Lecture 2: Words and Basic Text Processing

CS 585, Fall 2017

Introduction to Natural Language Processing

http://people.cs.umass.edu/~brenocon/inlp2017

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[Includes slides from SLP3 site]

Announcements

- Currently
  - HW0 due tomorrow
  - HW1 released next week
- HW0: Gradescope submission

- Collaboration policy
  - All of the content you submit, both code and text, needs to be produced independently.
  - You may discuss problems. List your collaborators you worked with.
  - Do not share code or written materials.
  - Cite sources.
- Course website will have more complete version.

- NLP is an active research area!
- Review of trends at ACL 2017: http://www.abigailsee.com/2017/08/30/four-deep-learning-trends-from-acl-2017-part-1.html

Today

- Python demo
- Basic text processing
- Word counts

Python

- This weekend: make sure you can run Python
  - Recommended: Anaconda Python https://www.continuum.io/downloads
  - Python 2.7
  - IPython Notebook http://ipython.org/notebook.html
- Python interactive interpreter
- Python scripts

Text normalization

- Every NLP task needs text normalization
  - 1. Segment/tokenize words in running text
  - 2. Normalizing word formats
  - 3. Sentence segmentation (typically)

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	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 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`

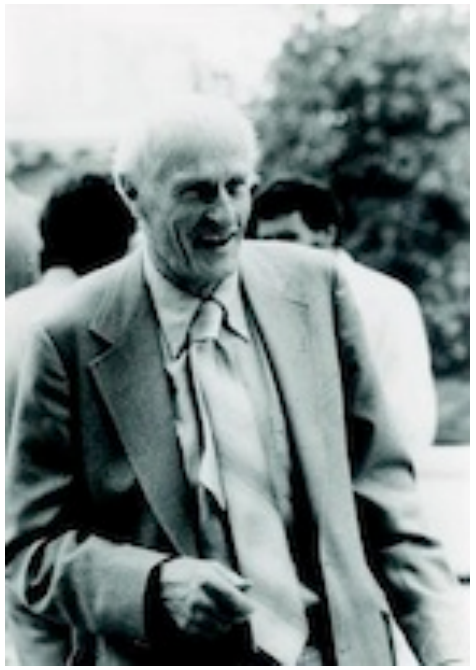
Regular Expressions: More Disjunction

- 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`	

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		begin begun begun beg3n



Stephen C Kleene

Kleene *, Kleene +

```
cat 2016-03-01.text.txt | grep -Poi '#[a-z0-9]*livesmatter' | sort | uniq -c | less

      3 #ALLLIVESMATTER
      1 #AllJonasLivesMatter
     81 #AllLivesMatter
      1 #Alllivesmatter
      2 #AmericanLivesMatter
      2 #ArmenianLivesMatter
     20 #BLACKLIVESMATTER
      1 #BLACKLivesMatter
      4 #BLackLivesMatter
      1 #BearLivesMatter
      1 #BeerLivesMatter
      1 #BeigeLivesMatter
    948 #BlackLivesMatter
      1 #BlackLlivesMatter
      1 #BlackMuslimLivesMatter
      1 #BlackTransLivesMatter
      1 #BlacklLivesMatter
      2 #BlacklivesMatter
     26 #Blacklivesmatter
      1 #Blackslivesmatter
      2 #BlueLIvesMatter
     90 #BlueLivesMatter
      1 #Bluelivesmatter
      1 #BookoutLivesMatter
      2 #BrownLivesMatter
      1 #BugLivesMatter
      1 #CatsLivesMatter
      1 #Chickenlivesmatter
```

```
grep -Poi '#[^ ]*livesmatter'

grep -Poi '#[a-z0-9]*livesmatter'
```

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]`

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 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

