https://xkcd.com/208/

CS 2731 Introduction to Natural Language Processing

Session 2: Text normalization

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August 30, 2023

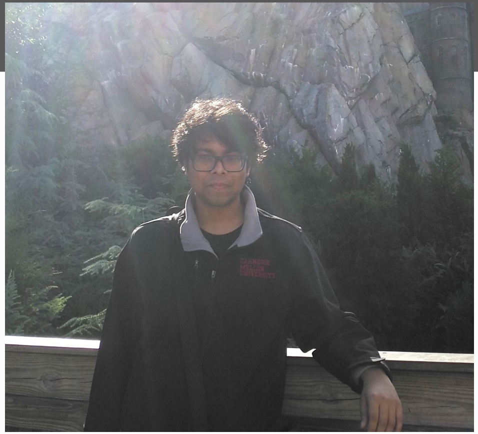
University of Pittsburgh School of Computing and Information

- Course logistics
- Basic terminology
- Regular expressions
- Text normalization
- Edit distance

Course logistics

- Michael's office hours: **Weds 1:30-2:30pm, Sennott Square 6505**
- Canvas site is live. Let Michael or Sabit know if you need to be added
- **Project survey due this Thursday, Aug 31 at 11:59pm**
  - See project description
- Project groups will often be 3 students instead of 2
- **First reading quiz is due next Wed, Sep 6 at noon before class**
- Please remind me of your name before asking or answering a question (just this class session)

About Sabit Hassan (TA)



- 3rd year PhD student, CSD
- I have another name: Pantho (means wanderer)
- **Research interests:**
    - Active Learning for NLP
    - Safety of Large Language Models
    - AI Moderation of Social Media
- Office Hours:
    - Thursday: 2.45pm-3.45pm (from next week)
    - Location: TBD

NLP terminology: words and corpora

How many words in this phrase?

they lay back on the San Francisco grass and looked at the stars and their

- How many?
  - 15 tokens (or 14 if you count "San Francisco" as one)
  - 13 types (or 12) (or 11?)
- **Type**: a unique word in the vocabulary
- **Token**: an instance of a word type in running text
- **Lemma**: same stem, part of speech, rough word sense
  - cat and cats = same lemma
- **Wordform**: the full inflected surface form
  - cat and cats = different wordforms

Slide adapted from Jurafsky & Martin

How many words in a corpus?

Corpus: a (machine-readable) collection of texts

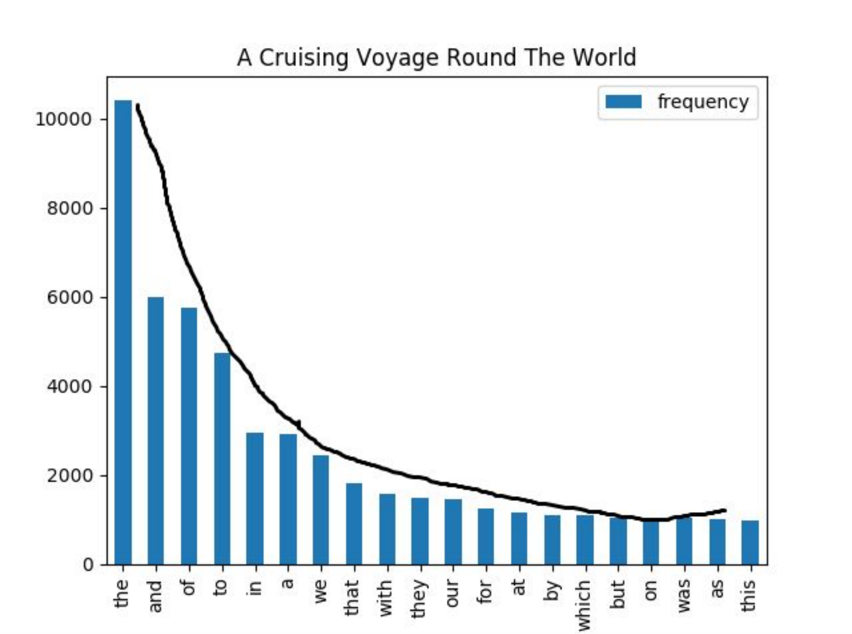
N = number of tokens

V = vocabulary = set of types, $|V|$ is size of vocabulary

	Tokens = N	Types = |V|
Switchboard phone conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
COCA	440 million	2 million
Google N-grams	1 trillion	13+ million

