Lecture 2: Basic Text Processing

Tokenization and Normalization of Text

Some content in these slides was adapted from J&M 3rd ed. and from Wei Xu's course.

Text comes in many shapes ...

The word "genius" is one of the most misused terms in history.

While it's often referenced accurately, the connotation that we commonly associate with it diverges away from the truth.

We correctly label intellectual brilliance and creative power as genius—and we should—but it's about time we stopped assuming that those things arise from talent or inborn giftedness alone.

Or for example ...

1)Who was the last dialogue with? ✨ 2) Who is your first friend? 👥 🚬 4) Do you have many friends? 💁‍♀️ 5) Favorite song? 🎶 6) Favorite movie? 🎬 7) Currently in love? 💜 8) Favorite season of the year? 🌉 9) Do you dance? 💃 10) Favorite fruit? 🍏
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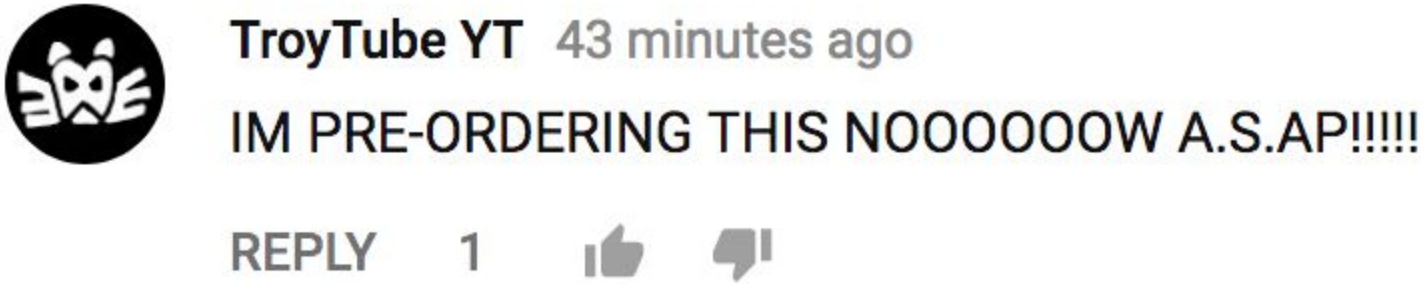
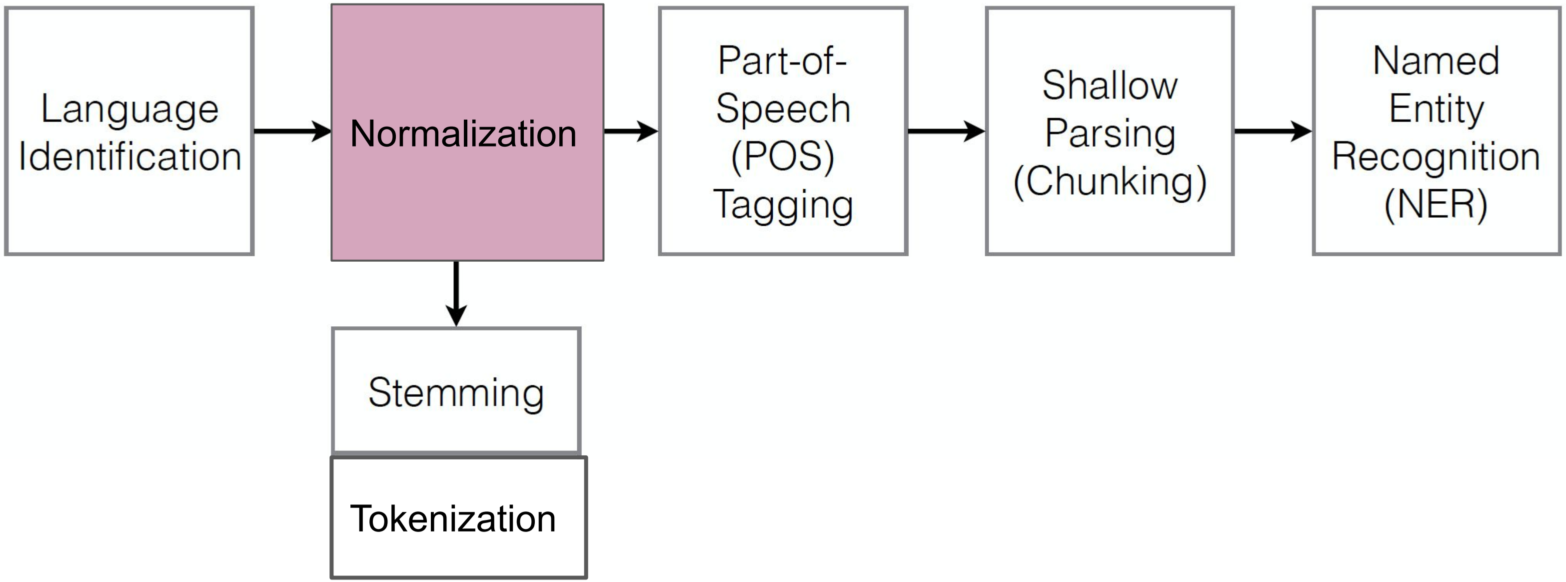
3 days ago

