Word Meaning: Distributional Semantics

CMSC 723 / LING 723 / INST 725

Hal Daumé III [he/him]

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(many slides c/o Marine Carpuat, Dan Jurafsky)

Stuff that was due today

- Read the syllabus
- Make sure you have access to canvas
- Read SLP3 6.2—6.5

- For next time:
  - Get started on homework 1 – due Thursday Sep 12 by 3:30pm
  - You get *five* attempts

From last time: Social Impact

- NLP experiments and applications can have a direct effect on individual users' lives

- Some issues
  - Privacy
  - Exclusion
  - Overgeneralization
  - Dual-use problems

[Hovy & Spruit ACL 2016]

The L in NLP is Language, language means people
(Schnoebelen 2017)

- Schnoebelen, summarizing EthNLP 2017 (Hovy et al 2017):
  - Look to NLP (and AI) to assist people, not replace them
  - Engage with scholarly disciplines that have a better understanding of people
- Value sensitive design (Friedman et al 2006, Friedman & Hendry to appear):
  - Identify stakeholders
  - Design to support stakeholders' values

Taxonomy and slides from **Emily Bender**'s March 2019 talk at the Future of AI workshop

The L in NLP is Language, language means people

Direct stakeholders	Indirect stakeholders
By choice	Subject of query
Not by choice	Contributor to broad corpus
	Subject of stereotypes

Taxonomy and slides from **Emily Bender's** March 2019 talk at the Future of AI workshop

Direct stakeholders: By choice

- *I choose to use this spell checker, autocorrect, voice assistant, MT system…*
  - … but it doesn't work for my language or language variety
    - Suggests that my language/language variety is inadequate
    - Makes the product unusable for me
  - … but the system doesn't indicate how reliable it is
    - Users reliant on MT/auto-captioning for important info left in the dark about what they might be missing

Taxonomy and slides from **Emily Bender's** March 2019 talk at the Future of AI workshop

Direct stakeholders: Not by choice

- *My screening interview was conducted by a virtual agent*
- *I can only access my account information via a virtual agent*
  - … but it doesn't work or doesn't work well for my language variety
    - I scored poorly on the interview, even though the content of my answers was good
    - I can't access my account information

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Indirect stakeholders: Subject of query

- *Someone searched for me online*
  - … but the search triggered display of negative ads including my name because stereotypes about my ethnic identity (Sweeney 2013)
- *Someone searched for critics of the government*
  - … and found my blog post/tweet
- *Someone put my words into an MT system*
  - … which got the translation wrong and led the police to arrest me (*The Guardian*, 24 Oct 2017; https://bit.ly/2zyEetp)

Taxonomy and slides from **Emily Bender's** March 2019 talk at the Future of AI workshop

Indirect stakeholders: Contributor to broad corpus

- *ASR doesn't caption my words as well as others'*
    - My contributions are rendered invisible to search engines
- *Language ID systems don't identify my dialect*
    - Social-media based disease warning systems fail to work in my community (Jurgens et al 2017)

Taxonomy and slides from **Emily Bender's** March 2019 talk at the Future of AI workshop

Indirect stakeholders: Subject of stereotypes

- *Virtual assistants are gendered as female and ordered around*
- *Systems are built using general webtext as a proxy for word meaning or world knowledge*
  - … but general web text reflects many types of bias (Bolukbasi et al 2016, Caliskan et al 2017, Gonen & Goldberg 2019)
    - My restaurant's positive reviews are underrated because of the name of the cuisine (Speer 2017)
    - My resume is rejected because the screening system has learned that typically "masculine" hobbies correlate with getting hired
    - My image search reflects stereotypes back to me

Taxonomy and slides from **Emily Bender's** March 2019 talk at the Future of AI workshop

Today: Word Meaning

2 core issues from an NLP perspective

- **Semantic similarity**: given two words, how similar are they in meaning?
- **Word sense disambiguation**: given a word that has more than one meaning, which one is used in a specific context?

Word similarity for question answering

"**fast**" is similar to "**rapid**"

"**tall**" is similar to "**height**"

Question answering:

*Q: "How **tall** is Mt. Everest?"*
*Candidate A: "The official **height** of Mount Everest is 29029 feet"*

Word similarity for plagiarism detection

MAINFRAMES

Mainframes are primarily referred to large computers with rapid, advanced processing capabilities that can execute and perform tasks equivalent to many Personal Computers (PCs) machines networked together. It is characterized with high quantity Random Access Memory (RAM), very large secondary storage devices, and high-speed processors to cater for the needs of the computers under its service.

