every token.
  - A **semantic concordance** is a corpus in which each open-class word (nouns, verbs, adjectives, and adverbs) is tagged with its word sense from the target dictionary or thesaurus.
  - SemCor is a semantic concordance built from 234K tokens of the Brown corpus.
    As of Sunday^{1}_{n} night^{1}_{n} there was^{4}_{v} no word^{2}_{n} ...

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- Approaches:
  - Knowledge-based
  - Supervised
  - Semi-supervised
  - Unsupervised

The Lesk Algorithm

- For each sentence s_i and target word w_{ij}
  - Set $maxOverlap \leftarrow 0$, $bestSense \leftarrow \varnothing$
  - For each possible sense t
    - Compute word overlap between s_i and definition $w_{ij}[t]$
    - If greater than $maxOverlap$, then update $maxOverlap$ and $bestSense$.

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Example text: I stopped by the **bank** to try to get a loan
Example definitions:

- Bank^1: financial institution which borrows and loans money
- Bank^2: body of land adjacent to a river

The first sense is preferred because the word "loan" appears in both the definition and the query sentence.

Selectional restrictions

Some verbs have strong selectional restrictions about their arguments:

- They closed the bank[1] after discovering its malfeasance.
- They rested on the bank[2] of the Seine.
- Closed can only take an argument which is an ORGANIZATION.
- Rested can only take an argument which is a PHYSICAL-OBJECT.

Some ontologies categorize common nouns in terms of such properties.

Supervised WSD

- With labeled data, we can treat WSD as a standard supervised learning problem.
- Some features
  - Bag-of-words
  - Positional (collocation) features
  - Patterns
  - Syntax
  - Document features

Bag-of-words features

Bag-of-words models are a very typical approach. For example,

$$f(y, \text{bank}, \text{I went to the bank to deposit my paycheck}) =$$
$$\{\langle \text{went}, y\rangle : 1, \langle \text{deposit}, y\rangle : 1, \langle \text{paycheck}, y\rangle : 1\}$$

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Some examples:

- bank[FINANCIAL]:

  a an and are ATM Bonnie card charges check Clyde criminals deposit famous for get I much My new overdraft really robbers the they think to too two went were

- bank[RIVER]:

  a an and big campus cant catfish East got grandfather great has his I in is Minnesota Mississippi muddy My of on planted pole pretty right River The the there University walk Wets

Positional (collocation) features

- An extension of bag-of-words models is to encode the position of each context word, e.g.,

$$f(y, \text{bank}, \text{I went to the bank to deposit my paycheck}) =$$
$$\{\langle i-3, \text{went}, y\rangle : 1, \langle i+2, \text{deposit}, y\rangle : 1, \langle i+4, \text{paycheck}, y\rangle : 1\}$$

- J&M (optional textbook) call these collocation features; the POS tag of each word can also be included.

Pattern features

Pattern features extend the idea of positional features with explicit, regex-like patterns:

- bank account
- bank of COUNTRY.

Such features are often used in combination with non-linear classifiers such as decision lists.

Syntactic features

- Rather than look at local neighbors, we can give special priority to the heads of phrases.
- For example, in

  I deposited my paycheck when I got to the bank

  the most revealing features are deposit and paycheck.
- deposit is the head of the main verb phrase for the sentence, and paycheck is the direct object.
- This is a clue that they are more relevant than the words immediately surrounding bank.

Document-level features

According to the "one-sense-per-discourse" heuristic, a document about financial institutions is very unlikely to use the word bank in the river bank sense.

Word	Senses	Accuracy	Applicblty
plant	living/factory	99.8 %	72.8 %
tank	vehicle/contnr	99.6 %	50.5 %
poach	steal/boil	100.0 %	44.4 %
palm	tree/hand	99.8 %	38.5 %
axes	grid/tools	100.0 %	35.5 %
sake	benefit/drink	100.0 %	33.7 %
bass	fish/music	100.0 %	58.8 %
space	volume/outer	99.2 %	67.7 %
motion	legal/physical	99.9 %	49.8 %
crane	bird/machine	100.0 %	49.1 %
Average		**99.8 %**	**50.1 %**

(Yarowsky 1995)

Is Word Sense Disambiguation Important?

- Early machine translation researchers were really worried about WSD.
  - bill[BIRD JAW] $\rightarrow$ pico
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  "Little John was looking for his toy box. Finally he found it. The box was in the pen." Is pen a writing instrument or a place where children play?

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- Bar-Hillel, an expert-turned-skeptic, poses this problem:

  > *"Little John was looking for his toy box. Finally he found it. The box was in the pen." Is pen a writing instrument or a place where children play?*

- The suggestion is this example requires deep knowledge and inference (a box is bigger than a pen[WRITING], but not bigger than a pen[ENCLOSURE]).
- Bar-Hillel was so discouraged that he gave up on MT!

The Role of WSD Today

- WSD was also thought to be important for information retrieval: bass experts, help with cures, etc.
- Many thought the NLP pipeline required a WSD module.
  preprocessing $\rightarrow$ POS tagging $\rightarrow$ WSD $\rightarrow$ application

[1] The survey argues that WSD will become relevant as performance improves.

The Role of WSD Today

- WSD was also thought to be important for information retrieval: bass experts, help with cures, etc.
- Many thought the NLP pipeline required a WSD module.
  preprocessing → POS tagging → WSD → application
- However, years of research on WSD have produced little evidence that it helps downstream applications. A recent survey of WSD notes:

  > *Unfortunately, to date explicit WSD has not yet demonstrated real benefits in human language technology applications (Navigli 2009).*[1]

[1] The survey argues that WSD will become relevant as performance improves.

The Role of WSD Today

- There is some evidence that WSD helps translation [CNC07, CW07]
- But in many tasks, higher-order n-grams encode much the same information as WSD.
  - If we have the bigram bank teller as a feature, we don't need to disambiguate bank.
  - Phrase-based machine translation uses a similar idea.

Homework 2

- Download the SemCor data.
- Compare the word sense annotations with WordNet online.
- Explain why alternative senses were not chosen.
- Do word sense annotations for one sentence of text from an (English language) blog that you like.


Yee Seng Chan, Hwee Tou Ng, and David Chiang.
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