NTNU
Norwegian University of Science and Technology

TDT4310, Lab session 3

Stemming/Lemmatization, TF-IDF, and part-of-speech tagging

Tollef Jørgensen, February 13, 2024.

The course so far

- Few seem to have problems with the course material
  - Surprisingly few questions
    - Please don't hesitate to ask us about whatever you're wondering about!

A recap: working with the labs

- The git repo will update throughout. You can clone it, and make sure you update with **git pull** when necessary
  - oooor: just check by the github page and download the exercise files directly.
    - Sometimes, I will change the material, but there will be no consequences if you deliver an "out of date" file.

Before we continue

- Are there any concerns about the setup so far?
- Are the topics interesting?
- I wish we could delve right into the most "hyped" implementation parts, but that would require another course :-)

Lab 3 topics

- Stemming/lemmatization
- TF-IDF
- Part-of-speech tagging

But why?

- **Stemming/lemmatization**
  - Common word forms, making your inputs more predictable
  - Mostly used in "basic" NLP systems (classification, for example)
- **TF-IDF**
  - Weight the importance of words relative to the current document in context of all available documents
    - Given a query, how relevant is it for each document in my collection?
      - Typically relies on text normalization!
- **Part-of-speech tagging**
  - Word structure!
  - Can be used to generate groups of words as we'll see in the next lab (dependency parsing)
  - If done correctly, we can resolve ambiguities.
    - Obviously relies on context, and this can be (naively) implemented with n-grams.

Stemming and Lemmatization

Stemming and Lemmatization

- Part of what we call "text normalization" or "text cleaning"
- Converting text to its standard form - either by:
  - Stemming - reducing words to their "stem", by removing suffixes
  - Lemmatization - using dictionaries and definitions to reduce words to their base form
- Both approaches will result in weird and ungrammatical sentences. For many applications, this won't matter!
  - Why?

Word	Stemming	Lemmatization
information	inform	information
informative	inform	informative
computers	comput	computer
feet	feet	foot

Stemming and Lemmatization

- Both approaches will result in weird and ungrammatical sentences.
  - But... For many applications, this won't matter!
    - Why?

Word	Stemming	Lemmatization
information	inform	information
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```
"this lecture describes some concepts within computational linguistics"
# STEMM.: "thi lectur describ some concept within comput linguist"
# LEMMA.: "this lecture describes some concept within computational linguistics"
```

Using wordnet to lemmatize

```
some
Synset('some.a.01') quantifier; used with either mass nouns or plural count nouns
Synset('some.s.02') relatively much but unspecified in amount or extent
Synset('some.s.03') relatively many but unspecified in number
Synset('some.s.04') remarkable
Synset('approximately.r.01') (of quantities) imprecise but fairly close to correct
concepts
Synset('concept.n.01') an abstract or general idea inferred or derived from specif
within
Synset('inside.r.02') on the inside
computational
Synset('computational.a.01') of or involving computation or computers
linguistics
Synset('linguistics.n.01') the scientific study of language
Synset('linguistics.n.02') the humanistic study of language and literature
```

TF-IDF

TF-IDF

$$\text{tf-idf}(t, d, D) = \text{tf}(t, d) \times \text{idf}(t, D)$$

- Term Frequency (TF)
  - How often a word appears in a document.
  - The more frequent, the higher its TF score.
- Inverse Document Frequency (IDF)
  - How rare a word is across the corpus.
  - The rarer, the higher its IDF score

TF-IDF

$$\text{tf-idf}(t, d, D) = \text{tf}(t, d) \times \text{idf}(t, D)$$

- A way to determine the *importance of a word*
  - In a document relative to a collection of documents
- Example:
  - You're interested in looking up info about "robots"
    - Probably frequent in sci-fi books, less so in historical novels, probably.
      - If the word is *rare*, it will receive a higher score

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TF-IDF

$$\text{tf-idf}(t, d, D) = \text{tf}(t, d) \times \text{idf}(t, D)$$

- Many applications!
  - Information retrieval (IR)
    - Given a query, find the relevant documents
  - Finding important keywords
    - Topic modeling and summarization
  - Sentiment analysis
    - By using the scores and weights of negative/ positive words

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Part-of-speech (POS) tagging

Tagging

- What?
  - Part-of-speech (POS) tagging
    - Adverb, verb, noun? Based on context
  - Labels that include extratextual information about a word
    - Not inferrable from the word itself, needs a predefined tagset
- Why?
  - Resolving ambiguities
  - Aiding downstream tasks
    - Speech recognition
    - Named entity recognition
    - Coreference resolution

Terms

- Tags
  - The labels
- Tagging
  - The process of assigning tags to a token
- Tag set
  - The collection of tags for a corpus/task

Let's look at some tags

- NLTK has different tagsets of tags, related to each corpora
  - nltk.help.upenn_tagset()
  - nltk.help.brown_tagset()
- With a given corpus:
  - nltk.corpus.<insert_corpus_here>.readme()
- Can be called with queries:
  - nltk.help.brown_tagset("VB.*")
    - Match all POS tags containing VB
      - VB+AT, VBN, VBZ, ...

nltk.help.brown_tagset("VB.*")