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
                .... …
```

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**

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 conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
Google N-grams	1 trillion	13 million

Word frequencies

Word	Frequency (f)
the	1629
and	844
to	721
a	627
she	537
it	526
of	508
said	462
i	400
alice	385

Alice's Adventures in Wonderland, by Lewis Carroll

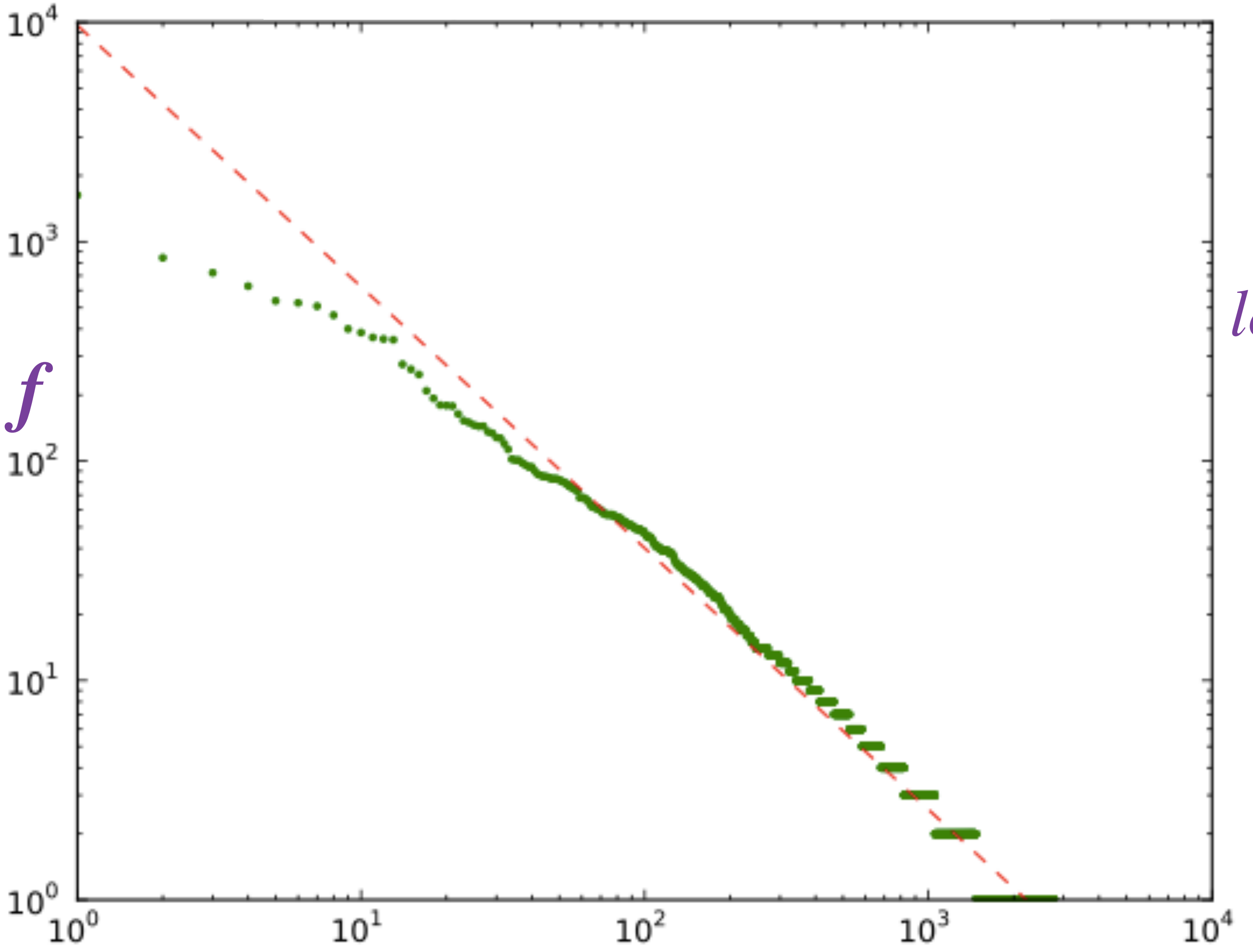
Zipf's Law

- When word types are ranked by frequency, then frequency (f) * rank (r) is roughly equal to some constant (k)

$$f \times r = k$$

Rank (r)	Word	Frequency (f)	$r \cdot f$
1	the	1629	1629
2	and	844	1688
3	to	721	2163
4	a	627	2508
5	she	537	2685
6	it	526	3156
7	of	508	3556
8	said	462	3696
9	i	400	3600
10	alice	385	3850
20	all	179	3580
30	little	128	3840
40	about	94	3760
50	again	82	4100
60	queen	68	4080
70	don't	60	4200
80	quite	55	4400
90	just	51	4590
100	voice	47	4700
200	hand	20	4000
300	turning	12	3600
400	hall	9	3600
500	kind	7	3500

Plot: log frequencies



log f

log r

recall:

$f * r = k$

$\log f + \log r = \log k$

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

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* $\rightarrow$ *be*
  - *car, cars, car's, cars'* $\rightarrow$ *car*
- *the boy's cars are different colors* $\rightarrow$ *the boy car be different color*
- Lemmatization: have to find correct dictionary headword form
- Machine translation
  - Spanish quiero (‘I want’), quieres (‘you want’) same lemma as querer ‘want’

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
…
```

Consider the IR query matching problem.
What are the precision/recall tradeoffs of the Porter stemmer?