

Basic Text Processing

Regular Expressions

Word Tokenization

Word Normalization

Sentence Segmentation

Many slides adapted from slides by Dan Jurafsky

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

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- Letters inside square brackets []

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

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- Ranges [A-Z]

Pattern	Matches	the First Match in an example
[A-Z]	An upper case letter	<u>D</u> renched Blossoms
[a-z]	A lower case letter	<u>m</u> y beans were impatient
[0-9]	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	Oyfn pripetchik
[^Ss]	Neither 'S' nor 's'	<u>I</u> have no exquisite reason"
[^e^]	Neither e nor ^	Look here
a^b	The pattern a carat b	Look up <u>a^b</u> now

Regular Expressions: More Disjunction

- Woodchucks is another name for groundhog!
- The pipe | for disjunction

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



Photo D. Fletcher

Regular Expressions: ? * + .

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



Stephen C Kleene

Kleene *, Kleene +

Regular Expressions: Anchors ^ \$

Pattern	Matches
<code>^[A-Z]</code>	<u>P</u> alo Alto
<code>^[^A-Za-z]</code>	<u>1</u> <u>"Hello"</u>
<code>\.\$</code>	The end <u>.</u>
<code>.\$</code>	The end <u>?</u> The end <u>!</u>

Example

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**
 - Matching strings that we should not have matched (**there, then, other**)
 - **False positives (Type I)**
 - Not matching things that we should have matched (The)
 - **False negatives (Type II)**

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 task
- For many hard tasks, we use machine learning classifiers
 - But regular expressions are used as features in the classifiers
 - Can be very useful in capturing generalizations

Basic Text Processing

Regular Expressions

Basic Text Processing

Word tokenization

Text Normalization

Text Normalization

- Every NLP task needs to do text normalization:
 1. Segmenting/tokenizing words in running text
 2. Normalizing word formats
 3. Segmenting sentences in running text

How many words?

- I do uh main- mainly business data processing
 - Fragments, filled pauses

How many words?

- 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?

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

- **Type:** an element of the vocabulary.

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- **Token:** an instance of that type in running text.

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- **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?

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N = number of tokens

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V = vocabulary = set of types

$|V|$ is the size of the vocabulary

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$|V|$ is the size of the vocabulary

	Tokens = N	Types = $ V $
Switchboard phone	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
Google N-grams	1 trillion	13 million

How many words?

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V = vocabulary = set of types

$|V|$ is the size of the vocabulary

Church and Gale (1990): $|V| > O(N^{1/2})$

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- (Inspired by Ken Church's UNIX for Poets.)
- Given a text file, output the word tokens and their frequencies

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| sort
```

tr: translate, -s: squeeze, -c: complement

```
| uniq -c
```

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```

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```
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```

The first step: tokenizing

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

(head: will print the first lines (10 by default) of its input. head -n NUM input)

```
THE  
SONNETS  
by  
William  
Shakespeare  
From  
fairest  
creatures
```

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

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- Merging upper and lower case

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```
tr 'A-Z' 'a-z' < shakes.txt | tr -sc 'A-Za-z' '\n' | sort | uniq -c
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- Sorting the counts (-n: numerical value, -k: column, -r: reverse)

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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
```

More counting

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What happened here?

Issues in Tokenization

- Finland's capital → Finland Finlands Finland's ?
- what're, I'm, isn't → What are, I am, is not
- Hewlett-Packard → Hewlett Packard ?
- state-of-the-art → state of the art ?
- Lowercase → lower-case lowercase lower case ?
- San Francisco → one token or two?
- m.p.h., PhD. → ??

Tokenization: language issues

- French
 - *L'ensemble* → one token or two?
 - *L ? L' ? Le ?*
 - Want *l'ensemble* to match with *un ensemble*
- German noun compounds are not segmented
 - *Lebensversicherungsgesellschaftsangestellter*
 - 'life insurance company employee'
 - German information retrieval needs **compound splitter**

