INTRODUCTION TO DATA SCIENCE

JOHN P DICKERSON

Lecture #18 – 10/29/2018

CMSC320
Mondays & Wednesdays
2:00pm – 3:15pm

COMPUTER SCIENCE
UNIVERSITY OF MARYLAND

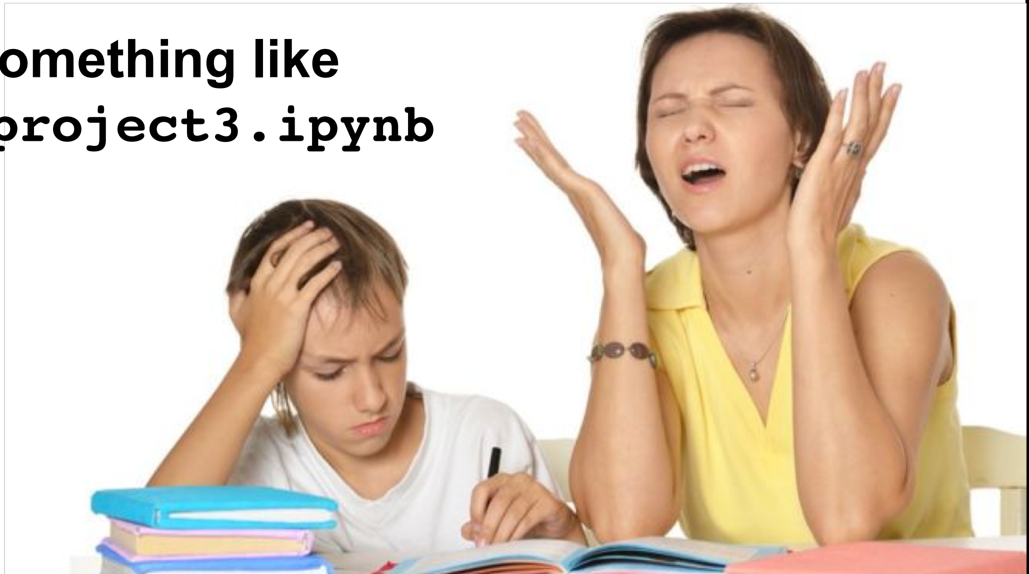
ANNOUNCEMENTS

Mini-Project #2 grades will be out by Thursday night!

Mini-Project #3 is out!

- It is linked to from ELMS; it is also be available at: https://github.com/umddb/cmsc641-fall2018/tree/master/project3
- Deliverable is a .ipynb file submitted to ELMS
- Due November 19th

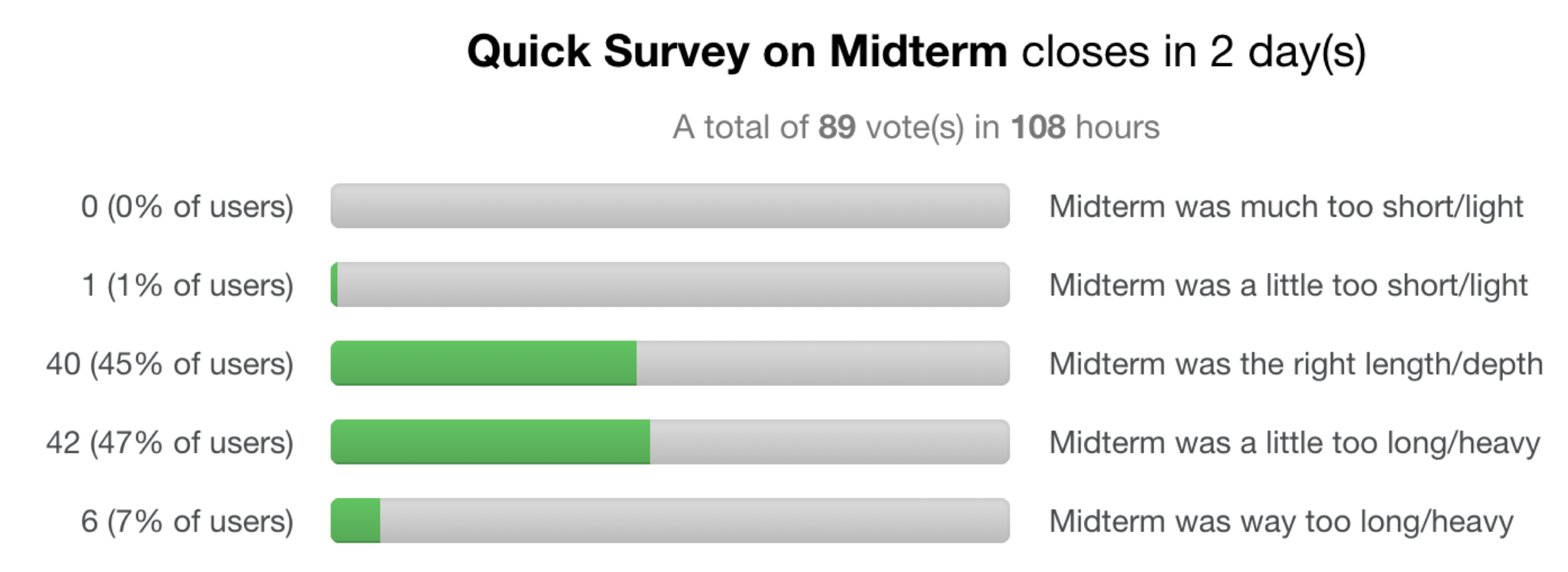
Please label your `ipynb` file something like
`<lastname>_<firstname>_project3.ipynb`



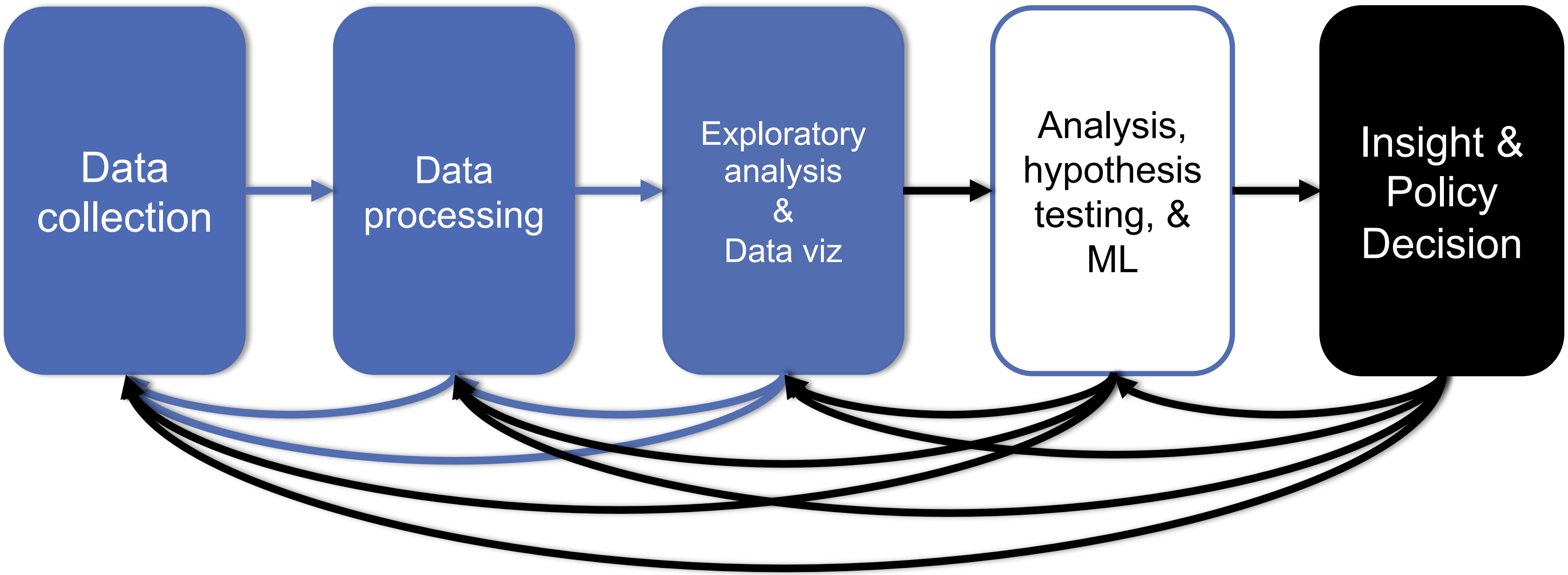
MIDTERMS

Not graded yet!

