

Basic Text Processing

Regular Expressions

Regular expressions

A formal language for specifying text strings

How can we search for any of these?

- woodchuck
- woodchucks
- Woodchuck
- Woodchucks



Regular Expressions: Disjunctions

Letters inside square brackets []

Pattern	Matches
<code>[wW]oodchuck</code>	Woodchuck, woodchuck
<code>[1234567890]</code>	Any digit

Ranges `[A-Z]`

Pattern	Matches	
<code>[A-Z]</code>	An upper case letter	<u>D</u> renched Blossoms
<code>[a-z]</code>	A lower case letter	<u>m</u> y beans were impatient
<code>[0-9]</code>	A single digit	Chapter <u>1</u> : Down the Rabbit Hole

Regular Expressions: Negation in Disjunction

Negations [^Ss]

- Carat means negation only when first in []

Pattern	Matches	
[^A-Z]	Not an upper case letter	O <u>y</u> fn pripetchik
[^Ss]	Neither 'S' nor 's'	<u>I</u> have no exquisite reason"
[^e^]	Neither e nor ^	Look h <u>e</u> re
a^b	The pattern a carat b	Look up <u>a^b</u> now

Regular Expressions: More Disjunction

Woodchuck is another name for groundhog!

The pipe | for disjunction

Pattern	Matches
<code>groundhog woodchuck</code>	woodchuck
<code>yours mine</code>	yours
<code>a b c</code>	= <code>[abc]</code>
<code>[gG]roundhog [Ww]oodchuck</code>	Woodchuck



Regular Expressions: ? * + .

Pattern	Matches	
colou?r	Optional previous char	<u>color</u> <u>colour</u>
oo*h!	0 or more of previous char	<u>oh!</u> <u>ooh!</u> <u>oooh!</u> <u>ooooh!</u>
o+h!	1 or more of previous char	<u>oh!</u> <u>ooh!</u> <u>oooh!</u> <u>ooooh!</u>
baa+		<u>baa</u> <u>baaa</u> <u>baaaa</u> <u>baaaaa</u>
beg.n		<u>begin</u> <u>begun</u> <u>begun</u> <u>beg3n</u>



Stephen C Kleene

Kleene *, Kleene +

Regular Expressions: Anchors [^] ^{\$}

Pattern	Matches
[^] [A-Z]	<u>P</u> alo Alto
[^] [[^] A-Za-z]	<u>1</u> " <u>H</u> ello"
\. ^{\$}	The end <u>.</u>
.\sup>\$	The end <u>?</u> The end <u>!</u>

Example

Find me 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]

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)

Errors cont.

In NLP we are always dealing with these kinds of errors.

Reducing the error rate for an application often involves two antagonistic efforts:

- Increasing accuracy or precision (minimizing false positives)
- Increasing coverage or recall (minimizing false negatives).

Summary

Regular expressions play a surprisingly large role

- 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 as features in the classifiers
- Can be very useful in capturing generalizations

Basic Text Processing

Regular Expressions

Basic Text Processing

More Regular Expressions: Substitutions and ELIZA

Substitutions

Substitution in Python and UNIX commands:

```
s/regex1/pattern/
```

e.g.:

```
s/colour/color/
```

Capture Groups

- Say we want to put angles around all numbers:
the 35 boxes → *the <35> boxes*
- Use parens () to "capture" a pattern into a numbered register (1, 2, 3...)
- Use \1 to refer to the contents of the register
`s / ([0-9] +) / < \1 > /`

Capture groups: multiple registers

`/the (.*)er they (.*) , the \1er we \2/`

Matches

*the **faster** they **ran**, the **faster** we **ran***

But not

*the **faster** they **ran**, the **faster** we ate*

But suppose we don't want to capture?

Parentheses have a double function: grouping terms, and capturing

Non-capturing groups: add a ?: after paren:

```
/(?:some|a few) (people|cats) like some \1/
```

matches

- some cats like some cats

but not

- some cats like some some

Lookahead assertions

`(?= pattern)` is true if pattern matches, but is **zero-width; doesn't advance character pointer**

`(?! pattern)` true if a pattern does not match

How to match, at the beginning of a line, any single word that doesn't start with "Volcano":

```
/^(?!Volcano)[A-Za-z]+/
```

Simple Application: ELIZA

Early NLP system that imitated a Rogerian psychotherapist

- Joseph Weizenbaum, 1966.

Uses pattern matching to match, e.g.,:

- "I need X"

and translates them into, e.g.

- "What would it mean to you if you got X?"

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

How ELIZA works

s/. * I'M (depressed|sad) . */I AM SORRY TO HEAR YOU ARE \1/
s/. * I AM (depressed|sad) . */WHY DO YOU THINK YOU ARE \1/
s/. * all . */IN WHAT WAY?/
s/. * always . */CAN YOU THINK OF A SPECIFIC EXAMPLE?/

Basic Text Processing

More Regular Expressions: Substitutions and ELIZA

Basic Text Processing

Words and Corpora

How many words in a sentence?

