

Class presentations

IR (3/30)

- Article 1: Scott and Maksym Article 2: Devin and Dandre
- MT (4/11)
- Article 1: Jonny, Chysanthia and Daniel M. Article 2: Eric and Benson
- IE (4/18)
 Article 1: Kathryn and Audrey Article 2: Josh and Michael
- QA (4/25)
- Article 1: Dustin and Brennen
 Article 2: Sam and Martin
- Summ (4/27???)
 - Article 1: Andres and Camille

Article 2: Jeremy and Dan F.

Admin

- Assignment 5 posted, due next Friday (4/1) at 6pm can turn in by Sunday at 6pm
- Class schedule

Final project

- Read the entire handout
- Groups of 2-3 people
- e-mail me asap if you're looking for a group research-oriented project
 - must involve some evaluation!
 - must be related to NLP
- Schedule
- Monday, 4/4 project proposal
- 4/15 status report 1
- 4/27 status report 2
- 5/2, 5/4 presentations 5/4 writeup
- There are lots of resources out there that you can leverage

Final project ideas

- pick a text classification task
- evaluate different machine learning methods
 implement a machine learning method
 analyze different feature categories

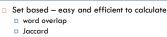
- Indigite and the formation of the second secon

- Implement alternative models
 parsing
 PCFG-based language modeling
 leckacitized PCFG (with smoothing)
 true n-best list generation
 parse output remarking
 implement enother parsing approach and compare
 parsing non-traditional domains (e.g. twitter)
- EM . word-alignment for text-to-text translation
 grammar induction

Final project ideas spelling correction part of speech tagger text chunker dialogue generation pronoun resolution compare word similarity measures (more than the ones we're looking at for assign. 5) word sense disambiguation machine translation compare sentence alignment techniques information retrieval information extraction question answering summarization speech recognition

Text Similarity
A common question in NLP is how similar are texts
score: sim(,) = ?
rank:

Text similarity recapped



Dice

Vector based

- create a feature vector based on word occurrences (or other features)
- Can use any distance measure
 L1 (Manhattan)
 - L2 (Euclidean)
 - Cosine
- Normalize the length
- Feature/dimension weighting
- inverse document frequency (IDF)

Stoplists: extreme weighting

- Some words like 'a' and 'the' will occur in almost every document
 - IDF will be 0 for any word that occurs in all document
 - For words that occur in almost all of the documents, they will be nearly 0
- A stoplist is a list of words that should not be considered (in this case, similarity calculations)
 Sometimes this is the n most frequent words
 - Often, it's a list of a few hundred words manually created

1	all-over	around	beneath	due	go
a	almost	as	beside	durin	goddamn
aboard	along	aside	besides	during	goody
about	alongside	astride	between	each	gosh
above	altho	at	bewteen	eh	half
across	although	atop	beyond	either	have
after	amid	avec	bi	en	he
afterwards	amidst	away	both	every	hell
against	among	back	but	ever	her
agin	amongst	be	by	everyone	herself
ago	an	because	ca.	everything	hey
agreed-upon	and	before	de	except	him
ah	another	beforehand	des	far	himself
alas	any	behind	despite	fer	his
albeit	anyone	behynde	do	for	ho
all	anythina	below	down	from	hew

Stoplists

Two main benefits

- More fine grained control: some words may not be frequent, but may not have any content value (alas, teh, gosh)
- Often does contain many frequent words, which can drastically reduce our storage and computation

□ Any downsides to using a stoplist?

For some applications, some stop words may be important

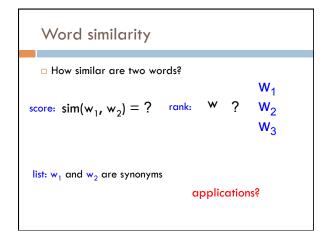
Our problems

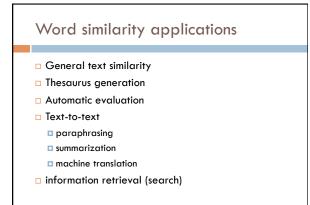
- □ Which of these have we addressed?
 - word order
 - length
 - synonym
 - spelling mistakesword importance
 - word frequency

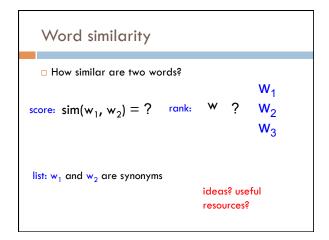
 - A model of word similarity!