If you still need to take a midterm exam, please please please please please please tell me. I know of exactly four of you who do.



THIS LECTURE



THIS LECTURE:

Words words words!

- Free text and natural language processing in data science
- Bag of words and TF-IDF
- N-Grams and language models
- Sentiment mining

Thanks to: Zico Kolter (CMU) & Marine Carpuat's 723 (UMD)

PRECURSOR TO NATURAL LANGUAGE PROCESSING

For we can easily understand a machine's being constituted so that it can utter words, and even emit some responses to action on it of a corporeal kind, which brings about a change in its organs; for instance, if touched in a particular part it may ask what we wish to say to it; if in another part it may exclaim that it is being hurt, and so on.

(But it never happens that it arranges its speech in various ways, in order to reply appropriately to everything that may be said in its presence, as even the lowest type of man can do.)

-- René Descartes, 1600s

PRECURSOR TO NATURAL LANGUAGE PROCESSING

Turing's Imitation Game [1950]:

- Person A and Person B go into separate rooms
- Guests send questions in, read questions that come out – but they are not told who sent the answers
- Person A (B) wants to convince group that she is Person B (A)

We now ask the question, "What will happen when a machine takes the part of [Person] A in this game?" Will the interrogator decide wrongly as often when the game is played like this as he does when the game is played between [two humans]? These questions replace our original, "Can machines think?"

PRECURSOR TO NATURAL LANGUAGE PROCESSING

Mechanical translation started in the 1930s

- Largely based on dictionary lookups

Georgetown-IBM Experiment:

- Translated 60 Russian sentences to English
- Fairly basic system behind the scenes
- Highly publicized, system ended up spectacularly failing

Funding dried up; not much research in “mechanical translation” until the 1980s …

STATISTICAL NATURAL LANGUAGE PROCESSING

Pre-1980s: primarily based on sets of hand-tuned rules

Post-1980s: introduction of machine learning to NLP

- Initially, decision trees learned what-if rules automatically
- Then, hidden Markov models (HMMs) were used for part of speech (POS) tagging
- Explosion of statistical models for language
- Recent work focuses on purely unsupervised or semi-supervised learning of models

We'll cover some of this in the machine learning lectures!

IBM Watson

NLP IN DATA SCIENCE

In Mini-Project #1, you used `requests` and `BeautifulSoup` to scrape structured data from the web

Lots of data come as unstructured free text: ???????????

- Facebook posts
- Amazon Reviews
- Wikileaks dump

Data science: want to get some meaningful information from unstructured text

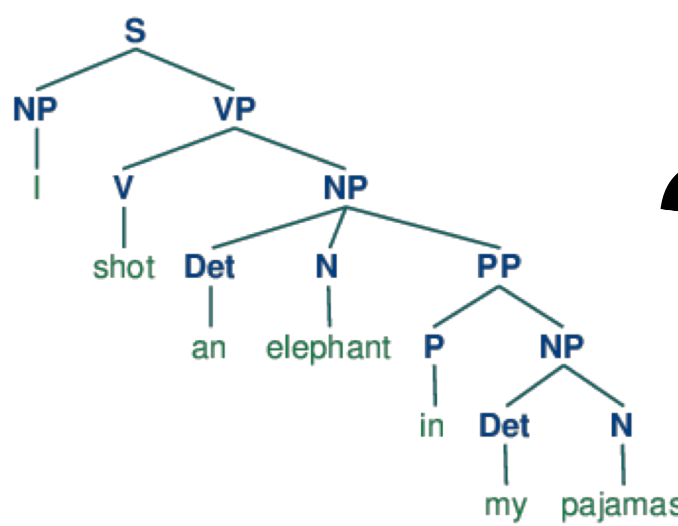
- Need to get some level of understanding what the text says

UNDERSTANDING LANGUAGE IS HARD

One morning I shot an elephant in my pajamas.

How he got into my pajamas, I'll never know.

Groucho Marx



?

UNDERSTANDING LANGUAGE IS HARD

The Winograd Schema Challenge:

- Proposed by Levesque as a complement to the Turing Test

Formally, need to pick out the antecedent of an ambiguous pronoun:

The city councilmen refused the demonstrators a permit because they [feared/advocated] violence.

Terry Winograd

Levesque argues that understanding such sentences requires more than NLP, but also commonsense reasoning and deep contextual reasoning

UNDERSTANDING LANGUAGE IS HARD?

I haven't played it that much yet, but it's shaping to be one of the greatest games ever made! It exudes beauty in every single pixel of it. It's a masterpiece. 10/10

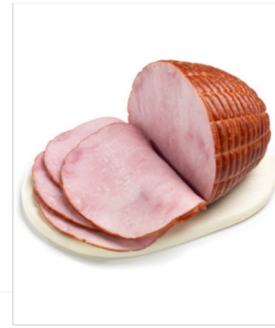
fabchan, March 3, 2017, Metacritic

a horrible stupid game,it's like 5 years ago game,900p 20~30f, i don't play this **** anymore it's like someone give me a **** to play ,no this time sorry,so Nintendo go f yourself pls

Nsucks7752, March 6, 2017, Metacritic

Perhaps we can get some signal (in this case, sentiment) without truly understanding the text …

“SOME SIGNAL”



or

Replication (Part 2 #1) Inbox x

CMSC 320 on Piazza <no-reply@piazza.com>
to me

11:56 PM (1 minute ago) Reply

-- Reply directly to this email above this line to add a comment to the follow up. Or Click here to view.--
A new feedback was posted by Josephine Chow.

does that mean we can use our solution to question 2 to answer question 1? Thank you!

Search or link to this question with @37.

Sign up for more classes at http://piazza.com/umd.

Tell a colleague about Piazza. It's free, after all.

Thanks,
The Piazza Team
--
Contact us at team@piazza.com

You're receiving this email because john@cs.umd.edu is enrolled in CMSC 320 at University of Maryland. Sign in to manage your email preferences or un-enroll from this class.

Possible signals ?????????

SECTIONS The New York Times SUBSCRIBE NOW LOG IN

POLITICS

Trump's New Travel Ban Blocks Migrants From Six Nations, Sparing Iraq

Leer en español

By GLENN THRUSH MARCH 6, 2017 561

President Trump during a meeting in the Roosevelt Room of the White House last week. Al Drago/The New York Times

WASHINGTON — President Trump signed an executive order on Monday blocking citizens of six predominantly Muslim countries from entering the United States, the most significant hardening of immigration policy in generations, even with changes intended to blunt legal and political opposition.

The order was revised to avoid the tumult and protests that engulfed the nation's airports after Mr. Trump signed his first immigration directive on Jan. 27. That order was ultimately blocked by a federal appeals court.

The new order continued to impose a 90-day ban on travelers, but it removed Iraq, a redaction requested by Defense Secretary Jim Mattis, who feared it would hamper coordination to defeat the Islamic State, according to administration officials.

It also exempts permanent residents and current visa holders, and drops language offering preferential status to persecuted religious

"SOME SIGNAL"

What type of article is this?

- Sports
- Political
- Dark comedy

What entities are covered?

- And are they covered with positive or negative sentiment?

Possible signals ????????

ASIDE: TERMINOLOGY

Documents: groups of free text

- Actual documents (NYT article, journal paper)
- Entries in a table

Corpus: a collection of documents

Terms: individual words

- Separated by whitespace or punctuation

NLP TASKS

Syntax: refers to the grammatical structure of language

- The rules via which one forms sentences/expressions

Semantics: the study of meaning of language

John is rectangular and a rainbow.