```
VB: verb, base: uninflected present, imperative or infinitive
    investigate find act follow inure achieve reduce take remedy re-set
    distribute realize disable feel receive continue place protect
    eliminate elaborate work permit run enter force ...
VB+AT: verb, base: uninflected present or infinitive + article
    wanna
VB+IN: verb, base: uninflected present, imperative or infinitive + prep
osition
    lookit
VB+JJ: verb, base: uninflected present, imperative or infinitive + adje
ctive
    die-dead
VB+PPO: verb, uninflected present tense + pronoun, personal, accusative
    let's lemme gimme
VB+RP: verb, imperative + adverbial particle
    g'ahn c'mon
VB+TO: verb, base: uninflected present, imperative or infinitive + infi
nitival to
    wanta wanna
```

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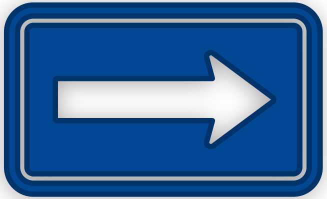
Ambiguity

- Resolving homonyms
  - Definition
    - *each of two or more words having the same spelling or pronunciation but different meanings and origins*
- *You shall know a word by the company it keeps*
  - Not only relevant to POS-tagging, but especially to word embeddings, as you've seen already.



Right (direction)

Right (correct)

Ok... so how do we "tag"?

- Rule-based
  - Regex (typically suffix-based)
- Transformation-based
  - Rule-based + learning
- Stochastic
  - Probability-based
  - N-gram
  - Hidden Markov Models
- Deep learning

Rule-based tagging

- Regex