"I do uh main- mainly business data processing"

- Fragments, filled pauses

"Seuss's **cat** in the hat is different from other **cats**!"

- **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

How many words in a sentence?

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

Type: an element of the vocabulary.

Token: an instance of that type in running text.

How many?

- 15 tokens (or 14)
- 13 types (or 12) (or 11?)

How many words in a corpus?

N = number of tokens

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

Heaps Law = Herdan's Law = $|V| = kN^\beta$ where often $.67 < \beta < .75$

i.e., vocabulary size grows with $>$ square root of the number of word tokens

	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

Corpora

Words don't appear out of nowhere!


A text is produced by

- a specific writer(s),
- at a specific time,
- in a specific variety,
- of a specific language,
- for a specific function.

Corpora vary along dimension like

LVCGA
L - Language
V - Variety
C - Code Switching
G - Genre
A - Author Demographics

- **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:
 - S/E: 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:]
 - H/E: dost tha or ra- hega ... dont worry ... 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

Socio Economic State 

Corpus datasheets

Gebbru et al (2020), Bender and Friedman (2018)

Motivation:

- Why was the corpus collected?
- By whom?
- Who funded it?

Situation: In what situation was the text written?

Collection process: If it is a subsample how was it sampled? Was there consent? Pre-processing?

+Annotation process, language variety, demographics, etc.

Basic Text Processing

Words and Corpora

Basic Text Processing

Word tokenization

Text Normalization

Every NLP task requires text normalization:

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

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

Unix tools for space-based tokenization

- The "tr" command
- Inspired by Ken Church's UNIX for Poets
- Given a text file, output the word tokens and their frequencies

Simple Tokenization in UNIX

(Inspired by Ken Church's UNIX for Poets.)

Given a text file, output the word tokens and their frequencies

```
tr -sc 'A-Za-z' '\n' < shakes.txt
```

Change all non-alpha to newlines

```
| sort
```

Sort in alphabetical order

```
| uniq -c
```

Merge and count each type

```
1945 A
```

```
72 AARON
```

```
19 ABBESS
```

```
5 ABBOT
```

```
... ..
```

```
25 Aaron
```

```
6 Abate
```

```
1 Abates
```

```
5 Abbess
```

```
6 Abbey
```

```
3 Abbot
```

```
.... ..
```

The first step: tokenizing

```
tr -sc 'A-Za-z' '\n' < shakes.txt | head
```

THE

SONNETS

by

William

Shakespeare

From

fairest

creatures

We

...

The second step: sorting

```
tr -sc 'A-Za-z' '\n' < shakes.txt | sort | head
```

A

A

A

A

A

A

A

A

A

...

More counting

Merging upper and lower case

```
tr 'A-Z' 'a-z' < shakes.txt | tr -sc 'A-Za-z' '\n' | sort | uniq -c
```

Sorting the counts

```
tr 'A-Z' 'a-z' < shakes.txt | tr -sc 'A-Za-z' '\n' | sort | uniq -c | sort -n -r
```

```
23243 the
22225 i
18618 and
16339 to
15687 of
12780 a
12163 you
10839 my
10005 in
8954 d
```

What happened here?

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](#)

Tokenization in NLTK

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

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

Tokenization in languages without spaces

Many languages (like Chinese, Japanese, Thai) don't use spaces to separate words!

How do we decide where the token boundaries should be?

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.

How to do word tokenization in Chinese?

姚明进入总决赛 “Yao Ming reaches the finals”

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

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

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

Word tokenization / segmentation

So in Chinese 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.

Basic Text Processing

Word tokenization

Word Normalization

Putting words/tokens in a standard format

- U.S.A. or USA
- uhhuh or uh-huh
- Fed or fed
- am, is, be, are

Case folding

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)

Lemmatization

Represent all 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*

Lemmatization is done by Morphological Parsing

Morphemes:

- The small meaningful units that make up words
- **Stems**: The core meaning-bearing units
- **Affixes**: Parts that adhere to stems, often with grammatical functions

Morphological Parsers:

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

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 the single exception of the red crosses and the written notes.



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 the singl except of the red cross and the written note .

Porter Stemmer

Based on a series of rewrite rules run in series

- A cascade, in which output of each pass fed to next pass

Some sample rules:

ATIONAL → ATE (e.g., relational → relate)

ING → ϵ if stem contains vowel (e.g., motoring → motor)

SSES → SS (e.g., grasses → grass)

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** `p1pl’ + **dan** `abl’
 - + **mis** `past’ + **siniz** `2pl’ + **casina** `as if’

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.