LING 331
Text Processing for Linguists

Week 9

Python for Text (and Beyond)

Roadmap for Our Last Two Days

Wednesday 3/2

- Assignment 6 FYIs
- Content:
  - Dependency Parsing
  - WordNet
  - Word Vectors
- Final Assignment

Monday 3/7

- Assignment 6 Notes
- Content:
  - Classification
- Final Self-Evaluation
- Where To Go From Here

Notes for Assignment 6

- `-PRON-` is a spaCy idiosyncrasy
  - Some weird version issues though...
- Stemming vs. Lemmatization
  - Stemmers are a much more coarse heuristic algorithm
  - Lemmatizers are machine learning models

    = more computationally expensive, but not crazily so

Notes for Assignment 6

- Sometimes you get a nice docstring, comments, etc sometimes you don't!
- Figuring out types of objects:
  - `type(obj)`, `dir(obj)`, `help(obj)`, `print(obj)`
- If you're running into trouble this is the first thing to try!
- With dicts, useful also to `print(d.keys())`
- E.g. `sentences` in 2.g., what's in a `row` in 5.a.

Notes for Assignment 6

- Nested dictionaries: dicts are key-value, but value can be anything, including another dict

```
intensity = {}

... # do some stuff

if not word in intensity:
    intensity[word] = {}

... # do some stuff

intensity[word][emotion] = score
```

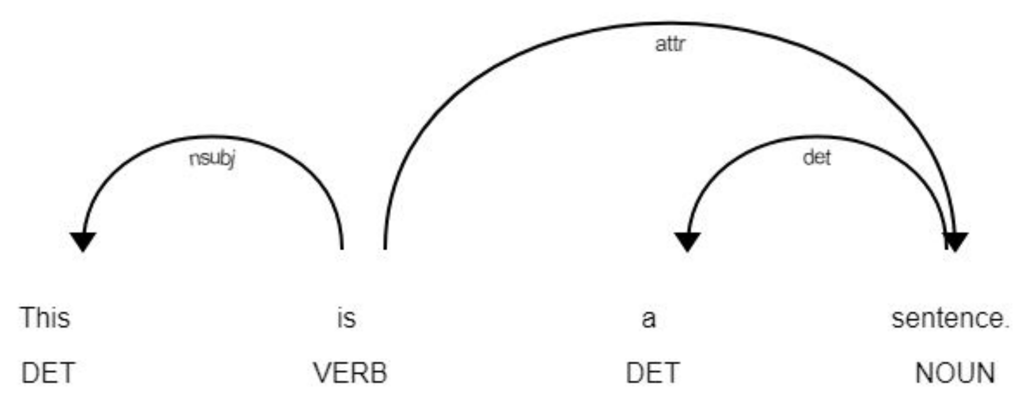
Notes for Assignment 6

- `left_adjectives`:
  This is another common sort of programming meme, requires a sort of "spatial orientation" / "navigation" skill
- `enumerate` to maintain an `index`,
  when current word matches, check `index - 1`
- Working with dependency trees is a yet-trickier version of this meme!

Dependency Parsing gives a syntax representation

- Words are connected to other words with a tag representing their relationship
- Main verb is the sentence root
- Directed:

  head → dependent
- Tag is role the played by the dependent



https://spacy.io/usage/visualizers

https://explosion.ai/demos/displacy

Dependency Parsing gives a syntax representation

- Most common formalism for syntax in Comp Ling / NLP
  - Interesting contrast with formal syntax!
- Partially because of computational feasibility
- Very exciting project: Universal Dependencies
  - https://universaldependencies.org/
  - (you can contribute!)

Dependency Parsing gives a syntax representation

- spaCy does dependency parsing inherently (if you don't disable `"parser"`)
- Access dependency tag with `token.dep_`
  List of children with `token.children`
- More info:
  https://spacy.io/usage/linguistic-features

WordNet is a lexical resource for semantic relations

- Represents semantic relationships in a large network
- Allows to calculate e.g. “path similarity”
- Play with directly: http://wordnetweb.princeton.edu/perl/webwn

