Preprocessing

NLP Week 2

Thanks to Dan Jurafsky for some of the slide inspirations!

Plan for today

1. What is preprocessing?
2. Characterizing strings with RegEx
3. Tokenization
4. Word normalization and lemmatization
5. *Group exercises*

What is preprocessing?

Preprocessing is the first step to all NLP tasks and models ; It involves *normalizing* text data.

Google is set to file its own suggestions for fixing the search monopoly by Dec. 20. Both sides can modify their requests before Judge Mehta is expected to hear arguments on the remedies this spring. He is expected to rule by the end of the summer.

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"D.O.J.'s wildly overbroad proposal goes miles beyond the court's decision," he said in a blog post. "It would break a range of Google products — even beyond Search — that people love and find helpful in their everyday lives."

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What about splitting text into words? Subwords?

What is preprocessing?

Preprocessing is the first step to all NLP tasks and models ; It involves *normalizing* text data, by:

- **Cleaning formatting**
- **Normalizing text**
- **Segmenting text into subwords, words, sentences, …**

Regular Expressions (RegEx)

RegEx is a formal language for specifying text strings

Eg. How can we search for mentions of these cute animals in text?

- woodchuck
- woodchucks
- Woodchuck
- Woodchucks
- Groundhog
- groundhogs

Can we write a formal specification that accounts for all of these?

RegEx: Disjunctions (Or)

- Letters or ranges inside brackets [ ] will represent disjunctive expressions

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

Pattern	Matches	
`[A-Z]`	An upper case letter	`Drenched Blossoms`
`[a-z]`	A lower case letter	`my beans were impatient`
`[0-9]`	A single digit	`Chapter 1: Down the Rabbit`

RegEx: Disjunctions (Or)

- The pipe symbol | is also for disjunction

Pattern	Matches
`groundhog|woodchuck`	`woodchuck`
`yours|mine`	`yours`
`a|b|c`	= [abc]
`[gG]roundhog|[Ww]oodchuck`	`Woodchuck`

RegEx: wildcards, etc: . ? * +

- Wildcards can match any symbol for a defined number of times.

Pattern	Matches	Examples
`beg.n`	Any char	`begin` `begun` `beg3n`
`woodchucks?`	Optional s	`woodchuck` `woodchucks`
`to*`	0 or more of previous	`t` `to` `too` `tooo`
`to+`	1 or more of previous	`to` `too` `tooo` `toooo`