- Syntactically correct
- Semantically meaningless

SYNTAX

Tokenization

- Splitting sentences into tokens

Lemmatization/Stemming

- Turning “organizing” and “organized” into “organiz”

Morphological Segmentation

- How words are formed, and relationships of different parts
- Easy for English, but other languages are difficult

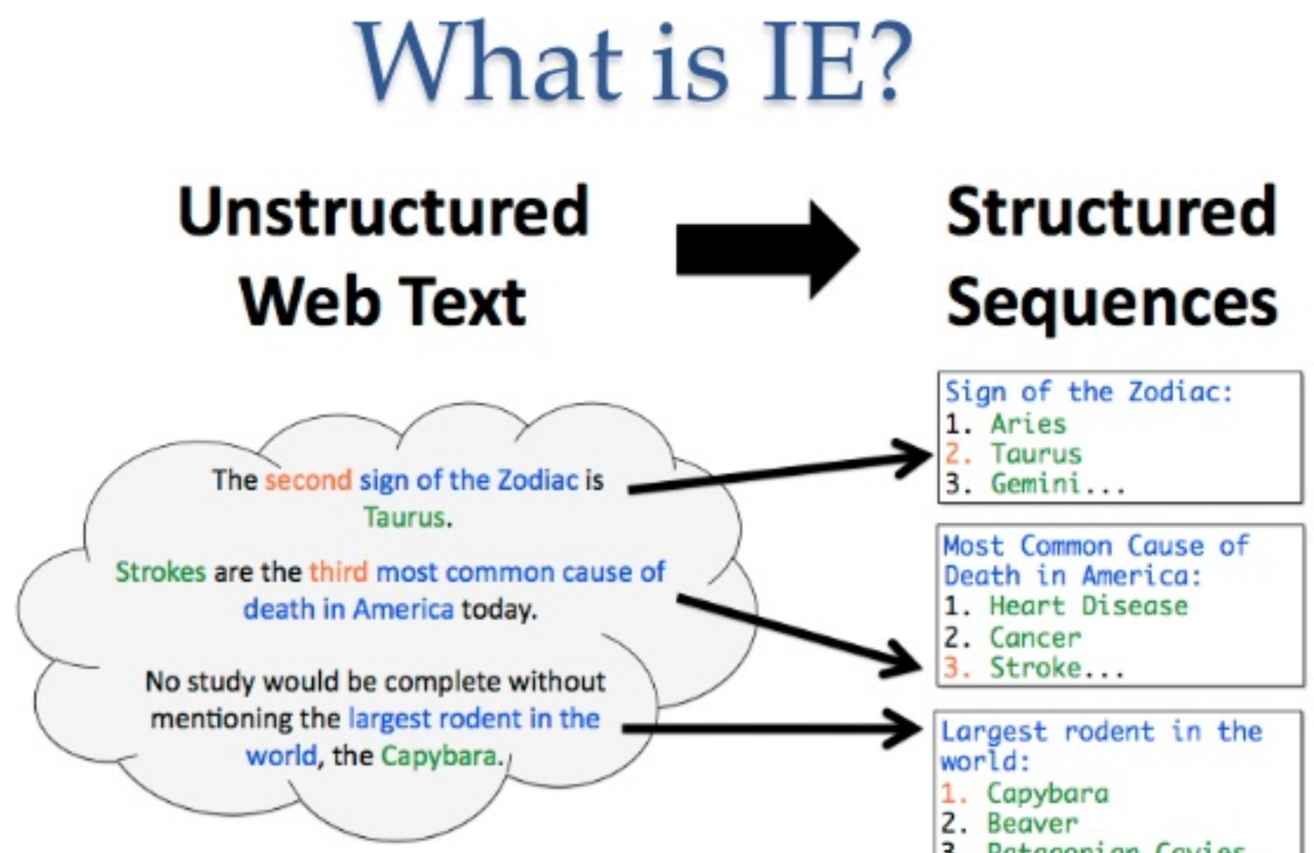
Part-of-speech (POS) Tagging

- Determine whether a word is a noun/adverb/verb etc.

Parsing

- Create a “parse tree” for a sentence

SEMANTICS: INFORMATION EXTRACTION



SEMANTICS: NAMED ENTITY RECOGNITION

Identifying key entities in text

In 1917, Einstein applied the general theory of relativity to model the large-scale structure of the universe. He was visiting the United States when Adolf Hitler came to power in 1933 and did not go back to Germany, where he had been a professor at the Berlin Academy of Sciences. He settled in the U.S., becoming an American citizen in 1940. On the eve of World War II, he endorsed a letter to President Franklin D. Roosevelt alerting him to the potential development of "extremely powerful bombs of a new type" and recommending that the U.S. begin similar research. This eventually led to what would become the Manhattan Project. Einstein supported defending the Allied forces, but largely denounced using the new discovery of nuclear fission as a weapon. Later, with the British philosopher Bertrand Russell, Einstein signed the Russell–Einstein Manifesto, which highlighted the danger of nuclear weapons. Einstein was affiliated with the Institute for Advanced Study in Princeton, New Jersey, until his death in 1955.

Tag colours:

LOCATION TIME PERSON ORGANIZATION MONEY PERCENT DATE

SEMANTICS: SENTIMENT ANALYSIS

Deciding if reviews/opinions are positive or negative

Heavily used by ad industry today

An extremely versatile machine!, November 22, 2006

By Dr. Nickolas E. Jorgensen "njorgens3"

This review is from: Cuisinart DGB-600BC Grind & Brew, Brushed Chrome (Kitchen)

This coffee-maker does so much! It makes weak, watery coffee! It grinds beans if you want it to! It inexplicably floods the entire counter with half-brewed coffee when you aren't looking! Perhaps it could be used to irrigate crops... It is time-consuming to clean, but in fairness I should also point out that the stainless-steel thermal carafe is a durable item that has withstood being hurled onto the floor in rage several times. And if all these features weren't enough, it's pretty expensive too. If faced with the choice between having a car door repeatedly slamming into my genitalia and buying this coffee-maker, I'd unhesitatingly choose the Cuisinart! The coffee would be lousy, but at least I could still have children...

SEMANTICS: MACHINE TRANSLATION

Translating from one language to another

Simple substitution of words doesn't work very well

(Image: Google)

Input sentence:	*Translation (PBMT):*	*Translation (GNMT):*	*Translation (human):*
李克強此行將啟動中加總理年度對話機制，與加拿大總理杜魯多舉行兩國總理首次年度對話。	Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau two prime ministers held its first annual session.	Li Keqiang will start the annual dialogue mechanism with Prime Minister Trudeau of Canada and hold the first annual dialogue between the two premiers.	Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada.

SEMANTICS: MACHINE TRANSLATION

0> how long before the next flight to Alice Springs?

1> wie lang vor dem folgenden Flug zu Alice Springs?

2> how long before the following flight to Alice jump?

3> wie lang vor dem folgenden Flug zu Alice springen Sie?

4> how long before the following flight to Alice do you jump?

5> wie lang, bevor der folgende Flug zu Alice tun, Sie springen?

6> how long, before the following flight to Alice does, do you jump?

7> wie lang bevor der folgende Flug zu Alice tut, tun Sie springen?

8> how long before the following flight to Alice does, do you jump?

9> wie lang, bevor der folgende Flug zu Alice tut, tun Sie springen?

10> how long, before the following flight does to Alice, do do you jump?

11> wie lang bevor der folgende Flug zu Alice tut, Sie tun Sprung?

12> how long before the following flight does leap to Alice, does you?