Consisting of advanced components, mainframes have the capability of running multiple large applications required by many and most enterprises and organizations. This is one of its advantages. Mainframes are also suitable to cater for those applications (programs) or files that are of very high demand by its users (clients). Examples of such organizations and enterprises using mainframes are online shopping websites such as Ebay, Amazon, and computing-giant

MAINFRAMES

Mainframes usually are referred those computers with fast, advanced processing capabilities that could perform by itself tasks that may require a lot of Personal Computers (PC) Machines. Usually mainframes would have lots of RAMs, very large secondary storage devices, and very fast processors to cater for the needs of those computers under its service.

Due to the advanced components mainframes have, these computers have the capability of running multiple large applications required by most enterprises, which is one of its advantage. Mainframes are also suitable to cater for those applications or files that are of very large demand by its users (clients). Examples of these include the large online shopping websites -i.e. : Ebay, Amazon, Microsoft, etc.

tesgüino

A bottle of ***tesgüino*** is on the table
Everybody likes ***tesgüino***
Tesgüino makes you drunk
We make ***tesgüino*** out of corn.

Intuition: two words are similar if they have similar word contexts.

Embedding word meaning in vector space

Vector Semantics

Distributional models of meaning
= vector-space models of meaning
= vector semantics

Intuitions

Zellig Harris (1954):

- “oculist and eye-doctor … occur in almost the same environments”
- “If A and B have almost identical environments we say that they are synonyms.”

Firth (1957):

- “You shall know a word by the company it keeps!”

Vector Semantics

- Model the meaning of a word by “embedding” in a vector space.
- The meaning of a word is a vector of numbers
  - Vector models are also called “**embeddings**”.
- Contrast: word meaning is represented in many NLP applications by a vocabulary index (“word number 545”)

Many varieties of vector models

Sparse vector representations

1. **Mutual-information weighted word co-occurrence matrices**

Dense vector representations:

2. Singular value decomposition (and Latent Semantic Analysis)
3. Neural-network-inspired models (skip-grams, CBOW)

Term-document matrix

- Each cell: count of term *t* in a document *d*: $\text{tf}_{t,d}$
  - Each document is a count vector in $\mathbb{N}^{|V|}$: a column below

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

Term-document matrix

- Two documents are similar if their vectors are similar

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

The words in a term-document matrix

- Each word is a count vector in $\mathbb{N}^D$: a row below

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
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The words in a term-document matrix

- Two **words** are similar if their vectors are similar

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The word-word or word-context matrix

- Instead of entire documents, use smaller contexts
  - Paragraph
  - Window of $\pm$ 4 words
- A word is now defined by a vector over counts of context words
  - Instead of each vector being of length D
- Each vector is now of length |V|
- The word-word matrix is |V|x|V|

Word-Word matrix
Sample contexts ± 7 words

sugar, a sliced lemon, a tablespoonful of **apricot** preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first **pineapple** and another fruit whose taste she likened
well suited to programming on the digital **computer**. In finding the optimal R-stage policy from
for the purpose of gathering data and **information** necessary for the study authorized in the

	aardvark	computer	data	pinch	result	sugar	…
apricot	0	0	0	1	0	1	
pineapple	0	0	0	1	0	1	
digital	0	2	1	0	1	0	
information	0	1	6	0	4	0	
…	…						

Word-word matrix

- The |V|x|V| matrix is very **sparse** (most values are 0)

- The size of windows depends on representation goals
  - The shorter the windows , the more **syntactic** the representation

    ± 1-3 very syntacticy

  - The longer the windows, the more **semantic** the representation

    ± 4-10 more semanticy

Positive Pointwise Mutual Information (PPMI)

Vector Semantics

Problem with raw counts

- Raw word frequency is not a great measure of association between words

- We'd rather have a measure that asks whether a context word is **particularly informative** about the target word.