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```
[gG]roundhogs?|[Ww]oodchucks?
```

RegEx: Negation (Not)

Carat (^) as first character in [ ] negates the list:

- Carat means negation only when it's first in [ ]
- Other Special characters (., *, +, ?) lose their special meaning inside [ ]

Pattern	Matches	Examples
`[^A-Z]`	Not an upper case	`Oyfn pripetchik`
`[^Ss]`	Neither ‘S’ nor ‘s’	`I have no exquisite`
`[^.]`	Not a period	`Our resident Djinn`
`[e^]`	Either e or ^	`Look up ^ now`

RegEx: Anchors ^ $

- ^ at the beginning of a regex is for at beginning of string
- $ marks the end of string

Pattern	Matches
^[A-Z]	Palo Alto
^[^A-Za-z]	1 “Hello”
\.$	The end.
.$	The end? The end!

RegEx aliases

- Common regex have shortcuts.

Pattern	Expansion	Matches	Examples
`\d`	`[0-9]`	Any digit	`Fahreneit 451`
`\D`	`[^0-9]`	Any non-digit	`Blue Moon`
`\w`	`[a-ZA-Z0-9_]`	Any alphanumeric or _	`Daiyu`
`\W`	`[^\w]`	Not alphanumeric or _	`Look!`
`\s`	`[ \r\t\n\f]`	Whitespace (space, tab)	`Look␣up`
`\S`	`[^\s]`	Not whitespace	`Look up`

RegEx in Python

Regex and Python both use backslash "\" for special characters.

- Must type an extra backslash for regexes in Python!
  - Eg. ”\\d+" to search for 1 or more digits
- **OR:** use Python's **raw string notation** for regex:
  - r"\d+" matches one or more digits (instead of “\\d+")

Why RegEx?

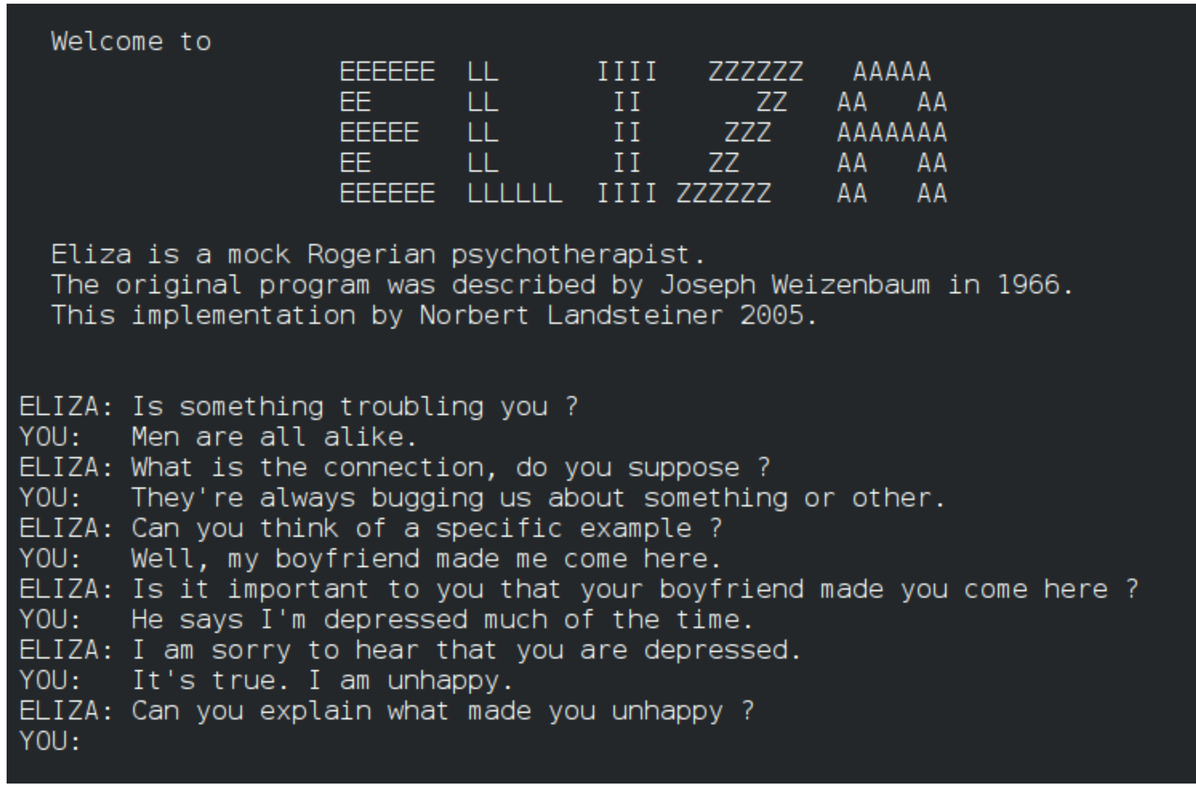
Widely used in both academics and industry:

1. Part of most text processing tasks, even for big LLM pipelines
2. Very useful for data analysis of any text data

.

First chatbot: ELIZA (1966)

- ELIZA was an early NLP system meant to imitate a Rogerian psychotherapist.
- It worked via **pattern matching:**
  - **Input:** “I need X.”
  - **Output:** “What would it mean if you got X?”



First chatbot: ELIZA (1966)

- Pattern matching examples from ELIZA:
    - r“.* I’m (depressed|sad)” -> “I am sorry to hear that you are X”
    - r“.* all .*” -> “In what way?”
    - r”.* always .*” -> “Can you think of a specific example?”

Tokenization

Tokenization is to segment text into tokens (or meaningful units for processing).

Sample Data:

"This is tokenizing."

Character Level

[T] [h] [i] [s] [i] [s] [t] [o] [k] [e] [n] [i] [z] [i] [n] [g] [.]

Word Level

[This] [is] [tokenizing] [.]

Subword Level

[This] [is] [token] [izing] [.]

Why is it important?

- **Tokenization is the first step to all NLP language models.**

- Language is a symbolic system that takes continuous signal (e.g. audio speech, or hand gestures) and transforms it into a sequence of meaningful symbols (e.g. morphemes, signs, or words) **-> tokenization is what decides what those meaningful units are in an NLP system.**

Tokens vs types

- **Type**: an element of the vocabulary.
- **Token**: an instance of that type in running text.

Eg. Assume we are tokenizing on the word-level:

“The NLP course students enjoyed the course very much”

How many tokens? **9**

How many types? **7**

Simple tokenization

- A very simple word tokenization algorithm could split text on spaces and punctuation marks.