From NLTK Book

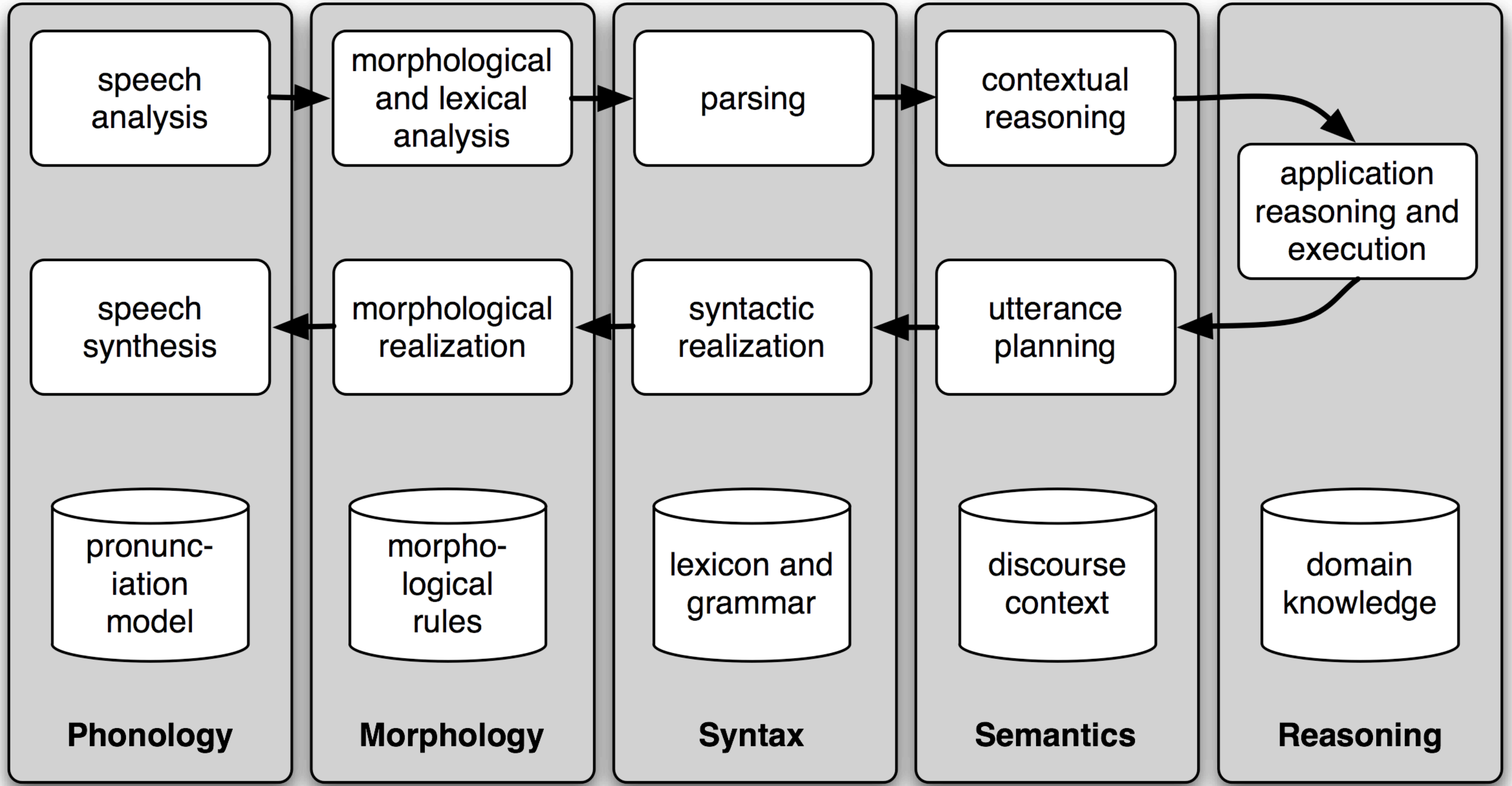
SEMANTICS: QUESTION ANSWERING

Answer questions posed a user with specific answers

WILLIAM WILKINSON’S
“AN ACCOUNT OF THE PRINCIPALITIES OF
WALLACHIA AND MOLDOVIA”
INSPIRED THIS AUTHOR’S
MOST FAMOUS NOVEL

Bram
Stoker

SEMANTICS: SPOKEN DIALOGUE SYSTEMS



SEMANTICS: TEXTUAL ENTAILMENT

Given two text fragments, determine if one being true entails the other, entails the other's negation, or allows the other to be either true or false

TEXT	HYPOTHESIS	ENTAILMENT
Eyeing the huge market potential, currently led by Google, Yahoo took over search company Overture Services Inc last year.	• *Yahoo bought Overture.*	• **TRUE**
Microsoft's rival Sun Microsystems Inc. bought Star Office last month and plans to boost its development as a Web-based device running over the Net on personal computers and Internet appliances.	• *Microsoft bought Star Office.*	• **FALSE**
The National Institute for Psychobiology in Israel was established in May 1971 as the Israel Center for Psychobiology by Prof. Joel.	• *Israel was established in May 1971.*	• **FALSE**

SEMANTICS: DOCUMENT SUMMARIZATION

Quite a few tools out there today… e.g., SMMRY

autotldr commented on a post in r/SkydTech

1

After Supreme Court detour, Apple v. Samsung goes to a fourth jury trial (arstechnica.com)

submitted 6 hours ago by cryoskyd to r/SkydTech

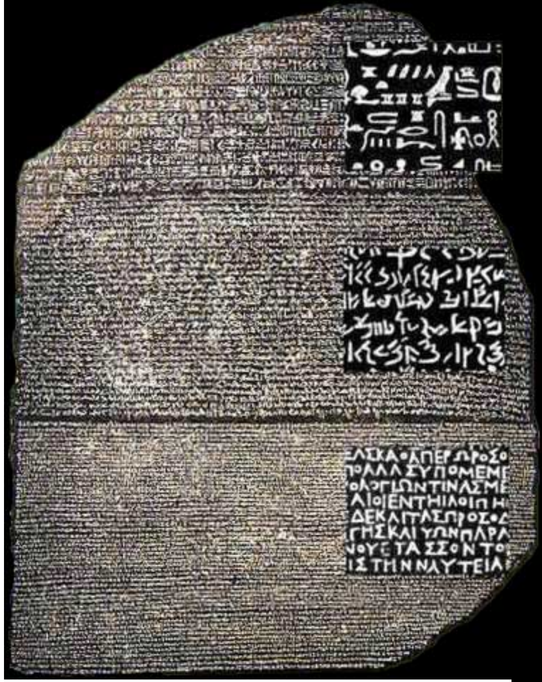
autotldr • 1 point • submitted 36 minutes ago

This is the best tl;dr I could make, original reduced by 86%. (I'm a bot)

> The Apple v. Samsung lawsuit is getting a big "Reset," thanks to last year's Supreme Court ruling on design patents.
>
> The US Supreme Court said that it was wrong to give Apple damages on the entire phone because of a few design patents.
>
> Apple and Samsung made their arguments over what the test should be, but Judge Koh ended up going with the test suggested by the US solicitor general, which has four factors to determine the right "Article of manufacture." It's closer to Apple's suggestion-Samsung had suggested basically taking only the part of the product that had the patented design physically applied to it, a test that Koh said wouldn't even pass the basics of what the Supreme Court had asked for.

Extended Summary | FAQ | Feedback | *Top keywords*: **design**[#1] **patent**[#2] **Apple**[#3] **Court**[#4] **product**[#5]

OTHER TASKS



Speech Recognition

Caption Generation

Natural Language Generation

Optical Character Recognition

Word Sense Disambiguation

- serve: help with food or drink; hold an office; put ball into play

…

Doing all of these for many different languages

SEMANTICS: TEXT CLASSIFICATION

Is it spam?