Slide adapted from Jurafsky & Martin

Word frequencies: Zipf's Law



The Lexical Learner blog

- Word (type) frequency is inversely proportional to word frequency rank

$$\text{frequency} \propto \frac{1}{(\text{rank} + b)^a}$$

- "Long tail" of infrequent words

Corpora vary along dimensions like

- Texts don't appear out of nowhere!
- **Language**: 7097 languages in the world
- **Variety**, like African American Language varieties.
    - AAE Twitter posts might include forms like "*iont*" (*I don't)*
- **Code switching**, e.g., Spanish/English, Hindi/English:

    Por primera vez veo a @username actually being hateful! It was beautiful:)

    [For the first time I get to see @username actually being hateful! it was beautiful:)]

    dost tha or ra- hega ... dont wory ... but dherya rakhe

    [“he was and will remain a friend ... don’t worry ... but have faith”]

- **Genre:** newswire, fiction, scientific articles, Wikipedia
- **Author Demographics**: writer's age, gender, ethnicity, SES
- Corpus datasheets [Bender & Friedman 2018, Gebru+ 2020] ask about this information

Regular expressions (regex)

Regular expressions

- A formal language for specifying text strings
- How can we search for any of these?
  - woodchuck
  - woodchucks
  - Woodchuck
  - Woodchucks

Slide adapted from Jurafsky & Martin

Regular Expressions: Disjunctions (OR)

- Letters inside square brackets []

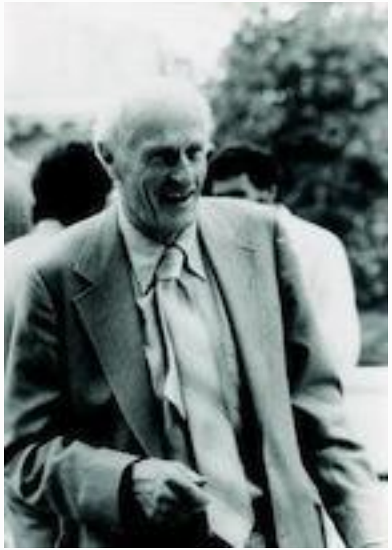
Pattern	Matches
`[wW]oodchuck`	Woodchuck, woodchuck
`[1234567890]`	Any digit

- Ranges `[A-Z] [a-z] [0-9]`
- Negations `[^A-Z]`
  - Carat means negation only when first in []
- Sequence disjunctions with pipe |
  - `groundhog|woodchuck`

Slide adapted from Jurafsky & Martin

Regular Expressions wildcards: *+.

Pattern	Matches	
`oo*h`	0 or more of previous char	oh ooh oooh ooooh
`o+h`	1 or more of previous char	oh ooh oooh ooooh
`beg.n`	Any char	begin begun begun beg3n

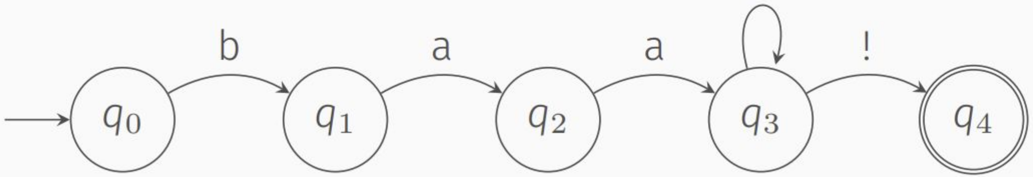


Stephen C Kleene

Slide adapted from Jurafsky & Martin

Finite state automata (briefly)

A sheep language



Recognizes:

- baa!
- baaa!
- baaaa!

Rejects:

- ba
- ba!
- baaa

- When you follow such a transition, the symbol is "consumed"
- If consuming all of the symbols coincides with being at an accepting state, you win! (The FSA accepts the string).
- Otherwise, you lose! (The FSA rejects the string).