```
>>> patterns = [
...     (r'.*ing$', 'VBG'),               # gerunds
...     (r'.*ed$', 'VBD'),                # simple past
...     (r'.*es$', 'VBZ'),                # 3rd singular present
...     (r'.*ould$', 'MD'),               # modals
...     (r'.*\'s$', 'NN$'),               # possessive nouns
...     (r'.*s$', 'NNS'),                 # plural nouns
...     (r'^-?[0-9]+(\.[0-9]+)?$', 'CD'), # cardinal numbers
...     (r'.*', 'NN')                     # nouns (default)
... ]
```

- See section 4.2 in ch. 5 (nltk book)

Transformation-based tagging

- Brill tagging
  - Regex + training template rules
  - Read up in section 6, ch. 5, if you're interested! Not required for the lab

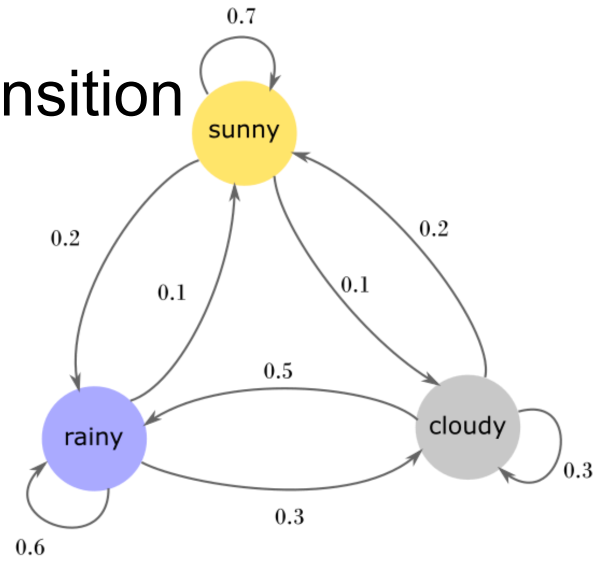
```
NN -> VB if the tag of the preceding word is 'TO'
NN -> VBD if the tag of the following word is 'DT'
NN -> VBD if the tag of the preceding word is 'NNS'
NN -> NNP if the tag of words i-2...i-1 is '-NONE-'
NN -> NNP if the tag of the following word is 'NNP'
NN -> NNP if the text of words i-2...i-1 is 'like'
NN -> VBN if the text of the following word is '*-1'
```

Stochastic tagging

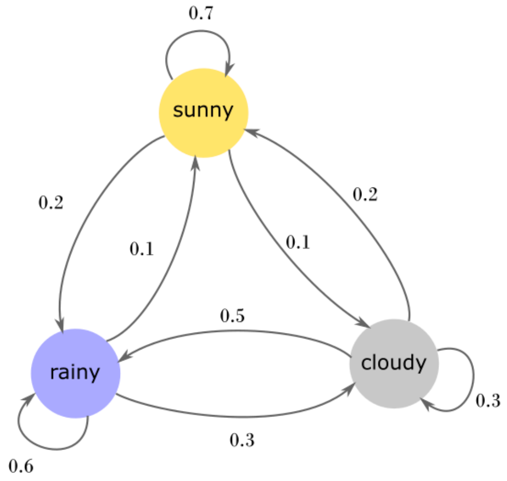
- What is the probability of the tag NN being assigned...
  - NN: Noun, singular
- Based on observed data
  - Find the probability of the next tag occurring
- Requires data
  - Train/Test/Eval (only train/test for now)

Hidden Markov Models (HMMs)

- Example:
  - The weather for any given day can be in any of the three states
    - Sunny, rainy, cloudy, with transition probabilities:



Hidden Markov Models (HMMs)



$$P(q_1, \dots, q_n) = \prod_{i=1}^{n} P(q_i | q_{i-1})$$

- It is now rainy, what's the chance of it raining tomorrow and then sunny the day after?
  = P(Rainy|Rainy) * P(Sunny|Rainy)
  = 0.1 * 0.9 = 0.09 = 9%
- This applies just as well to POS tags!

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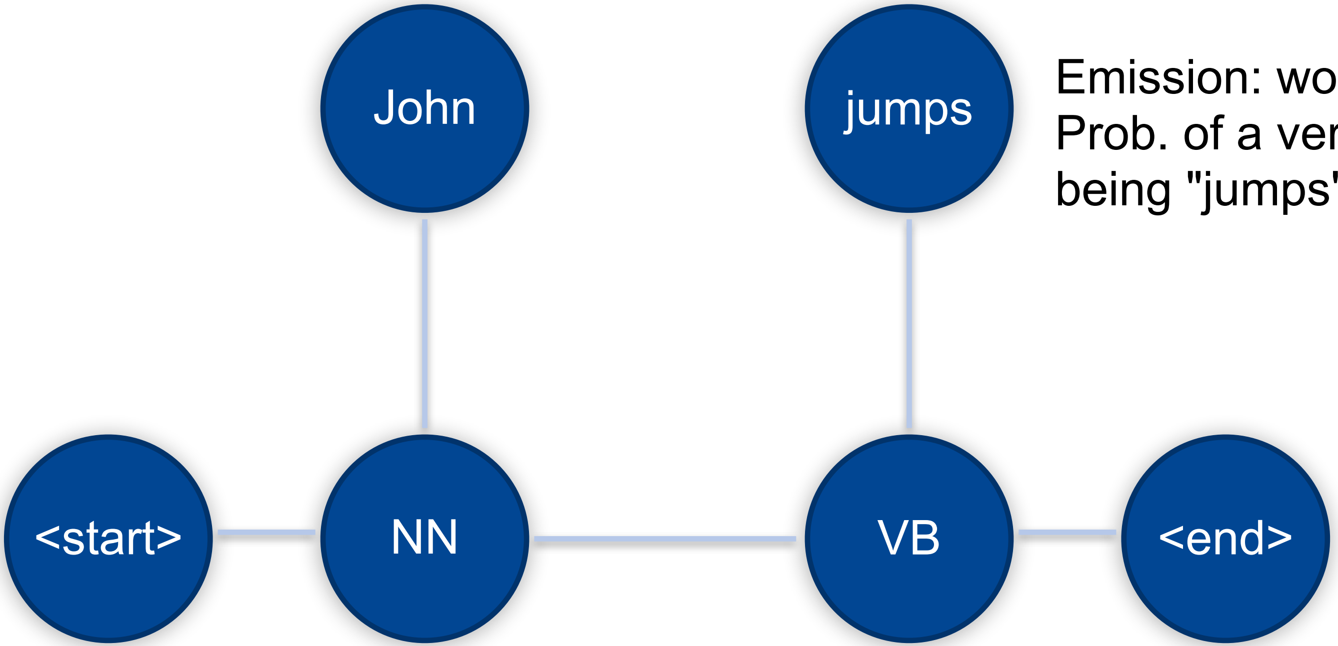
HMMs for POS-tagging



Emission: word-to-tag
Prob. of a verb (VB) being "jumps"?

Transition: tag-to-tag
Prob. of a verb (VB) occurring after a noun (NN)?

Example task

- Find the most ambiguous words in the bible
- Steps:
  - POS-tag the bible
  - Generate sets of tags for each word
- Why
  - Practical example of ambiguity
  - Illustrate the importance of a good POS-tagger

- Notebook in the examples folder on GitHub

Example task

Result: some of the words with > 8 tags