  - **Positive Pointwise Mutual Information (PPMI)**

Pointwise Mutual Information

Pointwise mutual information:

Do events x and y co-occur more than if they were independent?

$$\text{PMI}(X,Y) = \log_2 \frac{P(x,y)}{P(x)P(y)}$$

PMI between two words: (Church & Hanks 1989)

Do words x and y co-occur more than if they were independent?

$$\text{PMI}(word_1, word_2) = \log_2 \frac{P(word_1, word_2)}{P(word_1)P(word_2)}$$

Positive Pointwise Mutual Information

- PMI ranges from $-\infty$ to $+\infty$
- But the negative values are problematic
  - Things are co-occurring **less than** we expect by chance
  - Unreliable without enormous corpora

- So we just replace negative PMI values by 0
- Positive PMI (PPMI) between word1 and word2:

$$\text{PPMI}(word_1, word_2) = \max\left(\log_2 \frac{P(word_1, word_2)}{P(word_1)P(word_2)}, 0\right)$$

Computing PPMI on a term-context matrix

- Matrix F with W rows (words) and C columns (contexts)
- f_{ij} is # of times w_i occurs in context c_j

	aardvark	computer	data	pinch	result	sugar
apricot	0	0	0	1	0	1
pineapple	0	0	0	1	0	1
digital	0	2	1	0	1	0
information	0	1	6	0	4	0

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

$$pmi_{ij} = \log_2 \frac{p_{ij}}{p_{i*}p_{*j}} \qquad ppmi_{ij} = \begin{cases} pmi_{ij} & \text{if } pmi_{ij} > 0 \\ 0 & \text{otherwise} \end{cases}$$

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

Count(w,context)

	computer	data	pinch	result	sugar
apricot	0	0	1	0	1
pineapple	0	0	1	0	1
digital	2	1	0	1	0
information	1	6	0	4	0

p(w=information,c=data) = 6/19 = .32

p(w=information) = 11/19 = .58

p(c=data) = 7/19 = .37

$$p(w_i) = \frac{\sum_{j=1}^{C} f_{ij}}{N} \qquad p(c_j) = \frac{\sum_{i=1}^{W} f_{ij}}{N}$$

p(w,context) **p(w)**

	computer	data	pinch	result	sugar	
apricot	0.00	0.00	0.05	0.00	0.05	0.11
pineapple	0.00	0.00	0.05	0.00	0.05	0.11
digital	0.11	0.05	0.00	0.05	0.00	0.21
information	0.05	0.32	0.00	0.21	0.00	0.58
p(context)	0.16	0.37	0.11	0.26	0.11	

$$pmi_{ij} = \log_2 \frac{p_{ij}}{p_{i*}p_{*j}}$$

	p(w,context)					p(w)
	computer	data	pinch	result	sugar	
apricot	0.00	0.00	0.05	0.00	0.05	0.11
pineapple	0.00	0.00	0.05	0.00	0.05	0.11
digital	0.11	0.05	0.00	0.05	0.00	0.21
information	0.05	0.32	0.00	0.21	0.00	0.58
p(context)	0.16	0.37	0.11	0.26	0.11	

PPMI(w,context)

	computer	data	pinch	result	sugar
apricot	-	-	2.25	-	2.25
pineapple	-	-	2.25	-	2.25
digital	1.66	0.00	-	0.00	-
information	0.00	0.57	-	0.47	-

Weighting PMI

- PMI is biased toward infrequent events
  - Very rare words have very high PMI values
- Two solutions:
  - Give rare words slightly higher probabilities
  - Use add-*k* smoothing (which has a similar effect)

Weighting PMI: Giving rare context words slightly higher probability

- Raise the context probabilities to $\alpha = 0.75$:

$$\text{PPMI}_\alpha(w,c) = \max(\log_2 \frac{P(w,c)}{P(w)P_\alpha(c)}, 0)$$

$$P_\alpha(c) = \frac{count(c)^\alpha}{\sum_c count(c)^\alpha}$$

- Consider two events, P(a) = .99 and P(b)=.01

$$P_\alpha(a) = \frac{.99^{.75}}{.99^{.75}+.01^{.75}} = .97 \quad P_\alpha(b) = \frac{.01^{.75}}{.01^{.75}+.01^{.75}} = .03$$

Add-2 smoothing

	Add-2 Smoothed Count(w,context				
	computer	data	pinch	result	sugar
apricot	2	2	3	2	3
pineapple	2	2	3	2	3
digital	4	3	2	3	2
information	3	8	2	6	2