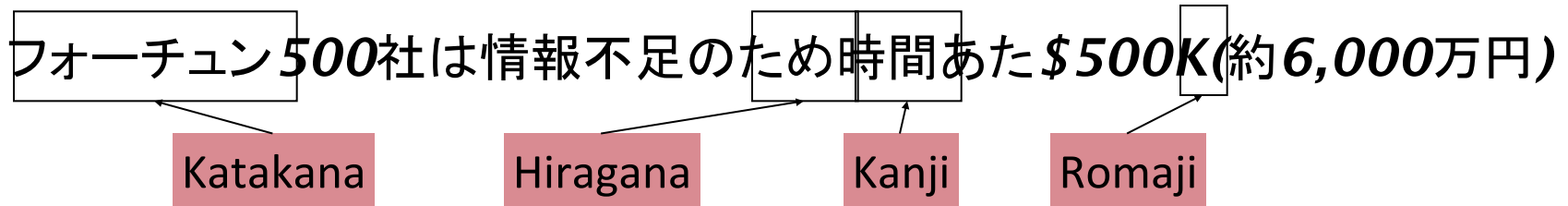
Tokenization: language issues

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- Chinese and Japanese no spaces between words:
 - 莎拉波娃现在居住在美国东南部的佛罗里达。
 - 莎拉波娃 现在 居住在 美国 东南部 的 佛罗里达
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 - Sharapova now lives in US southeastern Florida
- Further complicated in Japanese, with multiple alphabets intermingled
 - Dates/amounts in multiple formats



End-user can express query entirely in hiragana!

Word Tokenization in Chinese

- Also called **Word Segmentation**
- Chinese words are composed of characters
 - Characters are generally 1 syllable and 1 morpheme.
 - Average word is 2.4 characters long.
- Standard baseline segmentation algorithm:
 - Maximum Matching (also called Greedy)

Maximum Matching Word Segmentation Algorithm

- Given a wordlist of Chinese, and a string.
 - 1) Start a pointer at the beginning of the string
 - 2) Find the longest word in dictionary that matches the string starting at pointer
 - 3) Move the pointer over the word in string
 - 4) Go to 2

Max-match segmentation illustration

Max-match segmentation illustration

- Thecatinthehat

Max-match segmentation illustration

- Thecatinthehat

the cat in the hat

Max-match segmentation illustration

- Thecatinthehat the cat in the hat
- Thetabledownthere

Max-match segmentation illustration

- Thecatinthehat the cat in the hat
- Thetabledownthere the table down there

Max-match segmentation illustration

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Max-match segmentation illustration

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- Modern probabilistic segmentation algorithms even better

Basic Text Processing

Word tokenization

Basic Text Processing

Word Normalization and Stemming

Normalization

- Need to “normalize” terms
 - Information Retrieval: indexed text & query terms must have same form.
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- Alternative: asymmetric expansion:
 - Enter: ***window*** Search: ***window, windows***
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 - Enter: ***Windows*** Search: ***Windows***
- Potentially more powerful, but less efficient

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***

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 - 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

- Reduce inflections or variant forms to base form

- *am, are, is* → *be*
- *car, cars, car's, cars'* → *car*

Context dependent. for instance:
in our last meeting (noun, meeting).
We're meeting (verb, meet) tomorrow.

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- Machine translation
 - Spanish **quiero** ('I want'), **quieres** ('you want') same lemma as **querer** 'want'

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Morphology

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

context independent

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

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Porter's algorithm

The most common English stemmer

fixed rules put in groups, applied in order. <https://tartarus.org/martin/PorterStemmer/>

Text

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Step 1a

sses → ss caresses → caress

ies → i ponies → poni

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s → ∅ cats → cat

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Step 1b

(*v*)ing	→ ∅	walking	→ walk
		sing	→ sing
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Step 2 (for long stems)

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izer	→ ize	digitizer	→ digitize
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Step 3 (for longer stems)

al → ∅	revival → reviv
able → ∅	adjustable → adjust
ate → ∅	activate → activ
...	

Viewing morphology in a corpus

Why only strip –ing if there is a vowel?

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541 nothing  
388 king  
375 bring  
358 thing  
307 ring  
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307 ring          120 living  
152 something     117 loving  
145 coming        116 Being  
130 morning       102 going
```

