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

- Ranges `[A-Z]`

Pattern	Matches	
`[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]`: `not any of the following`
  - Carat means negation only when first in []
  - Check: regexpal.com
  - Try it in Arabic also!

Pattern	Matches	
`[^A-Z]`	Not an upper case letter	`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 [^not first]`

Dan Jurafsky

Regular Expressions: More Disjunction

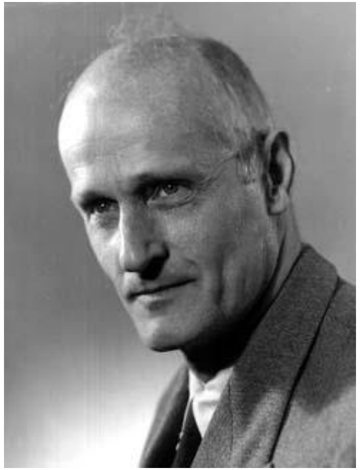
- Woodchucks is another name for groundhog!
- The pipe | for disjunction

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

Photo D. Fletcher

Regular Expressions: ? * + .

Pattern	Matches	
colou?r	Optional 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 character	begin begun begun beg3n



Stephen C Kleene

Kleene *, Kleene +

Regular Expressions: Anchors ^ $

Pattern		Matches
^[A-Z]	^: Start of line	Palo Alto
^[^A-Za-z]		1 "Hello"
\.$	$: end of line	The end.
.$		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]` try this!

Errors

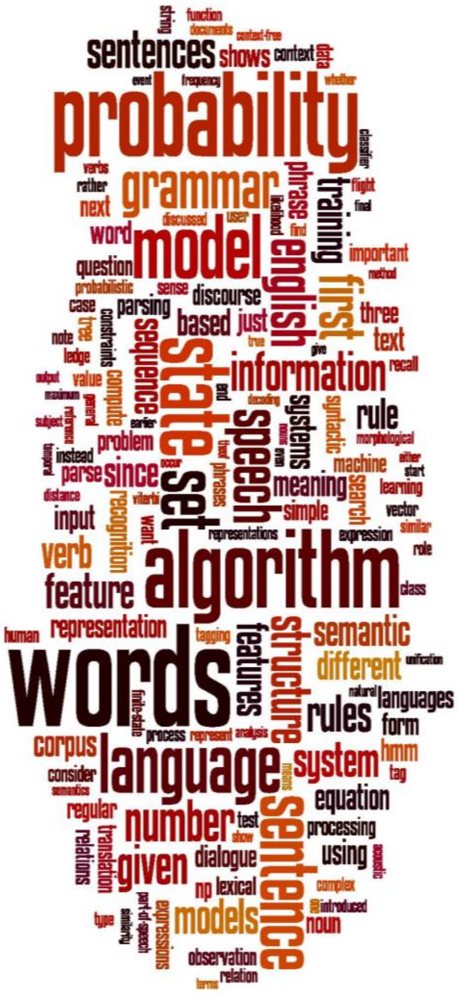
- The process we just went through was based on fixing two kinds of errors
  - Matching strings that we should not have matched (there, then, other)
    - False positives (Type I)
  - Not matching things that we should have matched (The)
    - False negatives (Type II)

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 text
- 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

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 مدرس،مدرسة، مدرسون، مدرسات
  - **Wordform**: the full inflected surface form
    - cat and cats = different wordforms (words)

How many words?

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

- **Type**: an element of the vocabulary (could be a word or stem or even a root, repitition doesn't count).
- **Token**: an instance of that type in running text.
- How many?
  - 15 tokens (or 14)
  - 13 types (or 12) (or 11?)
  - Generally more tokens than types (usually much more)!

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 = $\lvert V \rvert$
Switchboard phone conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
Google N-grams	1 trillion	13 million
Quran (in Arabic)	**77413**	**18994**

How many words? Quran Statistics

- Tokens = 77,430
- Number of *unique* surface forms= 18994
- Token to Term Ration(final)=4.1
- Number of unique words by *stem* = 12183
- Number of unique words by *root* = 1685
- Number of unique words by *lemma* = 3382 (excluding verbs, and other words where lemma is not annotated)

http://quickestwaytoquran.blogspot.com/2013/08/number-of-unique-words-in-quran.html

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
     | sort
     | uniq -c
```

Change all non-alpha to newlines

Sort in alphabetical order

Merge and count each type