PPMI vs add-2 smoothed PPMI

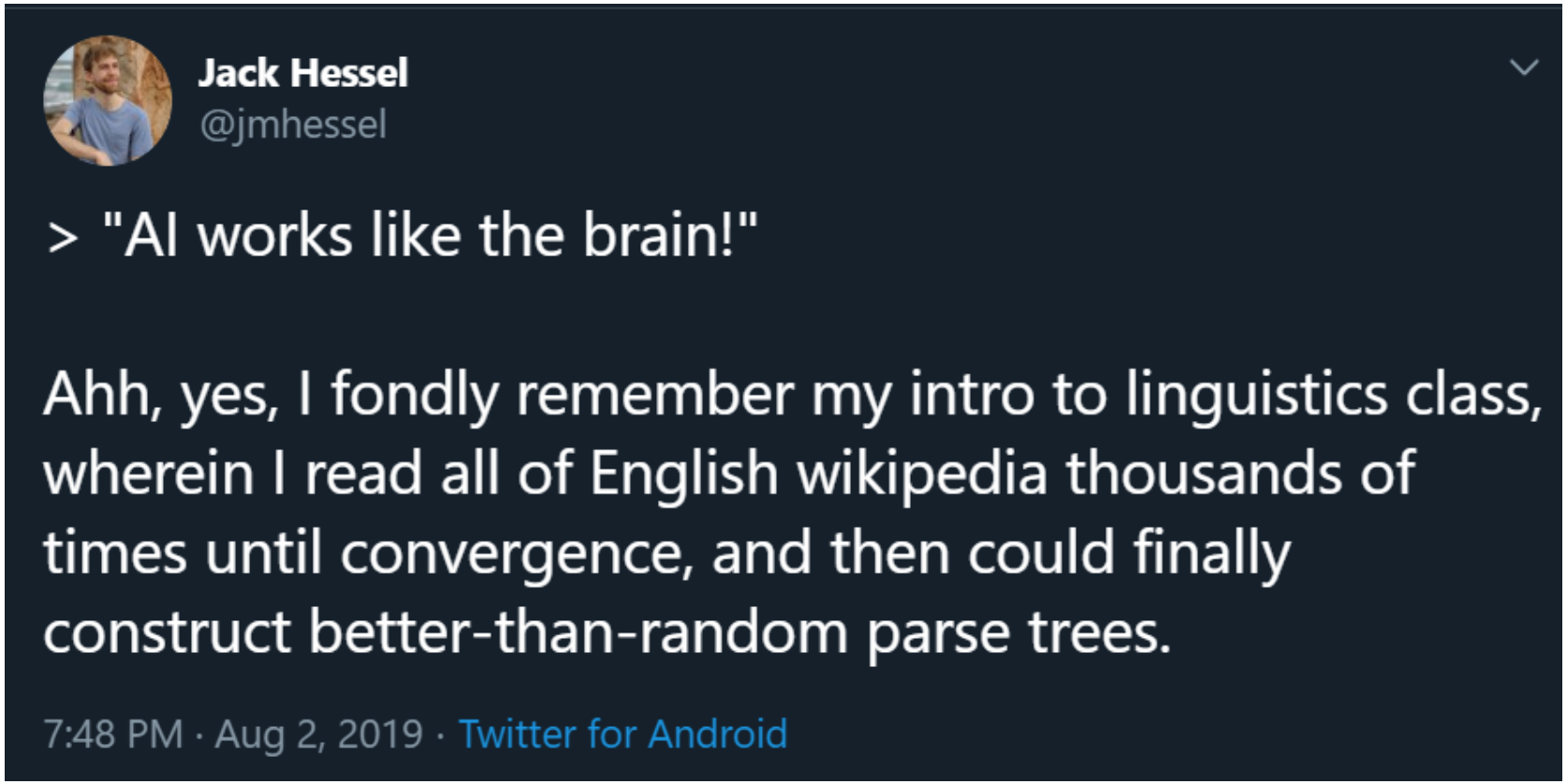
PPMI(w,context)

	computer	data	pinch	result	sugar
apricot	-	-	2.25	-	2.25
pineapple	-	-	2.25	-	2.25
digital	1.66	0.00	-	0.00	-
information	0.00	0.57	-	0.47	-