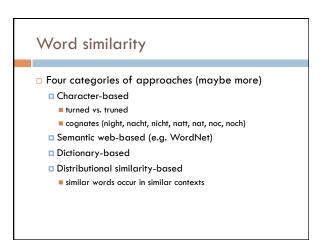
Word overlap problems

- A: When the defendant and his lawyer walked into the court, some of the victim supporters turned their backs to him.
- B: When the defendant walked into the courthouse with his attorney, the crowd truned their backs on him.







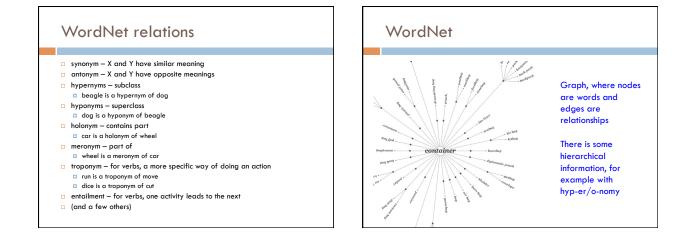


WordNet

- Lexical database for English
 - 155,287 words
 - 206,941 word senses
 - 117,659 synsets (synonym sets) ~400K relations between senses
 - Parts of speech: nouns, verbs, adjectives, adverbs
- Word graph, with word senses as nodes and edges as relationships
- Psycholinguistics
 - WN attempts to model human lexical memory
 - Design based on psychological testing
- Created by researchers at Princeton
- http://wordnet.princeton.edu/
- Lots of programmatic interfaces

WordNet relations

- 🗆 synonym
- antonym
- □ hypernyms
- hyponyms
- □ holonym
- meronym
- □ troponym
- entailment
- □ (and a few others)



WordNet: dog

Noun

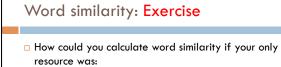
- S: (n) dog. domestic dog. Canit familiaris (a member of the genus Canis (probably descended from the common well) that has been domesticated by man since prehistoric times; occurs in many breeds) "the dog barked all right"
 S: (n) framp, dog (a dull unattractive unpleasant girl or woman) "she got a reputation as a frump"; "she's a real dog."
 S: (n) dog. (informal term for a man) "you lacky dog."
 S: (n) dog. (informat term for a man) "you lacky dog."
 S: (n) dog. (informat term for a man) "you lacky dog."
 S: (n) dog. (informat term for a man) "you lacky dog."
 S: (n) dog. (informat, bakky, hot dog. dog., where, wiener, wirener, werently exprehensible) "you dirty dog."
 S: (n) any, destin, cloked, hot dog. dog., where, wiener, wirener, werently (a smooth-textured sausage of minece beer op roky usually smodel; don as read roll)
 S: (n) any, destin, cloked, dog (a hinged catch that fits into a notch of a ratchet to move a wheel forward or prevent if from moving backward)
 S: (n) andiron, firedog, dog, dog., dog. (metal supports for logs in a fireplace) "the andirons were too hot to towch"

- Verb

S: (v) chase, chase after, trail, tail, tag, give chase, dog, go after, track (go after with the intent to catch) "The
policeman chased the mugger down the alley"; "the dog chased the rabbit"

WordNet: dog

- direct hyperium / full hypersym
 S: (n) pappy (a young dog)
 S: (n) having dog (any of sevenal breeds of very small dogs keep purely as pets)
 S: (n) having dog (any of sevenal breeds of very small dogs keep purely as pets)
 S: (n) having dog (any of sevenal breeds of very small dogs keep purely as pets)
 S: (n) having dog (any of sevenal breeds of very small dogs keep purely as pets)
 S: (n) having dog (ang og sevenal breeds of versal hereds of



- . the words themselves
- 2. WordNet
- 3. a dictionary
- 4. a corpus

Word similarity

Four general categories

- Character-based
 - turned vs. truned
 - cognates (night, nacht, nicht, natt, nat, noc, noch)
- Semantic web-based (e.g. WordNet)
- Dictionary-based
- Distributional similarity-based
- similar words occur in similar contexts

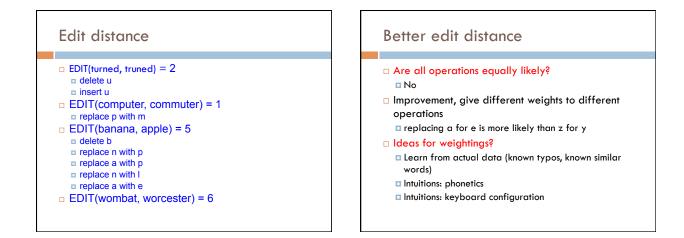
Character-based similarity

sim(turned, truned) = ?