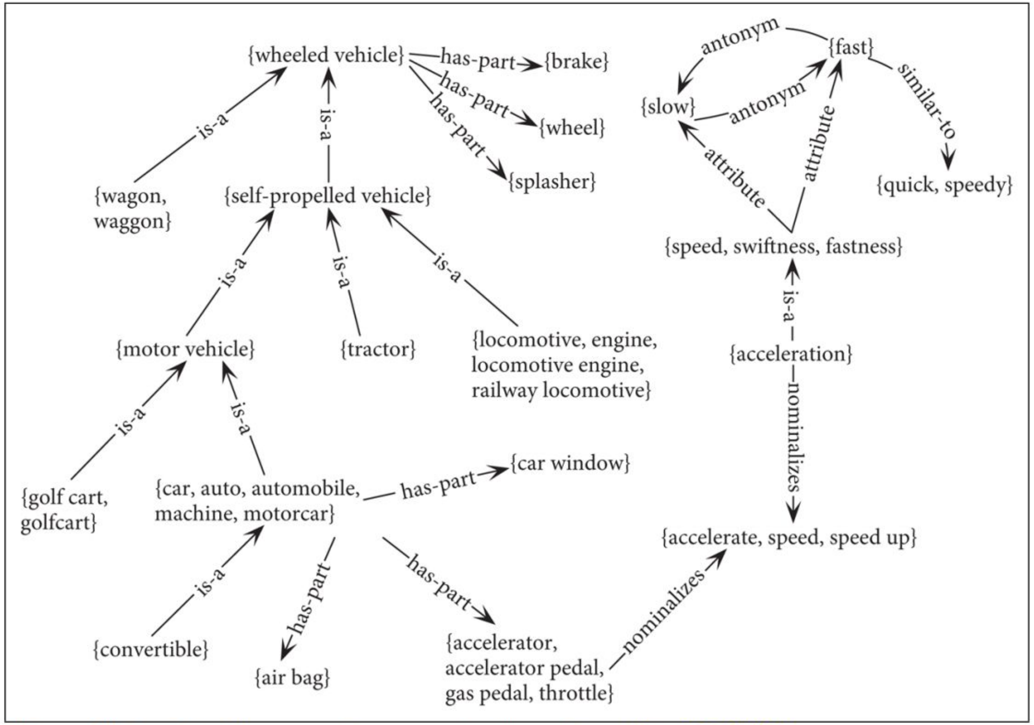


Figure 19.6 WordNet viewed as a graph. Figure from Navigli (2016).

WordNet is a lexical resource for semantic relations

- NLTK has an interface for working with WordNet
- … but it's not the most intuitive thing in the world
- More info here: https://www.nltk.org/howto/wordnet.html

Sparsity is a property of natural language

- Language is creative, flexible, and ever-evolving; there are many ways to say the "same thing"
- Translations for instance! But even within a language.

Q: Where is he?

He went to the store

Oh, Johnny left to get groceries

Out to grab the essentials

Sparsity is a property of natural language

- Zipf's Law:

If you order words by frequency rank, e.g.

1	the
2	and
3	I
4	to
5	of

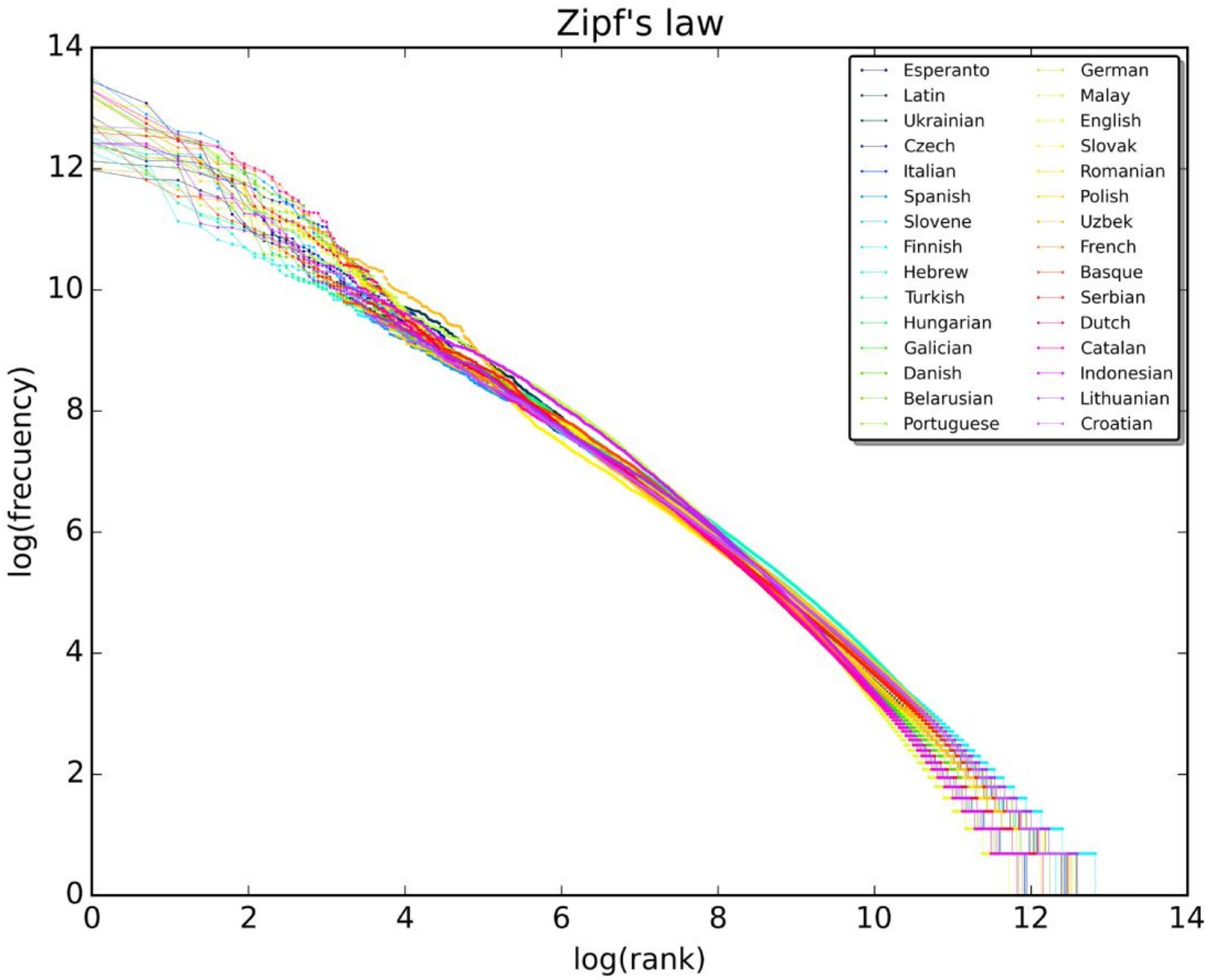
Counts will be inversely proportional to rank!