PPMI(w,context) [add-2]

	computer	data	pinch	result	sugar
apricot	0.00	0.00	0.56	0.00	0.56
pineapple	0.00	0.00	0.56	0.00	0.56
digital	0.62	0.00	0.00	0.00	0.00
information	0.00	0.58	0.00	0.37	0.00

This is a very language-centric measure of meaning



Measuring similarity: the cosine

Vector Semantics

Cosine for computing similarity

Dot product

Unit vectors

$$\cos(\vec{v},\vec{w}) = \frac{\vec{v}\bullet\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\vec{v}}{|\vec{v}|}\bullet\frac{\vec{w}}{|\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

v_i is the PPMI value for word *v* in context *i*
w_i is the PPMI value for word *w* in context *i.*

$\text{Cos}(\vec{v},\vec{w})$ is the cosine similarity of $\vec{v}$ and $\vec{w}$

Other possible similarity measures

$$\text{sim}_{\text{cosine}}(\vec{v},\vec{w}) = \frac{\vec{v}\cdot\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\sum_{i=1}^{N} v_i \times w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

$$\text{sim}_{\text{Jaccard}}(\vec{v},\vec{w}) = \frac{\sum_{i=1}^{N} \min(v_i,w_i)}{\sum_{i=1}^{N} \max(v_i,w_i)}$$

$$\text{sim}_{\text{Dice}}(\vec{v},\vec{w}) = \frac{2\times\sum_{i=1}^{N} \min(v_i,w_i)}{\sum_{i=1}^{N} (v_i+w_i)}$$

$$\text{sim}_{\text{JS}}(\vec{v}||\vec{w}) = D(\vec{v}|\frac{\vec{v}+\vec{w}}{2}) + D(\vec{w}|\frac{\vec{v}+\vec{w}}{2})$$

Evaluating similarity

Vector Semantics

Evaluating similarity

- Extrinsic (task-based, end-to-end) Evaluation:
  - Question Answering
  - Spell Checking
  - Essay grading

- Intrinsic Evaluation:
  - Correlation between algorithm and human word similarity ratings
    - Wordsim353: 353 noun pairs rated 0-10. *sim(plane,car)=5.77*
  - Taking TOEFL multiple-choice vocabulary tests
    - `Levied is closest in meaning to:`

`imposed, believed, requested, correlated`

Today: Word Meaning

2 core issues from an NLP perspective

- **Semantic similarity**: given two words, how similar are they in meaning?
- **Word sense disambiguation**: given a word that has more than one meaning, which one is used in a specific context?

“Big rig carrying fruit crashes on 210 Freeway, creates jam”

http://articles.latimes.com/2013/may/20/local/la-me-ln-big-rig-crash-20130520

How do we know that a word (lemma) has distinct senses?

- Linguists often design tests for this purpose
- e.g., **zeugma** combines distinct senses in an uncomfortable way

```
Which flight serves breakfast?

Which flights serve BWI?

*Which flights serve breakfast
and BWI?
```

Word Senses

- “Word sense” = distinct meaning of a word
- Same word, different senses
  - Homonyms (homonymy): unrelated senses; identical orthographic form is coincidental
    - E.g., financial bank vs. river bank
  - Polysemes (polysemy): related, but distinct senses
    - E.g., Financial bank vs. blood bank vs. tree bank
  - Metonyms (metonymy): “stand in”, technically, a sub-case of polysemy
    - E.g., use “Washington” in place of “the US government”
- Different word, same sense
  - Synonyms (synonymy)

- Homophones: same pronunciation, different orthography, different meaning
  - Examples: would/wood, to/too/two

- Homographs: distinct senses, same orthographic form, different pronunciation
  - Examples: bass (fish) vs. bass (instrument)

Relationship Between Senses

- **IS-A relationships**
  - From specific to general (up): hypernym (hypernymy)
  - From general to specific (down): hyponym (hyponymy)
- **Part-Whole relationships**
  - wheel is a meronym of car (meronymy)
  - car is a holonym of wheel (holonymy)

WordNet:
a lexical database for English

https://wordnet.princeton.edu/

- Includes most English nouns, verbs, adjectives, adverbs
- Electronic format makes it amenable to automatic manipulation: used in many NLP applications
- “WordNets” generically refers to similar resources in other languages

Synonymy in WordNet

- WordNet is organized in terms of “synsets”
  - Unordered set of (roughly) synonymous “words” (or multi-word phrases)