Who wrote this paper? (Author identification)

- https://en.wikipedia.org/wiki/The_Federalist_Papers#Authorship
- https://www.uwgb.edu/dutchs/pseudosc/hidncode.htm

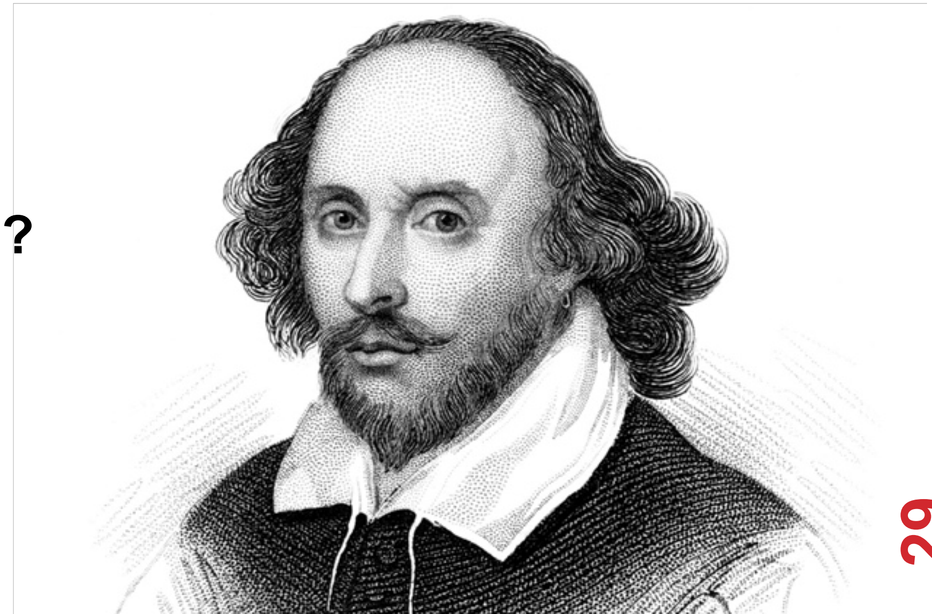
¡Identificación del idioma!

Sentiment analysis

What type of document is this?

When was this document written?

Readability assessment



TEXT CLASSIFICATION

Input:

- A document w
- A set of classes $Y = \{y_1, y_2, \ldots, y_J\}$

Output:

- A predicted class $y \in Y$

(You will spend much more time on classification problems throughout the program, this is just a light intro!)

TEXT CLASSIFICATION

Hand-coded rules based on combinations of terms (and possibly other context)

If email *w*:

- Sent from a DNSBL (DNS blacklist) **OR**
- Contains "Nigerian prince" **OR**
- Contains URL with Unicode **OR** …

Then: y_w = spam

Pros: ?????????

- Domain expertise, human-understandable

Cons: ?????????

- Brittle, expensive to maintain, overly conservative

TEXT CLASSIFICATION

Input:

- A document w
- A set of classes $Y = \{y_1, y_2, \ldots, y_J\}$
- A training set of m hand-labeled documents
  $\{(w_1, y_1), (w_2, y_2), \ldots, (w_m, y_m)\}$

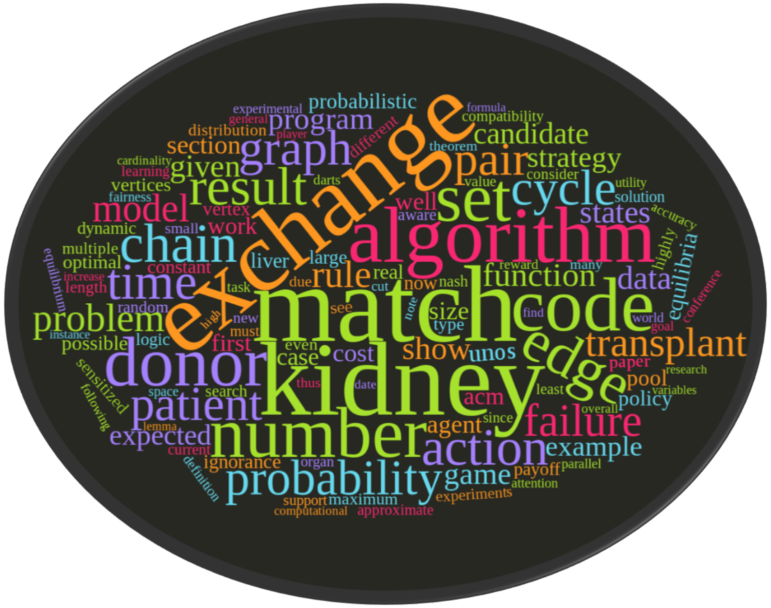
Output:

- A learned classifier $w \rightarrow y$

This is an example of supervised learning

REPRESENTING A DOCUMENT “IN MATH”

Simplest method: **bag of words**



Represent each document as a vector of word frequencies

- Order of words does not matter, just #occurrences

BAG OF WORDS EXAMPLE

the quick brown fox jumps over the lazy dog

I am he as you are he as you are me

he said the CMSC320 is 189 more CMSCs than the CMSC131

	the	CMSC320	you	he	I	quick	dog	me	CMSCs	…	than
Document 1	2	0	0	0	0	1	1	0	0		0
Document 2	0	0	2	2	1	0	0	1	0	…	0
Document 3	2	1	0	1	0	0	0	0	1		1

TERM FREQUENCY

Term frequency: the number of times a term appears in a specific document

- tf_{ij}: frequency of word *j* in document *i*

This can be the raw count (like in the BOW in the last slide):

- $tf_{ij} \in \{0,1\}$ if word *j* appears or doesn't appear in doc *i*
- $\log(1 + tf_{ij})$ – reduce the effect of outliers
- $tf_{ij} / \max_j tf_{ij}$ – normalize by document i's most frequent word

What can we do with this?

- Use as features to learn a classifier $w \rightarrow y$ …!

DEFINING FEATURES FROM TERM FREQUENCY

Suppose we are classifying if a document was written by The Beatles or not (i.e., binary classification):

- Two classes $y \in Y = \{ 0, 1 \} = \{$ not_beatles, beatles $\}$

Let's use $\mathbf{tf}_{ij} \in \{0,1\}$, which gives:

	the	CMSC641	you	he	_	quick	dog	me	CMSCs	…	than	
$x_1^T =$	1	0	0	0	0	1	1	0	0		0	$y_1 = 0$
$x_2^T =$	0	0	1	1	1	0	0	1	0	…	0	$y_2 = 1$
$x_3^T =$	1	1	0	1	0	0	0	0	1		1	$y_3 = 0$

Then represent documents with a feature function:

$$\mathbf{f}(\mathbf{x}, y = \text{not\_beatles} = 0) = [\mathbf{x}^T, \mathbf{0}^T, 1]^T$$
$$\mathbf{f}(\mathbf{x}, y = \text{beatles} = 1) = [\mathbf{0}^T, \mathbf{x}^T, 1]^T$$

LINEAR CLASSIFICATION

We can then define weights $\boldsymbol{\theta}$ for each feature

$\boldsymbol{\theta}$ = { <CMSC320, not_beatles> = +1,
<CMSC320, beatles> = -1,
<walrus, not_beatles> = -0.3,
<walrus, beatles> = +1,
<the, not_beatles> = 0,
<the, beatles>, 0, … }

Write weights as vector that aligns with feature mapping

Score ψ of an instance x and class y is the sum of the weights for the features in that class:

$$\boldsymbol{\psi}_{\mathbf{x}y} = \Sigma\, \theta_n f_n(\mathbf{x}, y)$$

$$= \boldsymbol{\theta}^{\mathrm{T}}\, \mathbf{f}(\mathbf{x}, y)$$

LINEAR CLASSIFICATION

We have a feature function f(x, *y*) and a score $\psi_{xy} = \theta^\top f(x, y)$

And return the class with highest score!

Compute the score of the document for that class

$$\hat{y} = \arg\max_{y} \theta^\top \mathbf{f}(\mathbf{x}, y)$$

For each class y ∈ { not_beatles, beatles }

Where did these weights come from? We'll talk about this in the ML lectures …

(… and also this whole "linear classifier" thing.)