So 'the' will appear roughly 2x as often as 'and', which will appear 2x as often as 'I', etc

Zipf's Law

Across languages on Wikipedia

https://en.wikipedia.org/wiki/Zipf%27s_law



Sparsity is a property of natural language

Closed-Class Words

of, she, or, the, no, and

- a.k.a. ‘function words’
- Includes pronouns, articles, conjunctions, particles
- Rarely gain new members
- Very dense!
- Perform grammatical and discourse functions

Open-Class Words

walrus, fleek, margarine, poindexter

- a.k.a. ‘content words’
- Includes nouns, verbs, adjectives, etc.
- Frequently gain new members
- Very sparse!
- Perform semantic functions, i.e. carry most of the meaning

Sparsity is a problem for computing with language

`'cat' != 'cat,' != 'CAT' != ‘Cat’ != ‘cats’`

We’ve seen some ways to deal with this:

- Stripping punctuation
- Downcasing
- Tokenization
- Stemming
- Lemmatization

... and more abstractly:

- POS tagging
- Lexicons (concreteness, emotion)
- Syntactic roles and relations

Sparsity is a problem for computing with language

But what if we want a different semantic operation than a pure exact match?

For instance, how can we know if words are more or less similar?

Answer: create a numerical representation that can be operated on mathematically - word vectors!

Word Vectors provide a numerical representation of the meaning of a word

- Key mathematical notes:
  - A vector is simply a list of numbers
  - Those numbers form an abstract representation of a word
  - Each “dimension” refers to the number at a certain index
  - Dimensions can be meaningful or not depending on how the vectors are constructed

Word Vectors provide a numerical representation of the meaning of a word

You could imagine manually constructing them:

word	**cuteness**	**furriness**	**animacy**	**growth_stage**

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`kitten`	8	8	5	-4

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word	**cuteness**	**furriness**	**animacy**	**growth_stage**
`cat`	5	7	7	6
`kitten`	8	8	5	-4
`lizard`	-3	-8	4	0

Word Vectors provide a numerical representation of the meaning of a word

You could imagine manually constructing them:

word	cuteness	furriness	animacy	growth_stage
cat	5	7	7	6
kitten	8	8	5	-4
lizard	-3	-8	4	0
houseplant	2	-4	2	2

Word Vectors provide a numerical representation of the meaning of a word

You could imagine manually constructing them:

word	**cuteness**	**furriness**	**animacy**	**growth_stage**
`cat`	5	7	7	6
`kitten`	8	8	5	-4
`lizard`	-3	-8	4	0
`houseplant`	2	-4	2	2
`teddy_bear`	6	6	-10	0

Word Vectors provide a numerical representation of the meaning of a word

- But this would be unthinkably time-consuming and arbitrary
- Solution: the **distributional hypothesis**

  "You shall know a word by the company it keeps."

  -Firth 1957
- Intuitively:
  - "Cat" occurs near "furry", "claws", "cute", "feline" in everyday speech, so does "kitten", so they are similar.