Slide credit: David Mortensen

Regular expression example

- Find all instances of the word “the” in a text.

  `the`

- Misses capitalized examples

  `[tT]he`

- Incorrectly returns "other" or "theology"

  `[^a-zA-Z][tT]he[^a-zA-Z]`

Slide adapted from Jurafsky & Martin

Errors

The process we just went through was based on **fixing two kinds of errors:**

1. Matching strings that we should not have matched (there, then, other)

   False positives (Type I errors)

2. Not matching things that we should have matched (The)

   False negatives (Type II errors)

Capture groups and regular expression substitution

- Say we want to put angles around all numbers after the word *the*:

  the 35 boxes □ the <35> boxes

- Use parens () to "capture" a pattern group and save to a numbered register \1

  ```
  the ([0-9]+)
  ```

- Can substitute something for the group

  In Python:

  ```
  re.sub(r'the ([0-9]+)', 'the <\1>', input_text)
  ```


Slide adapted from Jurafsky & Martin

Simple Application: ELIZA

- Early NLP system that imitated a Rogerian psychotherapist [Weizenbaum 1966]
- Uses pattern matching to match phrases

  `“I need X”`
- and translates them into, e.g.

  `“What would it mean to you if you got X?`

Slide adapted from Jurafsky & Martin

Simple Application: ELIZA

Men are all alike.
IN WHAT WAY

They're always bugging us about something or other.
CAN YOU THINK OF A SPECIFIC EXAMPLE

Well, my boyfriend made me come here.
YOUR BOYFRIEND MADE YOU COME HERE

He says I'm depressed much of the time.
I AM SORRY TO HEAR YOU ARE DEPRESSED

Slide adapted from Jurafsky & Martin

How ELIZA works

```
.* I'M (depressed|sad) .* → I AM SORRY TO HEAR YOU ARE \1

.* all .* → IN WHAT WAY?

.* always .* → CAN YOU THINK OF A SPECIFIC EXAMPLE?/
```

Slide adapted from Jurafsky & Martin

Regular expressions summary

- Regular expressions play a surprisingly large role in NLP
  - Sophisticated sequences of regular expressions are often the first model for any text processing text
- For hard tasks, we use machine learning classifiers
  - But regular expressions are still used for pre-processing, or used to extract features for the classifiers

Slide adapted from Jurafsky & Martin

Text normalization (preprocessing)

Every NLP task requires text normalization

1. Tokenizing (separating) words
2. Normalizing word formats
3. Segmenting sentences

Slide adapted from Jurafsky & Martin

Tokenization

Space-based tokenization

- A very simple way to tokenize
- For languages that use space characters between words
  - Arabic, Cyrillic, Greek, Latin, etc., based writing systems
- Segment off a token between instances of spaces

Slide adapted from Jurafsky & Martin

Issues in Tokenization

- Can't just blindly remove punctuation:
  - m.p.h., Ph.D., AT&T, cap’n
  - prices ($45.55)
  - dates (01/02/06)
  - URLs (http://www.stanford.edu)
  - hashtags (#nlproc)
  - email addresses (someone@cs.colorado.edu)
- Clitic: a word that doesn't stand on its own
  - "are" in we're, French "je" in j'ai, "le" in l'honneur
- When should multiword expressions (MWE) be words?
  - New York, rock ’n’ roll

Slide adapted from Jurafsky & Martin

Regex-based tokenization

```
>>> text = 'That U.S.A. poster-print costs $12.40...'
>>> pattern = r'''(?x)    # set flag to allow verbose regexps
...     ([A-Z]\.)+        # abbreviations, e.g. U.S.A.
...   | \w+(-\w+)*        # words with optional internal hyphens
...   | \$?\d+(\.\d+)?%?  # currency and percentages, e.g. $12.40, 82%
...   | \.\.\.            # ellipsis
...   | [][.,;"'?():-_`]  # these are separate tokens; includes ], [
... '''
>>> nltk.regexp_tokenize(text, pattern)
['That', 'U.S.A.', 'poster-print', 'costs', '$12.40', '...']
```

- NLTK [Bird+ 2009] provides regex and ML models for tokenization (like punkt)
- spaCy, other packages provide good tokenization

Slide adapted from Jurafsky & Martin

Tokenization in languages without spaces between words

- Many languages (like Chinese, Japanese, Thai) don't use spaces to separate words!
- How do we decide where the token boundaries should be?