```
str = “He is expected by the end of the summer.”

delimiter = r“[,?\.!]\s?|\s”

tokens = str.split(delimiter)



[“He”,“is”,“expected”,“by”,“the”,“end”,“of”,“the”,“summer”]
```

Issues with 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.hec.ca)
- hashtags (#hec)
- email addresses (someone@cs.colorado.edu)
- **Clitic:** a word that doesn't stand on its own, eg. ”are” in we're, French "je" in j'ai, "le" in l’honneur

What about spaces? When should multiword expressions be words?

- New York, rock ’n’ roll

Tokenization with NLTK

- **Alternative:** instead of matching delimiters between words, lets try to match sets of characters that can be words!

```
>>> 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', '...']
```

Bird, Loper and Klein (2009), *Natural Language Processing with Python*. O'Reilly

Tokenization in other languages

But… Not all languages uses spaces or single characters!

So what determines token boundaries in other languages?

The example of 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.

Tokenization in other languages

So how should we tokenize 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

Statistical tokenization

Can we be *smarter* with tokenization and try to *learn* the relevant morphemes of a language based on a corpus?

Three common algorithms:

- **Byte-Pair Encoding (BPE)** (Sennrich et al., 2016)
- Unigram language modeling tokenization (Kudo, 2018)
- WordPiece (Schuster and Nakajima, 2012)

Statistical tokenization

- There are two parts to any statistical tokenization algorithm:

    1. **A learner** which *learns* the vocabulary or set of tokens for a language given a train corpus
    2. **A segmenter** which *segments* a test corpus into a sequence of learnt vocabulary tokens.

Byte-Pair Encoding (BPE)

THE LEARNER

1. Initialize the vocabulary as the list of all individual characters:
   V = [A, B, C, D,…, a, b, c, d….]
2. Then repeat the following steps until termination condition is reached:
   1. Choose the two symbols that are most frequently adjacent in the training corpus (say 'A', ‘B')
   2. Add a new merged symbol 'AB' to the vocabulary
   3. Replace every adjacent 'A' 'B' in the corpus with 'AB'.
3. Termination condition: the vocabulary desired size is reached.

Byte-Pair Encoding (BPE)

THE LEARNER

function BYTE-PAIR ENCODING(strings C, number of merges k) **returns** vocab V

$V \leftarrow$ all unique characters in C # initial set of tokens is characters
for $i = 1$ **to** k **do** # merge tokens til k times
  $t_L, t_R \leftarrow$ Most frequent pair of adjacent tokens in C
  $t_{NEW} \leftarrow t_L + t_R$ # make new token by concatenating
  $V \leftarrow V + t_{NEW}$ # update the vocabulary
  Replace each occurrence of t_L, t_R in C with t_{NEW} # and update the corpus