How might we do this using only the words (i.e. no outside resources?

Edit distance (Levenshtein distance)

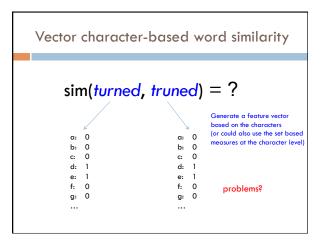
- $\hfill\square$ The edit distance between w_1 and w_2 is the minimum number of operations to transform w_1 into w_2
- Operations:
 - insertion
 - deletionsubstitution
- EDIT(turned, truned) = ?
- EDIT(computer, commuter) = ? EDIT(banana, apple) = ?
- EDIT(wombat, worcester) = ?

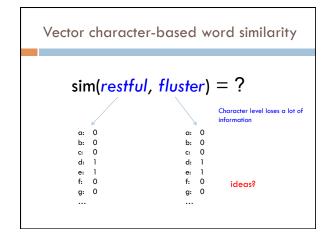


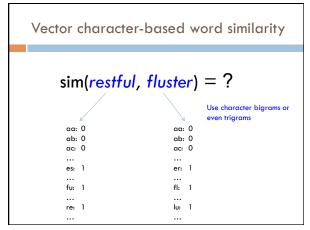
Vector character-based word similarity

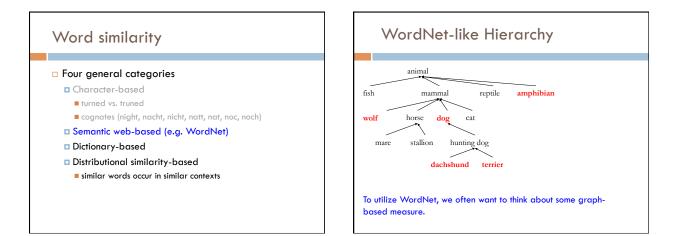
sim(turned, truned) = ?

Any way to leverage our vector-based similarity approaches from last time?

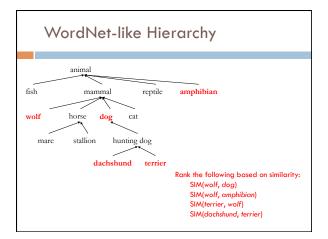


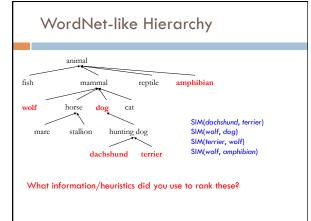


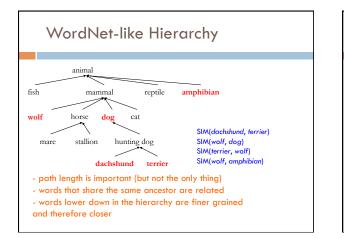


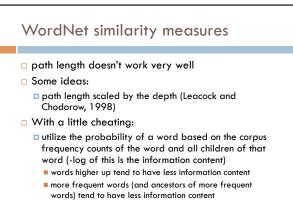


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WordNet similarity measures

Utilizing information content:

 information content of the lowest common parent (Resnik, 1995)

- information content of the words minus information content of the lowest common parent (Jiang and Conrath, 1997)
- information content of the lowest common parent divided by the information content of the words (Lin, 1998)

Word similarity

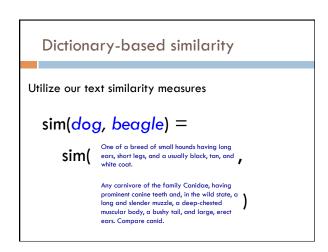
Four general categories

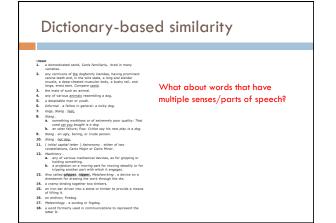
- Character-based
 - turned vs. truned
 - cognates (night, nacht, nicht, natt, nat, noc, noch)
- Semantic web-based (e.g. WordNet)

Dictionary-based

- Distributional similarity-based
- similar words occur in similar contexts

Dictionary-based similarity Word Dictionary blurb aardvark a large, nocturnal, burrowing mammal, Orycteropus afer, ofcentral and southern Africa, feeding on ants and termites andhowing a long, extensile tongue, strong claws, and long ears. beagle One of a breed of small hounds having long ears, short legs, and a usually black, tan, and white coat. dog Any carnivare of the family Canidae, having prominent conine teeth and, in the wild state, a long and slender muzzle, a deep-chested muscular body, a bushy tail, and large, erect ears. Compare conid.