Word Vectors provide a numerical representation of the meaning of a word

- So, use word vectors generated from co-occurrence statistics
- Methods described in more detail in SLP Ch. 6
    - Raw co-occurrence counts, TF-IDF, PPMI

	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	
strawberry	0	...	0	0	1	60	19	
digital	0	...	1670	1683	85	5	4	
information	0	...	3325	3982	378	5	13	

Figure 6.5 Co-occurrence vectors for four words in the Wikipedia corpus, showing six of the dimensions (hand-picked for pedagogical purposes). The vector for *digital* is outlined in red. Note that a real vector would have vastly more dimensions and thus be much sparser.

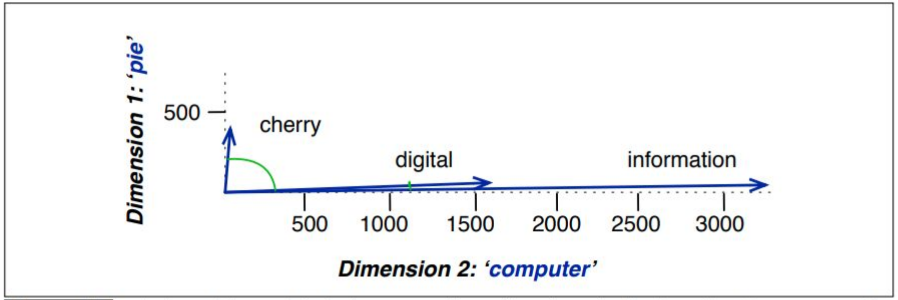

Figure 6.7 A (rough) graphical demonstration of cosine similarity, showing vectors for three words (*cherry*, *digital*, and *information*) in the two dimensional space defined by counts of the words *computer* and *pie* nearby. Note that the angle between *digital* and *information* is smaller than the angle between *cherry* and *information*.

Jurafsky and Martin Ch.6

Word Vectors provide a numerical representation of the meaning of a word

- These are still relatively sparse; most words don't co-occur with most other words, matrix is full of many zeroes
- Solution: Machine learning approach (e.g. word2vec)
- Generates compressed vectors of dimension ~500
    - **Pro**: learn dense vectors implicitly from natural language!
      Con: dimensions become much less interpretable!

Word Vectors == Word embeddings

- "Embeddings" are the same as vectors
- Representation is "embedded" in a shared "vector space" with other representations (i.e. they have comparable dimensions)

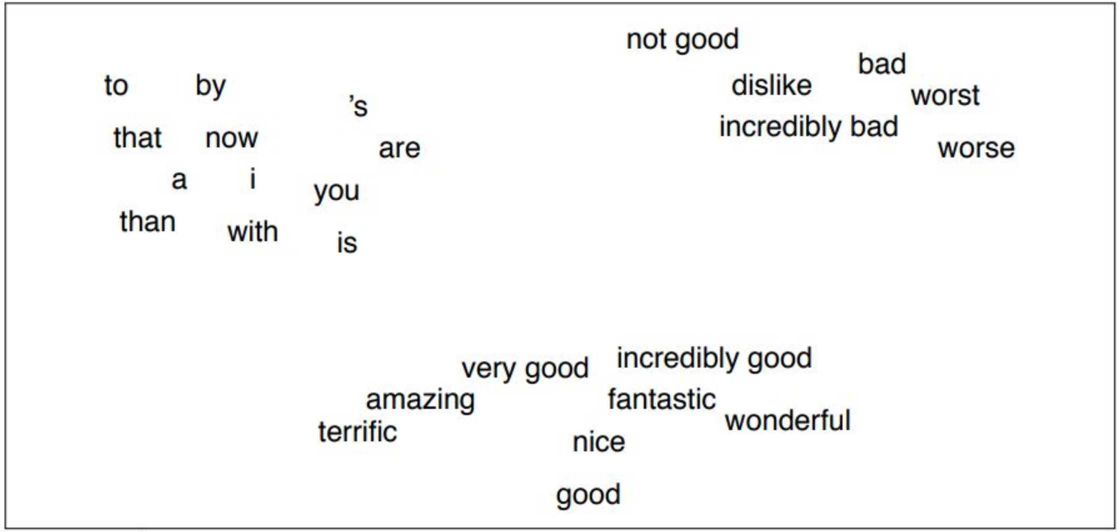

Figure 6.1 A two-dimensional (t-SNE) projection of embeddings for some words and phrases, showing that words with similar meanings are nearby in space. The original 60-dimensional embeddings were trained for sentiment analysis. Simplified from Li et al. (2015).

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Final Assignment

- More and more on your own! Get creative!
- *Key point!*
  - If you want to use LDC or BYU data, let me know by Wednesday
- Please turn in on time! March 15th, where you're at
  - For grading purposes, but I'm always available to talk more later if you keep working on it!