```
1945 A             25 Aaron
  72 AARON          6 Abate
  19 ABBESS         1 Abates
   5 ABBOT          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

- 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 [TTR for German?]***
  - '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
- Further complicated in Japanese, with multiple alphabets intermingled
  - Dates/amounts in multiple formats

フォーチュン500社は情報不足のため時間あた$500K(約6,000万円)

Katakana Hiragana Kanji Romaji

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)

Dan Jurafsky

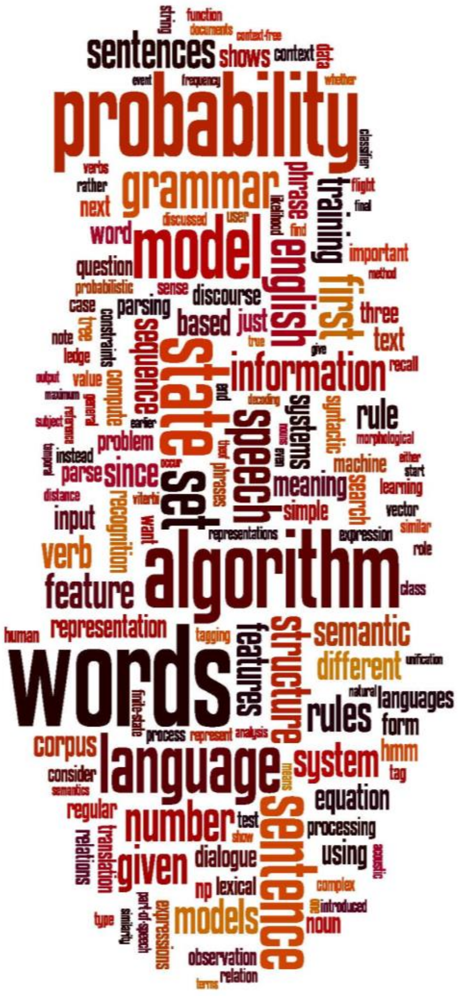
Maximum Matching
Word Segmentation Algorithm

- 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 [does it work for Arabic error correction?]

Max-match segmentation illustration

- Thecatinthehat — the cat in the hat
- Thetabledownthere — the table down there
  theta bled own there
- Doesn't generally work in English!
- But works astonishingly well in Chinese
  - 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
- Modern probabilistic segmentation algorithms even better



Basic Text Processing

Word Normalization and Stemming

Normalization (English)

- 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***
- Potentially more powerful, but less efficient

Normalization (Arabic)

- Need to “normalize” terms
  - Information Retrieval: indexed text & query terms must have same form.
    - Hamza, Alef Mqsoora and Ta Marboota: ***confusion letters***
    - We want to match على، علي   إلى، الى فدية، فديه

    - We implicitly define equivalence classes of terms
  - By matching different manifestations to a common (most frequent?) term
  - Index only one form and convert query terms to the representative of the class:

If Hamza is represented by ء then كفؤ بناء فئة are written as: كفء بناء فـءة

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***
- But: 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* $\rightarrow$ *be*
  - *car, cars, car's, cars'* $\rightarrow$ *car*
- *the boy's cars are different colors* $\rightarrow$ *the boy car be different color*
- اجتهاد الطالب الطريق الى النجاح   اجتهد طالب طريق الى نجاح
- Lemmatization: have to find correct dictionary headword form

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

- 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

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
…
```

Viewing morphology in a corpus
Why only strip –ing if there is a vowel?

```
(*v*)ing → ø   walking    → walk
               sing       → sing
Bring? Kling? King? Kying?
Nothing? Something?
```

Viewing morphology in a corpus
Why only strip –ing if there is a vowel?