Dictionary-based similarity -secart and the second s 1. part of speech tagging 2. word sense disambiguation 3. most frequent sense 4. average similarity between all senses 5. max similarity between all senses 6. sum of similarity between all senses

Dictionary + WordNet

- WordNet also includes a "gloss" similar to a dictionary definition
- Other variants include the overlap of the word senses as well as those word senses that are related (e.g. hypernym, hyponym, etc.)
 - $\hfill \ensuremath{\sc line \ensuremath{\sc line$
 - Banerjee and Pedersen, 2003

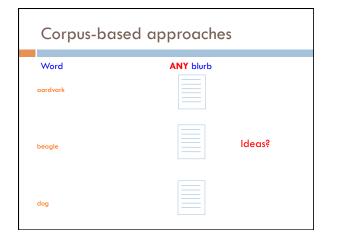
Word similarity

reaog. . a sundog or fogdog. rly used in communications to represent the

an andiror.
 Meteorolog
 a word for letter D.

Four general categories

- Character-based
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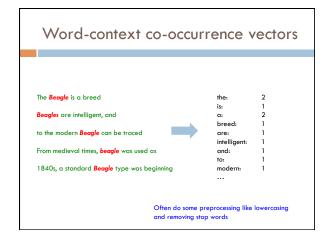
Corpus-based
The Beagle is a breed of small to medium-sized dog. A member of the Hound Group, it is similar in appearance to the Foxhound but smaller, with shorter leg Beogles are intelligent, and are popular as pets because of their size, even temper, and lock of instants houth problem:
and lack of inherited health problems. Dogs of similar size and purpose to the modern Beagle can be traced in Ancient Greece[2] back to around the 5th century BC.
From medieval times, beagle was used as a generic description for the smaller hounds, though these dogs differed considerably from the modern breed.
In the 1840s, a standard Beagle type was beginning to develop: the distinction between the North Country Beagle and Southern

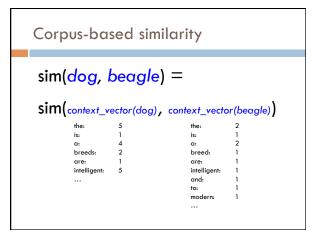
Corpus-based: feature extraction

- The **Beagle** is a breed of small to medium-sized dog. A member of the Hound Group, it is similar in appearance to the Foxhound but smaller, with shorter leg
- We'd like to utilize or vector-based approach
- □ How could we we create a vector from these occurrences?
 - $\hfill\square$ collect word counts from all documents with the word in it
 - $\hfill\square$ collect word counts from all sentences with the word in it
 - $\hfill\square$ collect all word counts from all words within X words of the word
 - collect all words counts from words in specific relationship: subjectobject, etc.

Word-context co-occurrence vectors

- The **Beagle** is a breed of small to medium-sized dog. A member of the Hound Group, it is similar in appearance to the Foxhound but smaller, with shorter leg
- Beagles are intelligent, and are popular as pets because of their size, even temper, and lack of inherited health problems.
- Dogs of similar size and purpose to the modern Beagle can be traced in Ancient Greece[2] back to around the 5th century BC.
- From medieval times, beagle was used as a generic description for the smaller hounds, though these dogs differed considerably from the modern breed.
- In the **1840s**, a standard **Beagle** type was beginning to develop: the distinction between the North Country Beagle and Southern





Another feature weighting

- TFIDF weighting tanks into account the general importance of a feature
- For distributional similarity, we have the feature (f_i), but we also have the word itself (w) that we can use for information
- $\hfill\square$ This is different from traditional text similarity where we only have f_i
- Another feature weighting idea
 - don't use raw co-occurrence
 - count how likely feature f_i and word w are to occur together
 incorporates co-occurrence
 - **•** but also incorporates how often w and f_i occur in other instances

Mutual information

A bit more probability [©]

$$I(X,Y) = \sum_{x} \sum_{y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

When will this be high and when will this be low?

Mutual information

A bit more probability

$$I(X,Y) = \sum_{x} \sum_{y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

- if x and y are independent (i.e. one occurring doesn't impact the other occurring) $p(x,y) \equiv p(x)p(y)$ and the sum is 0

- if they're dependent then p(x,y) = p(x)p(y | x) = p(y)p(x | y) then we get p(y | x)/p(y) (i.e. how much more likely are we to see y given x has a particular value) or vice versa p(x | y)/p(x)

