Text Preprocessing

Lecture 1

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

	Tokens = N	Types = |V|
Switchboard phone conversations	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*** $\rightarrow$ 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
- Further complicated in Japanese, with multiple alphabets intermingled
  - Dates/amounts in multiple formats

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)

Max-match segmentation illustration

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

- Doesn't generally work in English! theta bled own there

- 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

Stopping

- Function words (determiners, prepositions) have little meaning on their own
- High occurrence frequencies
- Treated as *stopwords* (i.e. removed)
  - reduce index space, improve response time, improve effectiveness
- Can be important in combinations
  - e.g., “to be or not to be”

Stopwords

Nouns	Verbs	Adjectives	Prepositions	Others
1. time	1. be	1. good	1. to	1. the
2. person	2. have	2. new	2. of	2. and
3. year	3. do	3. first	3. in	3. a
4. way	4. say	4. last	4. for	4. that
5. day	5. get	5. long	5. on	5. I
6. thing	6. make	6. great	6. with	6. it
7. man	7. go	7. little	7. at	7. not
8. world	8. know	8. own	8. by	8. he
9. life	9. take	9. other	9. from	9. as
10. hand	10. see	10. old	10. up	10. you
11. part	11. come	11. right	11. about	11. this
12. child	12. think	12. big	12. into	12. but
13. eye	13. look	13. high	13. over	13. his
14. woman	14. want	14. different	14. after	14. they
15. place	15. give	15. small	15. beneath	15. her
16. work	16. use	16. large	16. under	16. she
17. week	17. find	17. next	17. above	17. or
18. case	18. tell	18. early		18. an
19. point	19. ask	19. young		19. will
20. government	20. work	20. important		20. my
21. company	21. seem	21. few		21. one
22. number	22. feel	22. public		22. all
23. group	23. try	23. bad		23. would
24. problem	24. leave	24. same		24. there
25. fact	25. call	25. able		25. their

Stopping

- Stopword list can be created from high-frequency words or based on a standard list
- Lists are customized for applications, domains, and even parts of documents
  - e.g., “click” is a good stopword for anchor text
- Best policy is to index all words in documents, make decisions about which words to use at query time

Normalization

- Convert different forms of a word to normalized form in the vocabulary
  - U.S.A -> USA, St. Louis -> Saint Louis
- Solution
  - Rule-based
    - Delete periods and hyphens
    - All in lower case
  - Dictionary-based
    - Construct equivalent class
      - Car -> “automobile, vehicle”
      - Mobile phone -> “cellphone”

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)

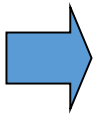
Morphology

- **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 Stemmer

- Algorithmic stemmer used in IR experiments since the 70s
- Consists of a series of rules designed to the longest possible suffix at each step
- Produces *stems* not *words*
- Makes a number of errors and difficult to modify

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	

Porter's algorithm

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

- Given the description you saw on earlier slides, the Porter stemmer would stem the word 'aching' as

A. aching
B. ach
C. ache
D. aches

Viewing morphology in a corpus

- Given the description you saw on earlier slides, the Porter stemmer would stem the word 'aching' as

A. aching
B. ach
C. ache
D. aches

Answer: B

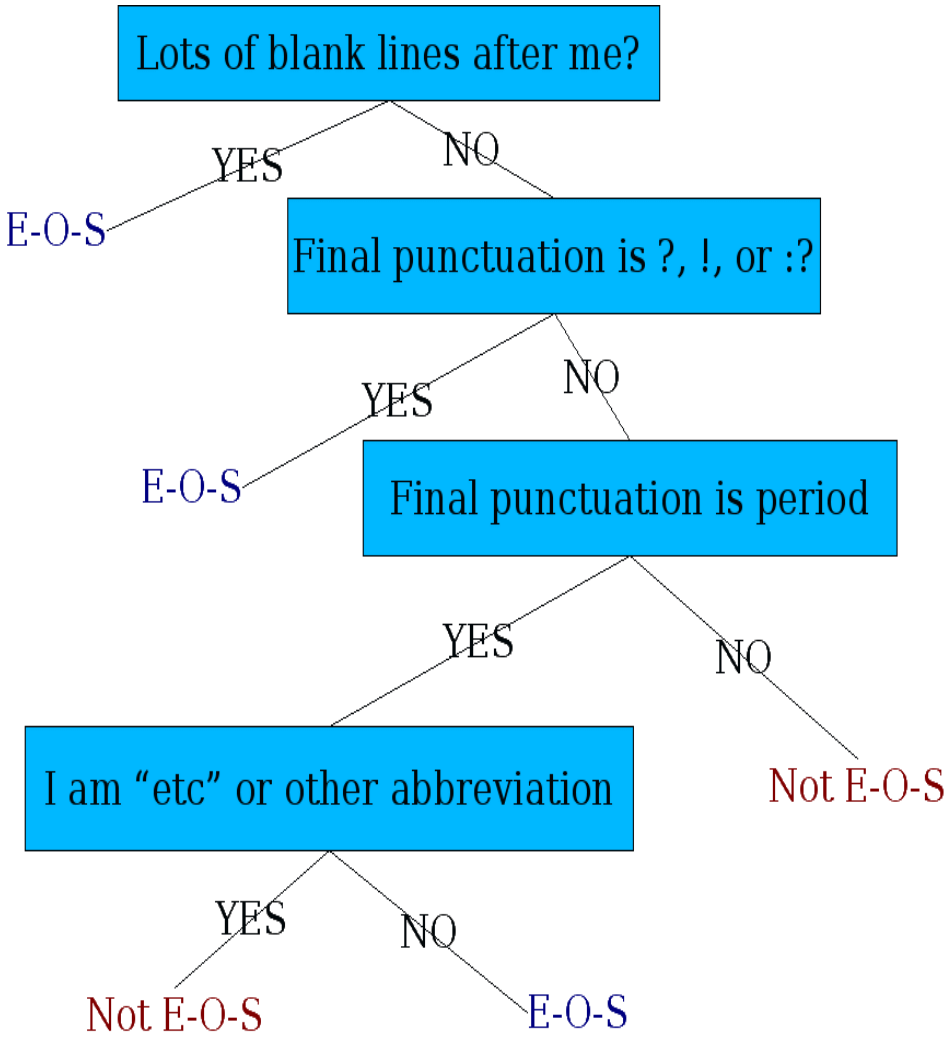
Basic Text Processing

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
  - 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
  - etc.

Slide Credits

- Lecture Notes, Natural Language Processing by Christopher Manning and Daniel Jurafsky, Stanford University