return V

Byte-Pair Encoding (BPE)

THE LEARNER

Note
To also account for existing signal coming from spaces in many languages a special end-of-word symbol '__' is commonly added to all words before spaces in the training corpus, before training the learner.

e.g. Tokenization_ is_ the_ first_ step_ to_ all_ NLP_ language_ models_ .

Byte-Pair Encoding (BPE)

THE SEGMENTER

- Now that we have learnt a set of tokens, how do we actually segment our test corpus?

- Looping over the vocabulary, with merged tokens **in the order in which we learned them**:

1. For every learnt merged symbol, eg, ‘AB’, in the the vocabulary:
    1.1. Greedily replace every adjacent 'A' 'B' in the corpus with 'AB'.
2.

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return V

If your train corpus = your test corpus, this last step takes care of the segmenter part of the algorithm.

Word Normalization

Tokenization is a preprocessing step; there are other forms of preprocessing we might want to consider, such as various forms of **word normalization.**

- **Case folding:** putting all characters in the same case (e.g. NLP -> nlp)

  Note: Case can be useful for some semantic-based tasks
  (e.g. US versus us mean different things)

- **Lemmatization:** replacing words by their dictionary word (e.g. am, are, is -> be)

  Note: Syntactic cues like tense, plural markers etc. can be useful for tasks like language generation.

- **Stemming:** removing affixes from words, keeping only stems (similar purpose to lemmatization)

Lemmatization

Represent words by their ***lemma,*** their shared root= dictionary headword form:

am, are, is -> be
car, cars, car's, cars' -> car

He is reading detective stories -> He be read detective story

Lemmatization

Lemmatization is done using a morphological parser (most often heuristic rule-based parsers that are language dependent) that splits words into morphemes.

Recall, last week we talked about ***morphemes***, the smallest units of meaning in a language. There are two types:

1. **Stems** : the core meaning-bearing units
2. **Affixes** : subwords that must attach to a stem, often have grammatical functions.

heavenly -> heaven/-ly
cars -> car/-s
Incompetent -> in-/competent

Stemming

Stemming is a slightly simpler approach with the same ethos as lemmatization where you remove all affixes, reducing all words to their stems.

heavenly -> heaven
cars -> car
Incompetent -> competent ?? Incompetent

In practice, stemming is often crude and selective in which affixes are removed, dependent of the set of heuristic rules used)

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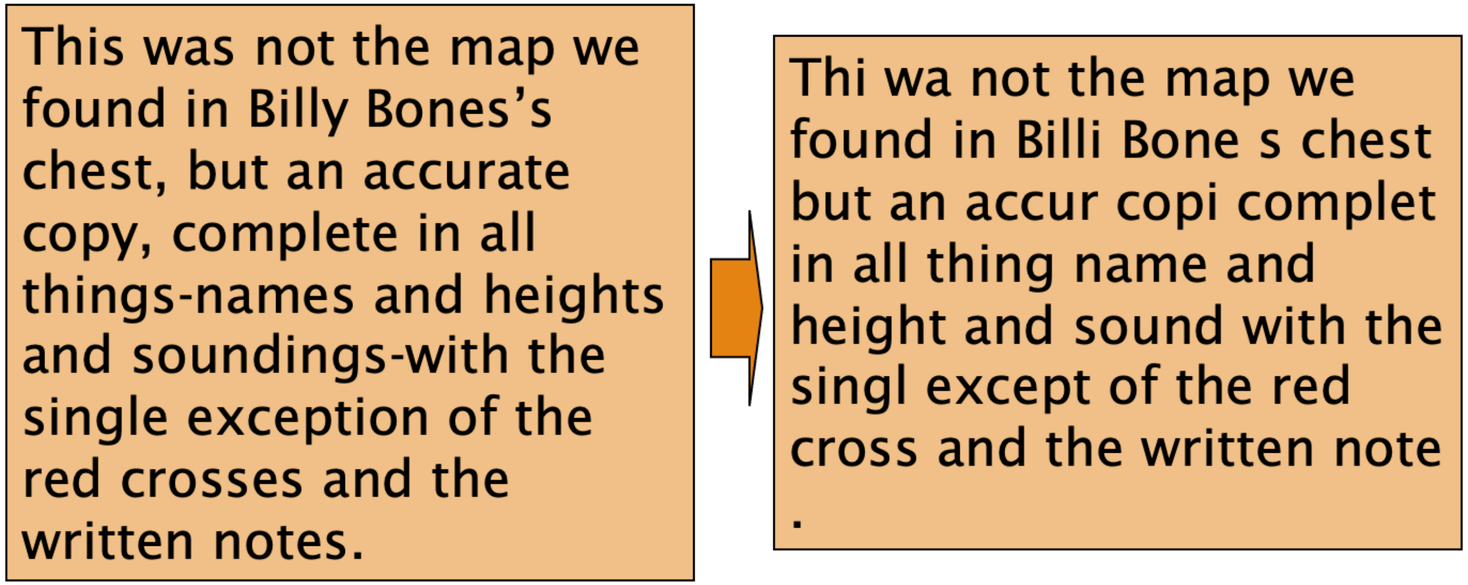

[15 minute break]

Let’s try preprocessing

Team up!

Open exercises/week 2 in your course folder and start writing/running code!