```
unto: {'NNS', 'PRP$', 'RB', 'NNP', 'CC', 'RP', 'MD', 'NN', 'VBD', 'JJ', 'VBP', 'VBZ', 'RBR'
, 'IN', 'VB'}
forth: {'NNS', 'RB', 'JJS', 'RP', 'PDT', 'NN', 'VBD', 'VBN', 'JJ', 'VBP', 'VBZ', 'IN', 'VB'
}
hath: {'RB', 'PDT', 'NN', 'VBD', 'MD', 'PRP', 'JJ', 'VBP', 'VBZ', 'IN', 'VB'}
wherein: {'RB', 'NNP', 'CC', 'EX', 'WP', 'NN', 'VBD', "''", 'WRB', 'VBP', 'VBZ', 'WDT', 'JJ
', 'IN', 'JJR', 'VB'}
behold: {'RB', 'CC', 'VBN', 'NN', 'VBD', 'UH', 'JJ', 'VBP', 'VB'}
till: {'RB', 'CC', 'EX', 'NN', 'JJ', 'VBP', 'VBZ', 'IN', 'VB'}
evil: {'RB', 'CC', 'EX', 'VBN', 'NN', 'VBD', 'JJ', 'VBP', 'NNS', 'VBZ', 'FW', 'VB'}
goeth: {'NNS', 'RB', 'NN', 'VBD', 'VBG', 'JJ', 'VBP', 'VBZ', 'VB'}
thou: {'NNS', 'RB', 'NNP', 'CC', 'EX', 'RP', 'VBN', 'NN', 'VBD', "''", 'PRP', 'MD', 'JJ', '
VBP', 'VBZ', 'IN', 'JJR', 'VB'}
eat: {'RB', 'NNP', 'NN', 'VBD', 'JJ', 'VBP', 'VBZ', 'IN', 'VB'}
shalt: {'RB', 'MD', 'NN', 'VBD', 'VBN', 'PRP', 'JJ', 'VBP', 'NNS', 'VBZ', 'JJR', 'FW', 'VB'
}
thereof: {'NNS', 'RB', 'EX', 'RP', 'NN', 'VBD', 'PRP', 'JJ', 'VBP', 'VBZ', 'WDT', 'VB'}
meet: {'RB', 'VBN', 'NN', 'VBD', 'JJ', 'VBP', 'NNS', 'VBZ', 'FW', 'VB'}
```

Example task

Result: some of the words with > 8 tags