Slide adapted from Jurafsky & Martin

Word tokenization in Chinese

- Chinese words are composed of characters called "**hanzi**" (or sometimes just "**zi**")
- Each one represents a meaning unit called a morpheme
- Each word has on average 2.4 of them.
- But deciding what counts as a word is complex and not agreed upon.

Slide adapted from Jurafsky & Martin

How to do word tokenization in Chinese?

姚明进入总决赛 “Yao Ming reaches the finals”

3 words?
姚明 进入 总决赛
YaoMing reaches finals

5 words?
姚 明 进入 总 决赛
Yao Ming reaches overall finals

7 characters? (don't use words at all):
姚 明 进 入 总 决 赛
Yao Ming enter enter overall decision game

Slide adapted from Jurafsky & Martin

Word tokenization / segmentation

- In Chinese NLP it's common to just treat each character (zi) as a token.
  - So the **segmentation** step is very simple
- In other languages (like Thai and Japanese), more complex word segmentation is required.
  - The standard algorithms are neural sequence models trained by supervised machine learning.

Slide adapted from Jurafsky & Martin

Subword tokenization & BPE

Another option for text tokenization

- **Use the data** to tell us how to tokenize.
- **Subword tokenization** (because tokens can be parts of words as well as whole words)
- Many modern neural NLP systems (like BERT) use this to handle unknown words
- 2 parts:
  - A token learner that takes a raw training corpus and induces a vocabulary (a set of tokens).
  - A token segmenter that takes a raw test sentence and tokenizes it according to that vocabulary

Slide adapted from Jurafsky & Martin

Byte Pair Encoding (BPE, Sennrich+ 2016) token learner

Let vocabulary be the set of all individual characters

= {A, B, C, D,…, a, b, c, d….}

Repeat:

- Choose the two symbols that are most frequently adjacent in the training corpus (say 'A', 'B')
- Add a new merged symbol 'AB' to the vocabulary
- Replace every adjacent 'A' 'B' in the corpus with 'AB'.

Until *k* merges have been done.

Slide adapted from Jurafsky & Martin

BPE token learner

Original (very fascinating🙄) corpus:

low low low low low lowest lowest newer newer newer newer newer newer wider wider wider new new

Split on whitespace, add end-of-word tokens _

corpus	
5	l o w _
2	l o w e s t _
6	n e w e r _
3	w i d e r _
2	n e w _

vocabulary

_, d, e, i, l, n, o, r, s, t, w

Slide adapted from Jurafsky & Martin

BPE token learner

- Merge e r to er

corpus		vocabulary
5	l o w _	_, d, e, i, l, n, o, r, s, t, w, er
2	l o w e s t _	
6	n e w er _	
3	w i d er _	
2	n e w _	

- Merge er _ to er_
- Merge n e to ne

Slide adapted from Jurafsky & Martin

BPE token learner

The next merges are:

Merge	Current Vocabulary
(ne, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new
(l, o)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo
(lo, w)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low
(new, er_)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_
(low, _)	_, d, e, i, l, n, o, r, s, t, w, er, er_, ne, new, lo, low, newer_, low_

BPE token segmenter algorithm

- On the test data, run each merge learned from the training data:
  - Greedily, in the order we learned them
- So merge every e r to er, then merge er _ to er_, etc.
- Result:
  - Test set "n e w e r _" would be tokenized as a full word
  - Test set "l o w e r _" would be two tokens: "low er_"

Slide adapted from Jurafsky & Martin

Properties of BPE tokens

Usually include:

- frequent words
- frequent subwords

Which are often morphemes (meaningful word units) like -*est* or –*er*

- But are often not, too! (@@ is a token break)

	peed	*deed*
Linguist_1	pe@@ ed	deed
Linguist_2	pee@@ d	deed
BPE_1	pe@@ ed	de@@ ed
BPE_2	peed	deed