- Each synset expresses a distinct meaning/concept

The *drive* card game

A. The miners drove a tunnel in the mountain
B. What are you driving at?
C. I drove a golf ball further than I'd ever done
D. Can you drive this four-wheel truck?
E. The hunters drive the forest for squirrels
F. He drives me mad
G. She drives for the taxi company in DC
H. They finally drove me to change jobs
I. Steam drives the engines of this train
J. The car drove around the corner
K. I drove a nail into the wall
L. We drove to the university every morning
M. My new truck drives well
N. The dog drove the cows into the barn
O. She is driven by her passion
P. She drove me to school every day
Q. I drove the football far across the field
R. They drove back the enemy forces
S. She is driving away at her doctoral thesis
T. The baseball player drove the ball into the field
U. We drive the turnpike to work
V. The hyenas drove the game into the open

WordNet: Example

Noun

{pipe, tobacco pipe} (a tube with a small bowl at one end; used for smoking tobacco)

{pipe, pipage, piping} (a long tube made of metal or plastic that is used to carry water or oil or gas etc.)

{pipe, tube} (a hollow cylindrical shape)

{pipe} (a tubular wind instrument)

{organ pipe, pipe, pipework} (the flues and stops on a pipe organ)

Verb

{shriek, shrill, pipe up, pipe} (utter a shrill cry)

{pipe} (transport by pipeline) “pipe oil, water, and gas into the desert”

{pipe} (play on a pipe) “pipe a tune”

{pipe} (trim with piping) “pipe the skirt”

WordNet 3.0: Size

Part of speech	Word form	Synsets
Noun	117,798	82,115
Verb	11,529	13,767
Adjective	21,479	18,156
Adverb	4,481	3,621
Total	155,287	117,659

Word Sense Disambiguation

- Task: automatically select the correct sense of a word
  - Input: a word in context
  - Output: sense of the word

- Motivated by many applications:
  - Information retrieval
  - Machine translation
  - …

How big is the problem?

- **Most words in English have only one sense**
  - 62% in Longman's Dictionary of Contemporary English
  - 79% in WordNet
- But the others tend to have several senses
  - Average of 3.83 in LDOCE
  - Average of 2.96 in WordNet

- **Ambiguous words are more frequently used**
  - In the British National Corpus, 84% of instances have more than one sense
- **Some senses are more frequent than others**

Baseline Performance

- Baseline: most frequent sense
  - Equivalent to “take first sense” in WordNet
  - Does surprisingly well!

Freq	Synset	Gloss
338	plant[1], works, industrial plant	buildings for carrying on industrial labor
207	plant[2], flora, plant life	a living organism lacking the power of locomotion
2	plant[3]	something planted secretly for discovery by another
0	plant[4]	an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience

62% accuracy in this case!

Upper Bound Performance

- Upper bound
  - Fine-grained WordNet sense: 75-80% human agreement
  - Coarser-grained inventories: 90% human agreement possible

Simplest WSD algorithm: Lesk's Algorithm

- Intuition: note word overlap between context and dictionary entries
  - **Unsupervised,** but knowledge rich