```
unto: {'NNS', 'PRP$', 'RB', 'NNP', 'CC', 'RP', 'MD', 'NN', 'VBD', 'JJ', 'VBP', 'VBZ', 'RBR'
, 'IN', 'VB'}
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}
hath: {'RB', 'PDT', 'NN', 'VBD', 'MD', 'PRP', 'JJ', 'VBP', 'VBZ', 'IN', 'VB'}
wherein: {'RB', 'NNP', 'CC', 'EX', 'WP', 'NN', 'VBD', "''", 'WRB', 'VBP', 'VBZ', 'WDT', 'JJ
', 'IN', 'JJR', 'VB'}
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till: {'RB', 'CC', 'EX', 'NN', 'JJ', 'VBP', 'VBZ', 'IN', 'VB'}
evil: {'RB', 'CC', 'EX', 'VBN', 'NN', 'VBD', 'JJ', 'VBP', 'NNS', 'VBZ', 'FW', 'VB'}
goeth: {'NNS', 'RB', 'NN', 'VBD', 'VBG', 'JJ', 'VBP', 'VBZ', 'VB'}
thou:                                                                              JJ', '
VBP', 'VBZ', 'IN', 'JJR', 'VB'}
eat: {'RB', 'NNP', 'NN', 'VBD', 'JJ', 'VBP', 'VBZ', 'IN', 'VB'}
shalt: {'RB', 'MD', 'NN', 'VBD', 'VBN', 'PRP', 'JJ', 'VBP', 'NNS', 'VBZ', 'JJR', 'FW', 'VB'
}
thereof: {'NNS', 'RB', 'EX', 'RP', 'NN', 'VBD', 'PRP', 'JJ', 'VBP', 'VBZ', 'WDT', 'VB'}
meet: {'RB', 'VBN', 'NN', 'VBD', 'JJ', 'VBP', 'NNS', 'VBZ', 'FW', 'VB'}
```

Most of these are unintuitive... VBN, VBP, VBZ

Simplified "Universal" POS-tags

Tag	Meaning	English Examples
ADJ	adjective	*new, good, high, special, big, local*
ADP	adposition	*on, of, at, with, by, into, under*
ADV	adverb	*really, already, still, early, now*
CONJ	conjunction	*and, or, but, if, while, although*
DET	determiner, article	*the, a, some, most, every, no, which*
NOUN	noun	*year, home, costs, time, Africa*
NUM	numeral	*twenty-four, fourth, 1991, 14:24*
PRT	particle	*at, on, out, over per, that, up, with*
PRON	pronoun	*he, their, her, its, my, I, us*
VERB	verb	*is, say, told, given, playing, would*
.	punctuation marks	*. , ; !*
X	other	*ersatz, esprit, dunno, gr8, univeristy*

- corpus.tagged_words(**tagset='universal'**)

Bible tagged with "simple" POS

- More understandable, less flexible for real-world systems

```
wherein: {'.', 'DET', 'NOUN', 'ADP', 'ADV', 'VERB', 'CONJ', 'ADJ', 'PRON'}
thou: {'.', 'DET', 'NOUN', 'ADP', 'PRT', 'ADV', 'VERB', 'CONJ', 'ADJ', 'PRON'}
ye: {'.', 'DET', 'NOUN', 'NUM', 'PRT', 'ADP', 'ADV', 'VERB', 'CONJ', 'ADJ', 'X', 'PRON
'}
doth: {'DET', 'NOUN', 'ADP', 'PRT', 'ADV', 'VERB', 'CONJ', 'ADJ', 'X'}
thee: {'DET', 'NOUN', 'ADP', 'PRT', 'ADV', 'VERB', 'CONJ', 'ADJ', 'PRON'}
```

Custom taggers

- What
  - A tagger that incorporates backoff
- How
  - Split data
  - Create custom backoff taggers
  - POS tag
  - Train taggers
  - Evaluate

```
Default (no backoff) acc:       0.1314479001902567
Unigram (backoff: def) acc:     0.8944463322541195
Bigram (backoff: uni) acc:      0.913963601112907
Trigram (backoff: bi) acc:      0.9137859361820668
```

- Why
  - Attempt to improve performance over a singular tagger

Norwegian resources

- Oslo-Bergen tagger
  - http://www.tekstlab.uio.no/obt-ny/om-taggeren.html
  - https://github.com/noklesta/The-Oslo-Bergen-Tagger
- spaCy
  - https://spacy.io/models/nb

spaCy!

- As one of the last tasks, you will use spaCy for tagging
- Very high level APIs

```
import spacy
nlp = spacy.load("en_core_web_sm")
text = "The quick brown fox jumps over the lazy dog."
doc = nlp(text)
for token in doc:
    print(token.text, token.pos_)
    # Detailed tag description
    print(token.text, token.pos_, spacy.explain(token.pos_))
```

spaCy!

```
custom_nlp = spacy.load("en_core_web_sm")

# Add a custom rule for hashtags
custom_nlp.add_pipe("tagger", last=True, name="custom_tagger")

@custom_nlp.annotators["custom_tagger"]
def custom_tagger(doc):
    for token in doc:
        if token.text.startswith("#"):
            token.pos_ = "HASHTAG"
    return doc

text = "I love #nlp!"
doc = custom_nlp(text)
```