Slide adapted from Jurafsky & Martin, David Mortensen

Other preprocessing

Case folding (lowercasing)

- Applications like IR: reduce all letters to lower case
  - Since users tend to use lower case
  - Possible exception: upper case in mid-sentence?
    - e.g., ***General Motors***
    - ***Fed*** vs. ***fed***
    - ***SAIL*** vs. ***sail***
- For sentiment analysis, MT, information extraction
  - Case is helpful (***US*** versus ***us*** is important)

Slide adapted from Jurafsky & Martin

Lemmatization

Represent words as their lemma, their shared root, dictionary headword form:

- *am, are, is* → *be*
- *car, cars, car's, cars'* → *car*
- Spanish quiero (‘I want’), quieres (‘you want’)
  → querer ‘want'
- *He is reading detective stories*
  → *He be read detective story*

Slide adapted from Jurafsky & Martin

Lemmatization is done by Morphological Parsing

- Morphemes: small meaningful units that make up words
  - **Roots**: The core meaning-bearing units
  - **Affixes**: Parts that adhere to roots

un-think-able; kitten-s

- Affixes can add grammatical meaning (inflections, 2nd column) or modify semantic meaning (derivations, 3rd column)

<root>	<root>ing	<root>er
run	running	runner
think	thinking	thinker
program	programming	programmer
kill	killing	killer

Slide adapted from Jurafsky & Martin, David Mortensen

Lemmatization is done by Morphological Parsing

- *cats* into two morphemes *cat* and *s*
- Spanish *amaren* (‘if in the future they would love’) into morpheme *amar* ‘to love’ + morphological features *3PL* + *future subjunctive*.

Slide adapted from Jurafsky & Martin

Dealing with complex morphology is necessary for many languages

- e.g., the Turkish word:

  Uygarlastiramadiklarimizdanmissinizcasina

  '(behaving) as if you are among those whom we could not civilize'

  Uygar 'civilized' + las 'become'

  \+ tir 'cause' + ama 'not able'

  \+ dik 'past' + lar 'plural'

  \+ imiz '1pl' + dan 'abl'

  \+ mis 'past' + siniz '2pl' + casina 'as if'

Slide adapted from Jurafsky & Martin

Stemming

- Reduce terms to stems, chopping off affixes crudely

This was not the map we found in Billy Bones's chest, but an accurate copy, complete in all things-names and heights and soundings-with	➡	Thi wa not the map we found in Billi Bone s chest but an accur copi complet in all thing name and height and sound with

$$\begin{array}{rcll} \text{ATIONAL} & \rightarrow & \text{ATE} & \text{(e.g., relational} \rightarrow \text{relate)} \\ \text{ING} & \rightarrow & \epsilon & \text{if stem contains vowel (e.g., motoring} \rightarrow \text{motor)} \\ \text{SSES} & \rightarrow & \text{SS} & \text{(e.g., grasses} \rightarrow \text{grass)} \end{array}$$

Slide adapted from Jurafsky & Martin

Stopword removal

- Do we want to keep "function words" like *the*, *of*, *and*, *I*, *you*, etc?
- Sometimes no (information retrieval)
- Sometimes yes (authorship attribution)

Sentence segmentation

!, ? mostly unambiguous but **period** "." is very ambiguous

- Sentence boundary
- Abbreviations like Inc. or Dr.
- Numbers like .02% or 4.3

Common algorithm: Tokenize first: use rules or ML to classify a period as either (a) part of the word or (b) a sentence boundary.

- An abbreviation dictionary can help

Sentence segmentation can then often be done by rules based on this tokenization.

Slide adapted from Jurafsky & Martin

Preprocessing decisions: example scenarios

- Build a Chinese - French machine translation system
- Study what topics are generally discussed on an online forum through what words people commonly use
- Extract prices from a stock ticker
- Build a dialogue agent in Turkish

Preprocessing considerations:

- Tokenization issues?
- Lowercasing/case folding?
- Stem/lemmatize?
- Morphological analysis needed?
- Use regular expressions?

Edit distance

How similar are two text strings?