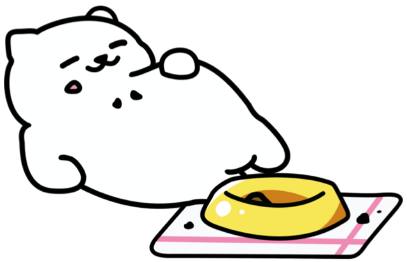
EXPLICIT EXAMPLE

We are interested in classifying documents into one of two classes $y \in Y$ = { 0, 1 } = { hates_cats, likes_cats}

Document 1: I like cats

Document 2: I hate cats

	I	like	hate	cats
x_1^T =	1	1	0	1
x_2^T =	1	0	1	1



y_1 = ?

y_2 = ?

Now, represent documents with a feature function:

$\mathbf{f}(\mathbf{x}, y = \text{hates\_cats} = 0) = [\mathbf{x}^T, \mathbf{0}^T, 1]^T$

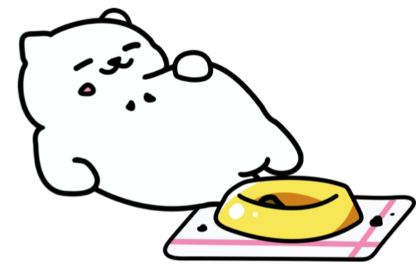
$\mathbf{f}(\mathbf{x}, y = \text{likes\_cats} = 1) = [\mathbf{0}^T, \mathbf{x}^T, 1]^T$

EXPLICIT EXAMPLE

$f(\mathbf{x}, y = 0) = \quad [\mathbf{x}^T, 0^T, 1]^T$

$f(\mathbf{x}, y = 1) = \quad [0^T, \mathbf{x}^T, 1]^T$

	I	like	hate	cats
$x_1^T =$	1	1	0	1
$x_2^T =$	1	0	1	1



$y_1 = ?$

$y_2 = ?$

y=0: hates_cats *y=1: likes_cats* (1)

	I	like	hate	cats	I	like	hate	cats	--
$f(\mathbf{x_1}, y = \text{hates\_cats} = 0) =$	1	1	0	1	0	0	0	0	1
$f(\mathbf{x_1}, y = \text{likes\_cats} = 1) =$	0	0	0	0	1	1	0	1	1
$f(\mathbf{x_2}, y = \text{hates\_cats} = 0) =$	1	0	1	1	0	0	0	0	1
$f(\mathbf{x_2}, y = \text{likes\_cats} = 1) =$	0	0	0	0	1	0	1	1	1

EXPLICIT EXAMPLE

Now, assume we have weights $\boldsymbol{\theta}$ for each feature

$\boldsymbol{\theta}$ = { <I, hates_cats> = 0, <I, likes_cats> = 0,

<like, hates_cats> = -1, <like, likes_cats> = +1,

<hate, hates_cats> = +1, <hate, likes_cats> = -1,

<cats, hates_cats> = -0.1, <cats, likes_cats = +0.5> }

Write weights as vector that aligns with feature mapping:

	y=0: hates_cats				*y=1: likes_cats*				(1)
Parameter vector $\boldsymbol{\theta}^T$ =	0	-1	1	-0.1	0	1	-1	0.5	1
	I	like	hate	cats	I	like	hate	cats	!
f($\mathbf{x}_1$, y = hates_cats = 0) =	1	1	0	1	0	0	0	0	1
f($\mathbf{x}_1$, y = likes_cats = 1) =	0	0	0	0	1	1	0	1	1
f($\mathbf{x}_2$, y = hates_cats = 0) =	1	0	1	1	0	0	0	0	1
f($\mathbf{x}_2$, y = likes_cats = 1) =	0	0	0	0	1	0	1	1	1

EXPLICIT EXAMPLE

Score ψ of an instance *x* and class *y* is the sum of the weights for the features in that class:

$$\psi_{\mathbf{x}y} = \sum \theta_n f_n(\mathbf{x}, y)$$

$$= \boldsymbol{\theta}^{\mathsf{T}} \mathbf{f}(\mathbf{x}, y)$$

Let's compute $\psi_{\mathbf{x1},y=hates\_cats}$ …

- $\psi_{\mathbf{x1},y=hates\_cats} = \boldsymbol{\theta}^{\mathsf{T}} \mathbf{f}(\mathbf{x_1}, y = \text{hates\_cats} = 0)$
- $= 0{*}1 + -1{*}1 + 1{*}0 + -0.1{*}1 + 0{*}0 + 1{*}0 + -1{*}0 + 0.5{*}0 + 1{*}1$
- $= -1 - 0.1 + 1 =$ **-0.1**

$\boldsymbol{\theta}^{\mathsf{T}} =$

0	-1	1	-0.1	0	1	-1	0.5	1

●

1	I	*hates_cats*
1	like	
0	hate	
1	cats	
0	I	*likes_cats*
0	like	
0	hate	
0	cats	
1	–	(1)

$\mathrm{f}(\mathbf{x_1}, y = 0)$

EXPLICIT EXAMPLE

Saving the boring stuff:

- $\psi_{\mathbf{x1},y=hates\_cats} = -0.1$; $\psi_{\mathbf{x1},y=likes\_cats} = +2.5$
- $\psi_{\mathbf{x2},y=hates\_cats} = +1.9$; $\psi_{\mathbf{x2},y=likes\_cats} = +0.5$

Document 1: I like cats

Document 2: I hate cats

We want to predict the class of each document:

$$\hat{y} = \arg\max_{y} \theta^\intercal \mathbf{f}(\mathbf{x}, y)$$

Document 1: argmax{ $\psi_{\mathbf{x1},y=hates\_cats}$, $\psi_{\mathbf{x1},y=likes\_cats}$ **} ????????**

Document 2: argmax{ $\psi_{\mathbf{x2},y=hates\_cats}$, $\psi_{\mathbf{x2},y=likes\_cats}$ **} ????????**

INVERSE DOCUMENT FREQUENCY

Recall:

- tf_{ij}: frequency of word *j* in document *i*

Any issues with this ??????????

- Term frequency gets overloaded by common words

Inverse Document Frequency (IDF): weight individual words negatively by how frequently they appear in the corpus:

$$\text{idf}_j = \log\left(\frac{\#\text{documents}}{\#\text{documents with word } j}\right)$$

IDF is just defined for a word j, not word/document pair j, i

INVERSE DOCUMENT FREQUENCY

	the	CMSC320	you	he	I	quick	dog	me	CMSCs	…	than
Document 1	2	0	0	0	0	1	1	0	0		0
Document 2	0	0	2	2	1	0	0	1	0	…	0
Document 3	2	1	0	1	0	0	0	0	1		1

$$\text{idf}_{\text{the}} = \log\left(\frac{3}{2}\right) = 0.405$$

$$\text{idf}_{\text{you}} = \log\left(\frac{3}{1}\right) = 1.098$$

$$\text{idf}_{\text{CMSC320}} = \log\left(\frac{3}{1}\right) = 1.098$$

$$\text{idf}_{\text{he}} = \log\left(\frac{3}{2}\right) = 0.405$$

TF-IDF

How do we use the IDF weights?

Term frequency inverse document frequency (TF-IDF):

- TF-IDF score: tf_{ij} x idf_j

	the	CMSC320	you	he	I	quick	dog	me	CMSCs	…	than
Document 1	0.8	0	0	0	0	1.1	1.1	0	0		0
Document 2	0	0	2.2	0.8	1.1	0	0	1.1	0	…	0
Document 3	0.8	1.1	0	0.4	0	0	0	0	1.1		1.1

This ends up working better than raw scores for classification and for computing similarity between documents.

TOKENIZATION

First step towards text processing

For English, just split on non-alphanumerical characters

- Need to deal with cases like: I’m, or France’s, or Hewlett-Packard
- Should “San Francisco” be one token or two?