```
tr -sc 'A-Za-z' '\n' < shakes.txt | grep '[aeiou].*ing$' | sort | uniq -c | sort -nr
```

Dealing with complex morphology is sometimes necessary

- Some languages requires complex morpheme segmentation
 - Turkish
 - **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`

Basic Text Processing

Word Normalization and Stemming

Basic Text Processing

Sentence Segmentation
and Decision Trees

Sentence Segmentation

Sentence Segmentation

- !, ? are relatively unambiguous

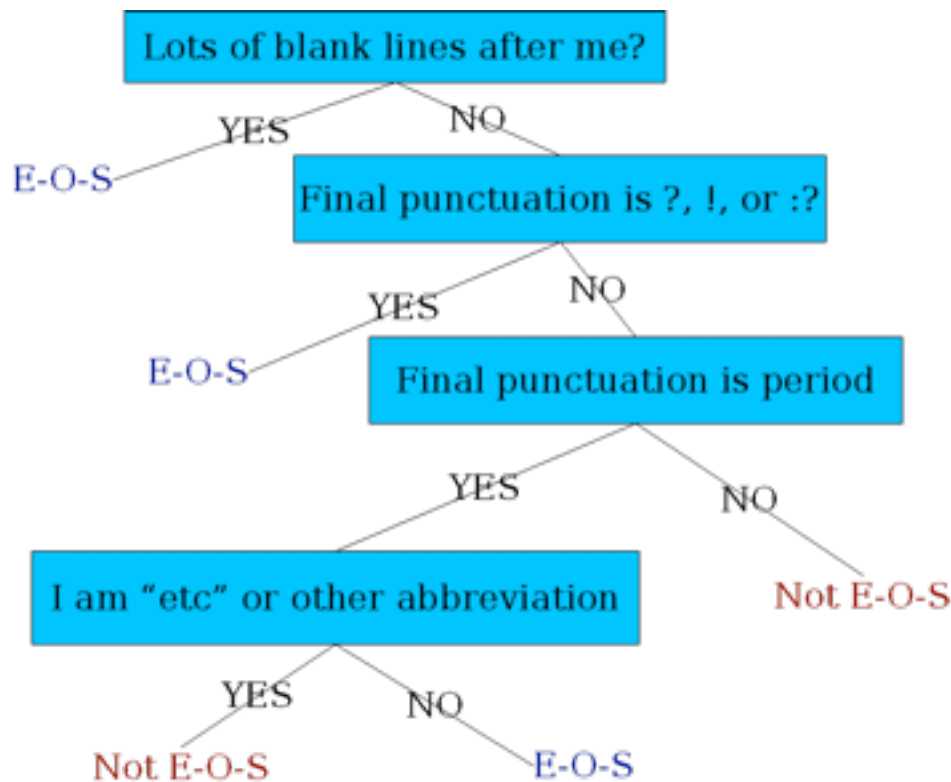
Sentence Segmentation

- !, ? are relatively unambiguous
- Period “.” is quite ambiguous
 - Sentence boundary
 - Abbreviations like Inc. or Dr.
 - Numbers like .02% or 4.3

Sentence Segmentation

- !, ? are relatively unambiguous
- Period “.” is quite ambiguous
 - Sentence boundary
 - Abbreviations like Inc. or Dr.
 - Numbers like .02% or 4.3
- Build a binary classifier
 - Looks at a “.”
 - Decides EndOfSentence/NotEndOfSentence
 - Classifiers: hand-written rules, regular expressions, or machine-learning

Determining if a word is end-of-sentence: a Decision Tree



More sophisticated decision tree features

More sophisticated decision tree features

- Case of word with “.”: Upper, Lower, Cap, Number

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More sophisticated decision tree features

- Case of word with “.”: Upper, Lower, Cap, Number
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- Numeric features
 - Length of word with “.”
 - Probability(word with “.” occurs at end-of-s)
 - Probability(word after “.” occurs at beginning-of-s)

Implementing Decision Trees

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- The interesting research is choosing the features

Implementing Decision Trees

- A decision tree is just an if-then-else statement
- The interesting research is choosing the features
- Setting up the structure is often too hard to do by hand
 - Hand-building only possible for very simple features, domains
 - For numeric features, it's too hard to pick each threshold
 - Instead, structure usually learned by machine learning from a training corpus

Decision Trees and other classifiers

Decision Trees and other classifiers

- We can think of the questions in a decision tree

Decision Trees and other classifiers

- We can think of the questions in a decision tree
- As features that could be exploited by any kind of classifier
 - Logistic regression
 - SVM
 - Neural Nets
 - etc.

Sentence Splitters

- Stanford coreNLP: (deterministic)
- <http://stanfordnlp.github.io/CoreNLP/>

- UIUC sentence splitter: (deterministic)
- https://cogcomp.cs.illinois.edu/page/tools_view/2

Basic Text Processing

Sentence Segmentation
and Decision Trees