Spell correction

- The user typed “graffe”
  - Which is closest?
- graf
- graft
- grail
- giraffe

Computational Biology

- Align two sequences of nucleotides

```
AGGCTATCACCTGACCTCCAGGCCGATGCCC
TAGCTATCACGACCGCGGTCGATTTGCCCGAC
```

- Resulting alignment:

```
-AGGCTATCACCTGACCTCCAGGCCGA--TGCCC---
TAG-CTATCAC--GACCGC--GGTCGATTTGCCCGAC
```

Also for Machine Translation, Information Extraction, Speech Recognition

Slide adapted from Jurafsky & Martin

Edit distance

- The minimum edit distance between two strings
- Is the minimum number of editing operations
  - Insertion
  - Deletion
  - Substitution
- Needed to transform one into the other

Slide adapted from Jurafsky & Martin

Minimum edit distance

- Two strings and their **alignment**:

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
```

Minimum edit distance

- If each operation has cost of 1
  - Distance between these is 5
- If substitutions cost 2 (Levenshtein)
  - Distance between them is 8

```
I N T E * N T I O N
| | | | | | | | | |
* E X E C U T I O N
d s s   i s
```

Slide adapted from Jurafsky & Martin

How to find the minimum edit distance?

- Searching for a path (sequence of edits) from the start string to the final string:
  - **Initial state**: the word we're transforming
  - **Operators**: insert, delete, substitute
  - **Goal state**: the word we're trying to get to
  - **Path cost**: what we want to minimize: the number of edits

Slide adapted from Jurafsky & Martin

Minimum edit as search

- But the space of all edit sequences is huge!
    - We can’t afford to navigate naïvely
    - Lots of distinct paths wind up at the same state
        - We don’t have to keep track of all of them
        - Just the shortest path to each of those intermediate states.

Slide adapted from Jurafsky & Martin

Dynamic Programming for Minimum Edit Distance

- **Dynamic programming**: A tabular computation of D(*n*,*m*)
  - Solving problems by combining solutions to subproblems.
  - Bottom-up
- For two strings: X of length *n*, Y of length *m*
- We define D(*i*,*j*)
  - the edit distance between X[1..*i*] and Y[1..*j*]
    - i.e., the first *i* characters of X and the first *j* characters of Y
  - The edit distance between X and Y is thus **D(*n*,*m*)**
- We compute D(i,j) for small *i*,*j*
- And compute larger D(i,j) based on previously computed smaller values
  - i.e., compute D(*i*,*j*) for all *i* (0 < *i* < n) and *j* (0 < j < m)

Slide adapted from Jurafsky & Martin

The edit distance table

N	9									
O	8									
I	7									
T	6									
N	5									
E	4									
T	3									
N	2									
I	1									
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

Slide adapted from Jurafsky & Martin

The edit distance table

N	9									
O	8									
I	7									
T	6									
N	5									
E	4									
T	3									
N	2									
I	1									
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

$$D(i,j) = \min \begin{cases} D(i-1,j) + 1 & \text{delete} \\ D(i,j-1) + 1 & \text{insert} \\ D(i-1,j-1) + \begin{cases} 2; & \text{if } S_1(i) \neq S_2(j) \\ 0; & \text{if } S_1(i) = S_2(j) \end{cases} & \text{substitute} \end{cases}$$

Slide adapted from Jurafsky & Martin

The edit distance table

D(n, m) = 8

N	9	8	9	10	11	12	11	10	9	**8**
O	8	7	8	9	10	11	10	9	8	9
I	7	6	7	8	9	10	9	8	9	10
T	6	5	6	7	8	9	8	9	10	11
N	5	4	5	6	7	8	9	10	11	10
E	4	3	4	5	6	7	8	9	10	9
T	3	4	5	6	7	8	7	8	9	8
N	2	3	4	5	6	7	8	7	8	7
I	1	2	3	4	5	6	7	6	7	8
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

Slide adapted from Jurafsky & Martin

Performance

Time:

$O(nm)$

Space:

$O(nm)$

Slide adapted from Jurafsky & Martin

Questions?

Enjoy Labor Day holiday

No class on Monday
Project survey due this Thu Aug 31 at 11:59pm
First reading quiz due next Wed Sep 6 at noon