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
  - woodchuck**s**
  - **W**oodchuck
  - **W**oodchuck**s**

Regular Expressions: Disjunctions

- Letters inside square brackets []

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

- Ranges `[A-Z]`

Pattern	Matches	the First Match in an example
`[A-Z]`	An upper case	`Drenched Blossoms`
`[a-z]`	A lower case letter	`my beans were impatient`
`[0-9]`	A single digit	`Chapter 1: 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	`Oyfn pripetchik`
`[^Ss]`	Neither 'S' nor 's'	`I have no exquisite reason"`
`[^e^]`	Neither e nor ^	`Look here`
`a^b`	The pattern a carat b	`Look up a^b now`

Regular Expressions: More Disjunction

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

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

Regular Expressions: ? * + .

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

Stephen C Kleene

Kleene *, Kleene +

Regular Expressions: Anchors ^ $

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

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

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Word tokenization

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
- 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?

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?

N = number of tokens

V = vocabulary = set of types

$|V|$ is the size of the vocabulary

Church and Gale (1990): $|V| > O(N^{½})$

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

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

- 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
  - Sharapova now lives in US southeastern Florida

Basic Text Processing

Word tokenization

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Word Normalization and Stemming

Normalization

- Need to “normalize” terms
  - Information Retrieval: indexed text & query terms must have same form.
    - We want to match ***U.S.A.*** and ***USA***
- We implicitly define equivalence classes of terms
  - e.g., deleting periods in a term
- Alternative: asymmetric expansion:
  - Enter: ***window*** Search: ***window, windows***
  - Enter: ***windows*** Search: ***Windows, windows, window***
  - Enter: ***Windows*** Search: ***Windows***

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

- Reduce inflections or variant forms to base form
  - *am, are, is* → *be*
  - *car, cars, car's, cars'* → *car*
- *the boy's cars are different colors* → *the boy car be different color*
- Lemmatization: have to find correct dictionary headword form

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

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

- 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

Porter's algorithm
The most common English stemmer

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

Step 1a

```
sses  → ss    caresses  → caress
ies   → i     ponies    → poni
ss    → ss    caress    → caress
s     → ø     cats      → cat
```

Step 1b

```
(*v*)ing → ø   walking    → walk
               sing       → sing
(*v*)ed  → ø   plastered  → plaster
…
```

Step 2 (for long stems)

```
ational→ ate   relational → relate
izer→ ize      digitizer  → digitize
ator→ ate      operator   → operate
…
```

Step 3 (for longer stems)

```
al    → ø   revival    → reviv
able  → ø   adjustable → adjust
ate   → ø   activate   → activ
…
```

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Word Normalization and Stemming

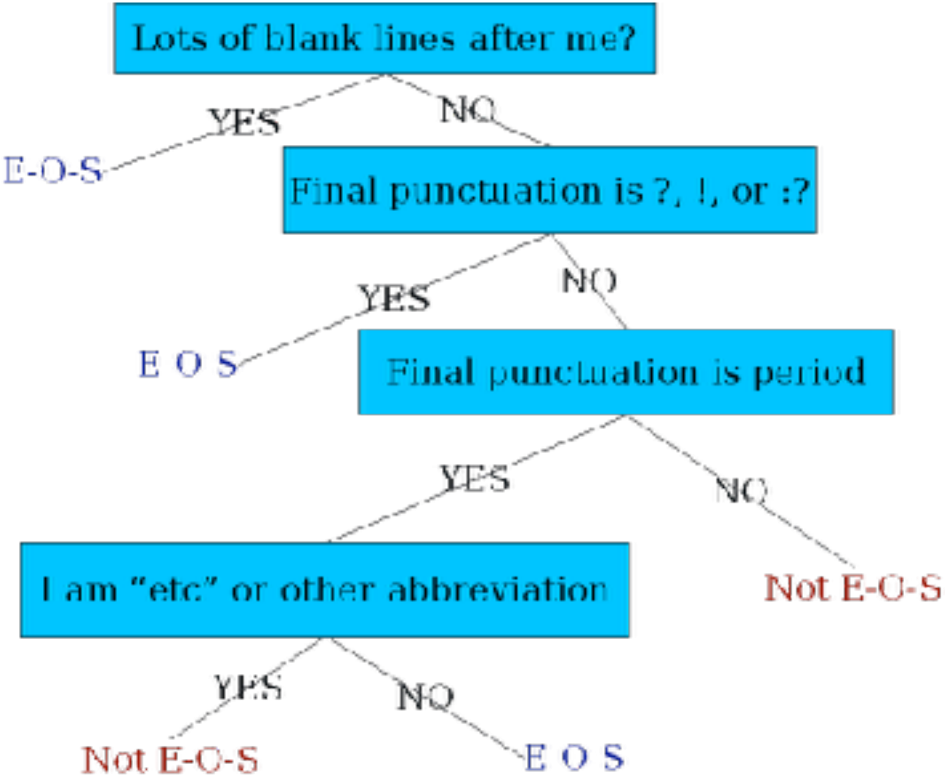
Basic Text Processing

Sentence Segmentation and Decision Trees

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



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

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Sentence Segmentation and Decision Trees