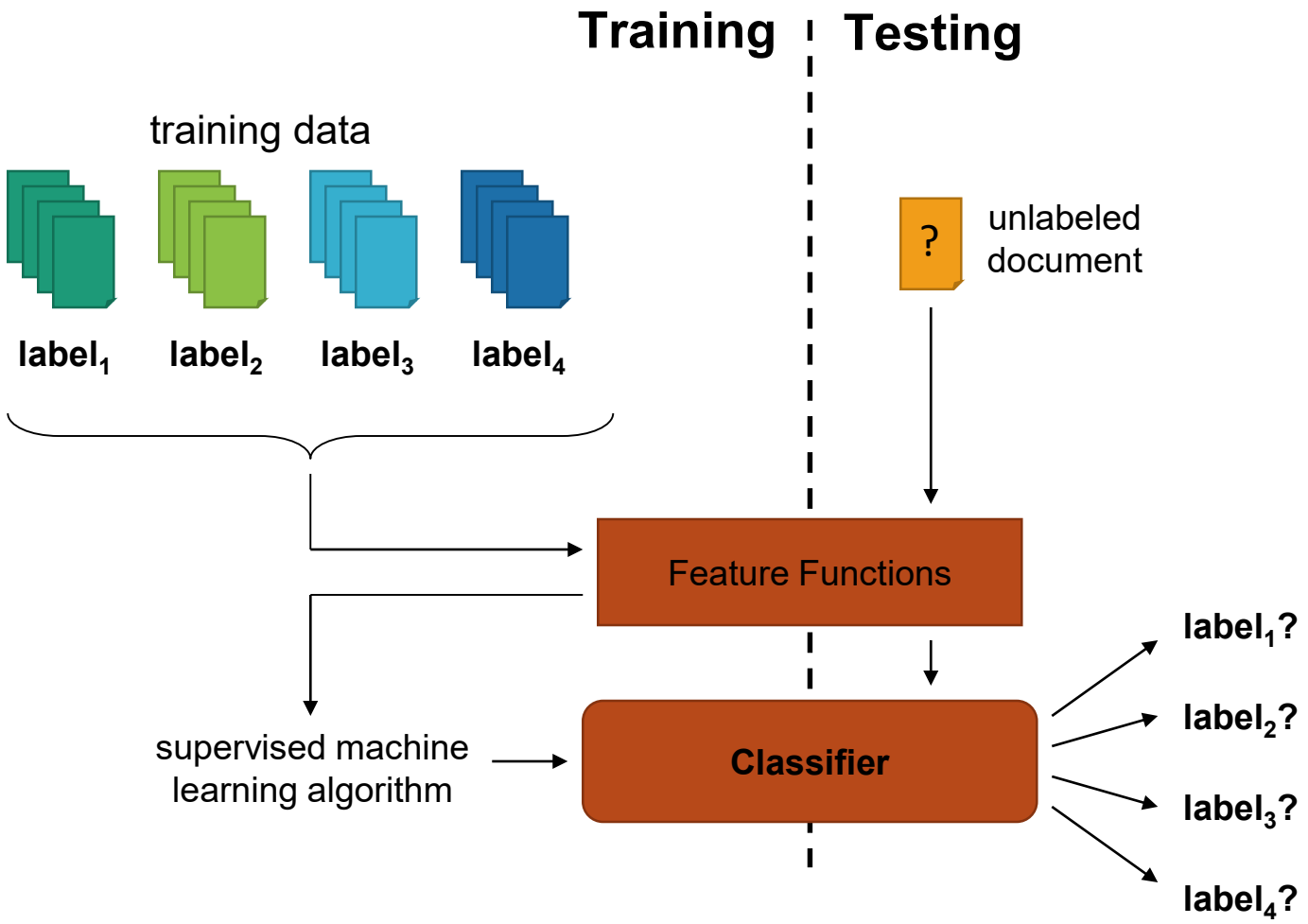
The bank can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

bank[1]	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	"he cashed a check at the bank", "that bank holds the mortgage on my home"
bank[2]	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	"they pulled the canoe up on the bank", "he sat on the bank of the river and watched the currents"

Lesk's Algorithm

- Simplest implementation:
  - Count overlapping content words between glosses and context
- Lots of variants:
  - Include the examples in dictionary definitions
  - Include hypernyms and hyponyms
  - Give more weight to larger overlaps (e.g., bigrams)
  - Give extra weight to infrequent words
  - …

Alternative: WSD as **Supervised** Classification



Existing Corpora

- Lexical sample
  - *line-hard-serve* corpus (4k sense-tagged examples)
  - *interest corpus* (2,369 sense-tagged examples)
  - …
- All-words
  - SemCor (234k words, subset of Brown Corpus)
  - Senseval/SemEval (2081 tagged content words from 5k total words)
  - …

Word Meaning

2 core issues from an NLP perspective

- **Semantic similarity**: given two words, how similar are they in meaning?
- Key concepts: vector semantics, PPMI and its variants, cosine similarity

- **Word sense disambiguation**: given a word that has more than one meaning, which one is used in a specific context?
- Key concepts: word sense, WordNet and sense inventories, unsupervised disambiguation (Lesk), supervised disambiguation

Before next class

- Start (looking at) HW1
  - If you have questions related to material we've already covered, feel free to ask about it in class next time

- Go over math review pieces
  - Tuesday is a *review* of linear model
  - Goal: remind you what you already know
  - Not Goal: teach you all of machine learning and statistics