```
(*v*)ing → ø   walking   → walk
               sing      → sing
```

```
tr -sc 'A-Za-z' '\n' < shakes.txt | grep ’ing$' | sort | uniq -c | sort –nr
```

1312	King	548	being
548	being	541	nothing
541	nothing	152	something
388	king	145	coming
375	bring	130	morning
358	thing	122	having
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

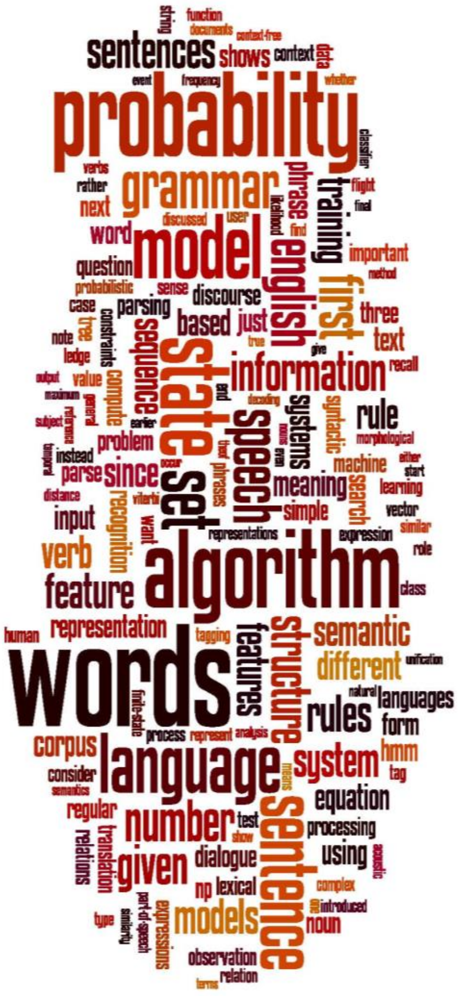
- Some languages requires complex morpheme segmentation
  - Turkish
  - Uygarlastiramadiklarimizdanmissinizcasina
  - `(behaving) as if you are among those whom we could not civilize'
  - Uygar `civilized' + las `become'

    + tir `cause' + ama `not able'

    + dik `past' + lar 'plural'

    + imiz 'p1pl' + dan 'abl'

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



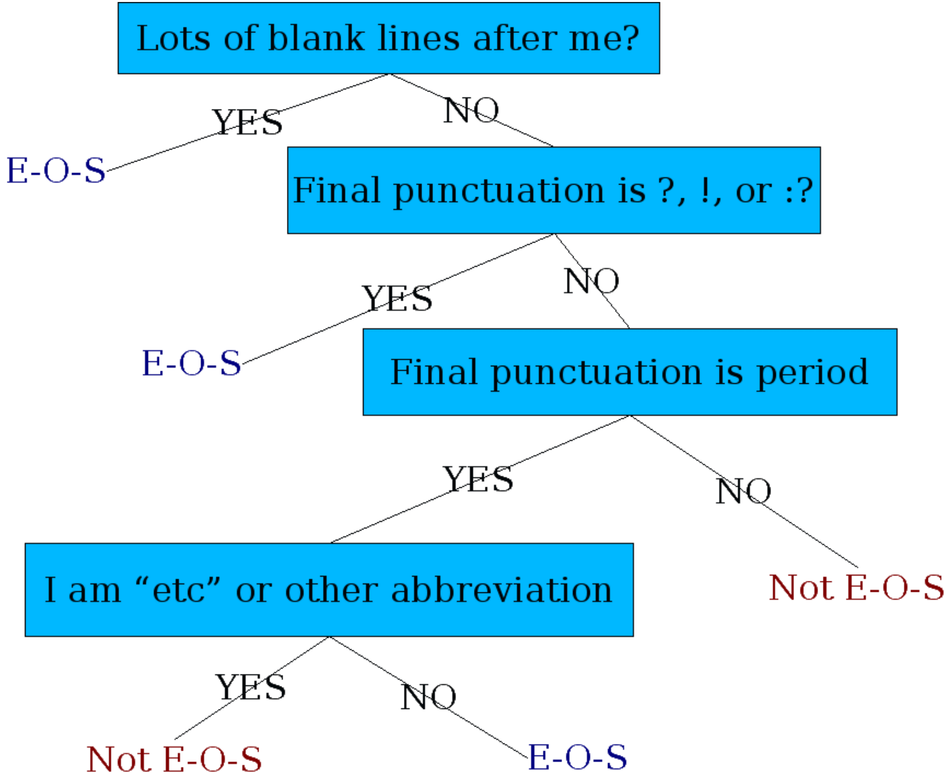
Basic Text Processing

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



More sophisticated decision tree features

- Case of word with ".": Upper, Lower, Cap, Number
- Case of word after ".": Upper, Lower, Cap, Number

- 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

- 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

- 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,….

  Here are some videos

  https://www.youtube.com/watch?v=hwDhO1GLb_4

  https://www.youtube.com/watch?v=RGLldper5II

  https://www.youtube.com/watch?v=jBk24DI8kg0