Other languages introduce additional issues

- L'ensemble → one token or two?
- German noun compounds are not segmented
  - Lebensversicherungsgesellschaftsangestellter
- Chinese/Japanese more complicated because of white spaces

OTHER BASIC TERMS

Lemmatization

- Reduce inflections or variant forms to base form
  - am, are, is $\rightarrow$ be
  - car, cars, car's, cars' $\rightarrow$ car
- the boy's cars are different colors $\rightarrow$ the boy car be different color

Morphology/Morphemes

- The small meaningful units that make up words
- Stems: The core meaning-bearing units
- Affixes: Bits and pieces that adhere to stems
  - Often with grammatical functions

STEMMING

Reduce terms to their stems in information retrieval

Stemming is crude chopping of affixes

- language dependent
- e.g., **automate(s)**, **automatic**, **automation** all reduced to **automat**.

for example compressed and compression are both accepted as equivalent to compress.

→

for exampl compress and compress ar both accept as equival to compress

Natural Language Analyses with NLTK

spaCy

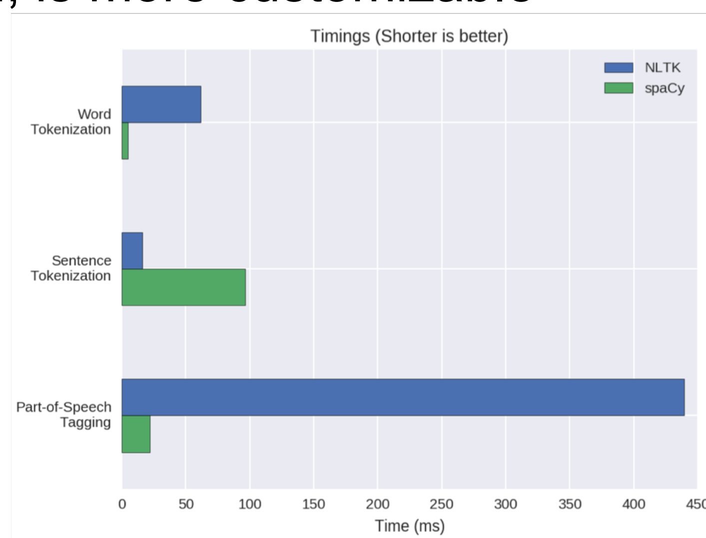
NLP IN PYTHON

Two majors libraries for performing basic NLP in Python:

- Natural Language Toolkit (NLTK): started as research code, now widely used in industry and research
- Spacy: much newer implementation, more streamlined

Pros and cons to both:

- NLTK has more “stuff” implemented, is more customizable
    - This is a blessing and a curse
- Spacy is younger and feature sparse, but can be much faster
- Both are Anaconda packages



NLTK EXAMPLES

```
import nltk

# Tokenize, aka find the terms in, a sentence
sentence = ”A wizard is never late, nor is he early.
He arrives precisely when he means to.”
tokens = nltk.word_tokenize(sentence)
```

```
LookupError:
**********************************************************************
  Resource 'tokenizers/punkt/PY3/english.pickle' not found.
  Please use the NLTK Downloader to obtain the resource:  >>>
  nltk.download()
  Searched in:
    - '/Users/spook/nltk_data'
    - '/usr/share/nltk_data'
    - '/usr/local/share/nltk_data'
    - '/usr/lib/nltk_data'
    - '/usr/local/lib/nltk_data'
    - ''
**********************************************************
```

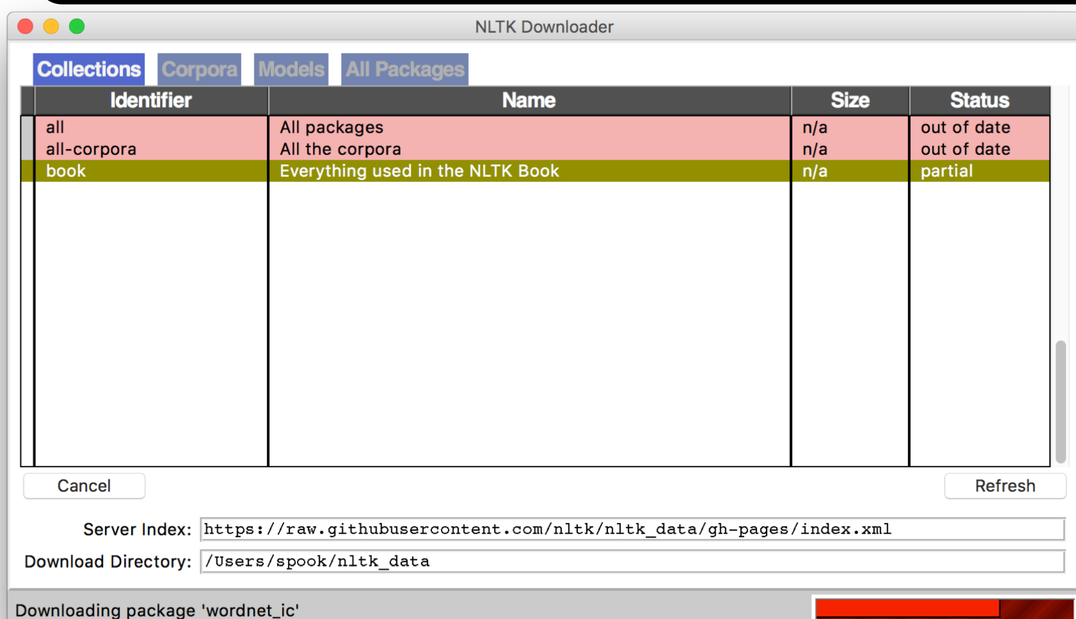
Fool of a Took!

NLTK EXAMPLES

Corpora are, by definition, large bodies of text

- **NLTK relies on a large corpus set to perform various functionalities; you can pick and choose:**

```
# Launch a GUI browser of available corpora
nltk.download()
```




```
# Or download
everything at once!
nltk.download(“all”)
```

NLTK EXAMPLES

punkt	Punkt Tokenizer Models	13.0 MB	installed

```
import nltk

# Tokenize, aka find the terms in, a sentence
sentence = "A wizard is never late, nor is he early.
He arrives precisely when he means to."
tokens = nltk.word_tokenize(sentence)
```

```
['A', 'wizard', 'is', 'never', 'late', ',', 'nor',
'is', 'he', 'early', '.', 'He', 'arrives',
'precisely', 'when', 'he', 'means', 'to', '.']
```

(This will also tokenize words like “o’clock” into one term, and “didn’t” into two term, “did” and “n’t”.)

NLTK EXAMPLES

```
# Determine parts of speech (POS) tags
tagged = nltk.pos_tag(tokens)
tagged[:10]
```

```
[('A', 'DT'), ('wizard', 'NN'), ('is', 'VBZ'),
('never', 'RB'), ('late', 'RB'), (',', ','), ('nor',
'CC'), ('is', 'VBZ'), ('he', 'PRP'), ('early', 'RB')]
```

Abbreviation	POS
DT	Determiner
NN	Noun
VBZ	Verb (3^{rd} person singular present)
RB	Adverb
CC	Conjunction
PRP	Personal Pronoun

Full list: https://cs.nyu.edu/grishman/jet/guide/PennPOS.html

NLTK EXAMPLES

```
# Find named entities & visualize
entities = nltk.chunk.ne_chunk( nltk.pos_tag(
nltk.word_tokenize(“””
     The Shire was divided into four quarters, the Farthings already referred
to. North, South, East, and West; and these again each into a number of
folklands, which still bore the names of some of the old leading families,
although by the time of this history these names were no longer found only in
their proper folklands. Nearly all Tooks still lived in the Tookland, but
that was not true of many other families, such as the Bagginses or the
Boffins. Outside the Farthings were the East and West Marches: the Buckland
(see beginning of Chapter V, Book I); and the Westmarch added to the Shire in
S.R. 1462.
    “””)))
entities.draw()
```

Measuring (semantic) similarity

VECTOR SEMANTICS OF DOCUMENTS/TERMS

“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”

Many thanks to Dan Jurafsky here!

INTUITION OF DISTRIBUTIONAL WORD SIMILARITY

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

From context words humans can guess tesgüino means

- an alcoholic beverage like beer

Intuition for algorithm:

- Two words are similar if they have similar word contexts.

[DJ]

FOUR KINDS OF VECTOR MODELS

Sparse vector representations

- Mutual-information weighted word co-occurrence matrices

Dense vector representations:

- Singular value decomposition (and Latent Semantic Analysis)
- Neural-network-inspired models (skip-grams, CBOW)
- Brown clusters
    - Won't go into these much – basically, classify terms into "word classes" using a particular clustering method
    - Hard clustering due to Brown et al. 1992, embed words in some space and cluster. Generally, better methods out there now …

[DJ]

SHARED INTUITION

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 computational linguistic applications by a vocabulary index (“word number 545”)

[DJ]

REMINDER: TERM-DOCUMENT MATRIX

Each cell: count of term t in a document d: $\mathbf{tf_{t,d}}$:

- 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

[DJ]

REMINDER: 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

[DJ]

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
clown	6	117	0	0

[DJ]

THE WORDS IN A TERM-DOCUMENT MATRIX

Two words 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

[DJ]

TERM-CONTEXT MATRIX FOR WORD SIMILARITY

Two words are similar in meaning if their context vectors are similar

	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	

[DJ]

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*|, not *D*x*D*

[DJ]

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	
…	…						

[DJ]

WORD-WORD MATRIX

We showed only 4x6, but the real matrix is 50,000 x 50,000

- So it's very sparse
  - Most values are 0.
- That's OK, since there are lots of efficient algorithms for sparse matrices.

The size of windows depends on your goals

- The shorter the windows , the more syntactic the representation
  - $\pm$ 1-3 very syntacticy
- The longer the windows, the more semantic the representation
  - $\pm$ 4-10 more semantically

[DJ]

MEASURING SIMILARITY

Given 2 target words v and w

- **Need a way to measure their similarity.**

Most measure of vectors similarity are based on the:

- **Dot product or inner product from linear algebra**

$$\text{dot-product}(\vec{v},\vec{w}) = \vec{v}\cdot\vec{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \ldots + v_N w_N$$

  - High when two vectors have large values in same dimensions.
  - Low (in fact 0) for orthogonal vectors with zeros in complementary distribution

[DJ]

PROBLEM WITH DOT PRODUCT

$$\text{dot-product}(\vec{v},\vec{w}) = \vec{v}\cdot\vec{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \ldots + v_N w_N$$

Dot product is longer if the vector is longer. Vector length:

$$|\vec{v}| = \sqrt{\sum_{i=1}^{N} v_i^2}$$

Vectors are longer if they have higher values in each dimension

That means more frequent words will have higher dot products

That's bad: we don't want a similarity metric to be sensitive to word frequency

[DJ]

SOLUTION: COSINE

Just divide the dot product by the length of the two vectors!

$$\frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|}$$

This turns out to be the cosine of the angle between them!

$$\begin{aligned} \vec{a} \cdot \vec{b} &= |\vec{a}||\vec{b}| \cos\theta \\ \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} &= \cos\theta \end{aligned}$$

SIMILARITY BETWEEN DOCUMENTS

Given two documents x and y, represented by their TF-IDF vectors (or any vectors), the cosine similarity is:

$$\text{similarity}(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x}^{\mathsf{T}}\mathbf{y}}{|\mathbf{x}| \times |\mathbf{y}|}$$

Formally, it measures the cosine of the angle between two vectors x and y:

- $\cos(0^o) = 1$, $\cos(90^o) = 0$??????????

Similar documents have high cosine similarity; dissimilar documents have low cosine similarity.

EXAMPLE

	large	data	computer
apricot	2	0	0
digital	0	1	2
information	1	6	1

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

Which pair of words is more similar?

cosine(apricot,information) =

$$\frac{2+0+0}{\sqrt{2+0+0}\ \sqrt{1+36+1}} = \frac{2}{\sqrt{2}\sqrt{38}} = .23$$

cosine(digital,information) =

$$\frac{0+6+2}{\sqrt{0+1+4}\ \sqrt{1+36+1}} = \frac{8}{\sqrt{38}\sqrt{5}} = .58$$

cosine(apricot,digital) =

$$\frac{0+0+0}{\sqrt{1+0+0}\ \sqrt{0+1+4}} = 0$$

(MINIMUM) EDIT DISTANCE

How similar are two strings?

Many different distance metrics (as we saw earlier when discussing entity resolution

- Typically based on the number of edit operations needed to transform from one to the other

Useful in NLP context for spelling correction, information extraction, speech recognition, etc.

Language Models

LANGUAGE MODELING

Assign a probability to a sentence

- Machine Translation:
  - P(**high** winds tonite) > P(**large** winds tonite)
- Spell Correction
  - The office is about fifteen **minuets** from my house
    - P(about fifteen **minutes** from) > P(about fifteen **minuets** from)
- Speech Recognition
  - P(I saw a van) >> P(eyes awe of an)
- + Summarization, question-answering, etc., etc.!!

LANGUAGE MODELING

Goal: compute the probability of a sentence or sequence of words:

- $P(W) = P(w_1,w_2,w_3,w_4,w_5\ldots w_n)$

Related task: probability of an upcoming word:

- $P(w_5|w_1,w_2,w_3,w_4)$

A model that computes either of these:

- $P(W)$ or $P(w_n|w_1,w_2\ldots w_{n-1})$ is called a language model.

(We won't talk about this much further in this class.)

BRIEF ASIDE: N-GRAMS

n-gram: Contiguous sequence of n tokens/words etc.

- Unigram, bigram, trigram, “four-gram”, “five-gram”, …

Figure 1 *n*-gram examples from various disciplines

Field	Unit	Sample sequence	1-gram sequence	2-gram sequence	3-gram sequence
Vernacular name			**unigram**	**bigram**	**trigram**
Order of resulting Markov model			**0**	**1**	**2**
Protein sequencing	amino acid	… Cys-Gly-Leu-Ser-Trp …	…, Cys, Gly, Leu, Ser, Trp, …	…, Cys-Gly, Gly-Leu, Leu-Ser, Ser-Trp, …	…, Cys-Gly-Leu, Gly-Leu-Ser, Leu-Ser-Trp, …
DNA sequencing	base pair	…AGCTTCGA…	…, A, G, C, T, T, C, G, A, …	…, AG, GC, CT, TT, TC, CG, GA, …	…, AGC, GCT, CTT, TTC, TCG, CGA, …
Computational linguistics	character	…to_be_or_not_to_be…	…, t, o, _, b, e, _, o, r, _, n, o, t, _, t, o, _, b, e, …	…, to, o_, _b, be, e_, _o, or, r_, _n, no, ot, t_, _t, to, o_, _b, be, …	…, to_, o_b, _be, be_, e_o, _or, or_, r_n, _no, not, ot_, t_t, _to, to_, o_b, _be, …
Computational linguistics	word	… to be or not to be …	…, to, be, or, not, to, be, …	…, to be, be or, or not, not to, to be, …	…, to be or, be or not, or not to, not to be, …

SIMPLEST CASE: UNIGRAM MODEL

$$P(w_1 w_2 \ldots w_n) \approx \prod_i P(w_i)$$

Some automatically generated sentences from a unigram model

```
fifth, an, of, futures, the, an, incorporated, a,
a, the, inflation, most, dollars, quarter, in, is,
mass

thrift, did, eighty, said, hard, 'm, july, bullish

that, or, limited, the
```

BIGRAM MODEL

Condition on the previous word:

$$P(w_i \mid w_1 w_2 \ldots w_{i-1}) \approx P(w_i \mid w_{i-1})$$

```
texaco, rose, one, in, this, issue, is, pursuing, growth, in,
a, boiler, house, said, mr., gurria, mexico, 's, motion,
control, proposal, without, permission, from, five, hundred,
fifty, five, yen

outside, new, car, parking, lot, of, the, agreement, reached

this, would, be, a, record, november
```

N-GRAM MODELS

We can extend to trigrams, 4-grams, 5-grams

In general this is an insufficient model of language

- because language has long-distance dependencies:

- **"The computer which I had just put into the machine room on the fifth floor crashed."**

But we can often get away with N-gram models