1)with daisy 2)max 4) yes 5) basta - samsara 6) pile 7) yes 8) summer 9) yes 10) apple. I will not share, I'm a rebel!😁😁😁

Or for example ...



Typical NLP Pipeline



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

Tokenization

Means taking an entire text stream and breaking into individual units (tokens) of analysis.

Why do we need to break the text into tokens?
Languages like English already include a word separator.

Tokenization

White space is not sufficient.

We need to handle:

- Contractions: don’t, couldn’t ⟶ do not (or do n’t), could not (could n’t)
- Punctuation marks: Are you done? --? Are you done ?
    - But be careful with abbreviations: Mrs. Hebert

How do we tokenize text?

- We use hand-crafted knowledge
  - regular expressions

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`

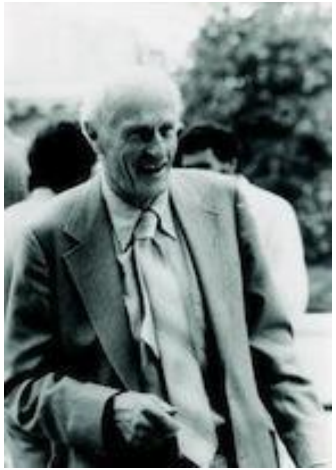
Regular Expressions: More Disjunction

- 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 +

Regular Expressions: Anchors ^ $

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

Errors

- The process of refining RE consists of fixing two kinds of errors
  - Matching strings that we should not have matched (cheat, features, meat)
    - False positives (Type I)
  - Not matching things that we should have matched (Eat)
    - 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
  - REs are often the first model for any text processing text
- For many hard tasks, we use machine learning classifiers
  - But REs are often used as features in the classifiers
  - Can be very useful in capturing generalizations

Basic Text Processing

Word tokenization

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?

Night gathers, and now my watch begins. It shall not end until my death.

- **Type**: an element of the vocabulary.
- **Token**: an instance of that type in running text.
- How many?
  - 14? 17? tokens
  - 13? 15? types

How many words?

Night gathers, and now my watch begins. It shall not end until my death. I shall take no wife, hold no lands, father no children. I shall wear no crowns and win no glory. I shall live and die at my post. I am the sword in the darkness. I am the watcher on the walls. I am the fire that burns against cold, the light that brings the dawn, the horn that wakes the sleepers, the shield that guards the realms of men. I pledge my life and honor to the Night's Watch, for this night and all the nights to come.

How many words?

N = number of tokens

V = vocabulary = set of types

$|V|$ is the size of the vocabulary

Herdan's law (1960): $|V| > O(N^{\beta})$

$\beta = 0.67 - 0.75$

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

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' < file.txt
      | sort
      | uniq -c
```

Change all non-alpha to newlines

Sort in alphabetical order

Merge and count each type

```
1945 A
  72 AARON
  19 ABBESS
   5 ABBOT
 ... ...
```

```
25 Aaron
 6 Abate
 1 Abates
 5 Abbess
 6 Abbey
 3 Abbot
.... ...
```

The first step: tokenizing

```
tr -sc ’A-Za-z’ ’\n’ < text.txt | head
```

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

The second step: sorting

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

A
A
A
A
A
A
A
A
A
...
```

More counting

- Merging upper and lower case

```
tr 'A-Z' 'a-z' < text.txt | tr –sc 'A-Za-z' '\n' | sort | uniq –c
```

- Sorting the counts

```
tr 'A-Z' 'a-z' < text.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., $79.99, #newyearsresolutions → ??

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
- 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)

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

- Thecatinthehat
- Thetabledownthere

the cat in the hat

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

- 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

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* $\longrightarrow$ *be*
  - *car, cars, car's, cars'* $\longrightarrow$ *car*
- *the boy's cars are different colors* $\longrightarrow$ *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
…
```

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

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

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 require 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’

Tokenization and Normalization

- tokenization: segmenting words in text
- normalization: mapping tokens to a standard format
- we use FSA to do most of the work
- each tokenizer will have its own rules and the end result will be different!
- preprocessing can make or break an experiment (Fokkens et al., 2013)

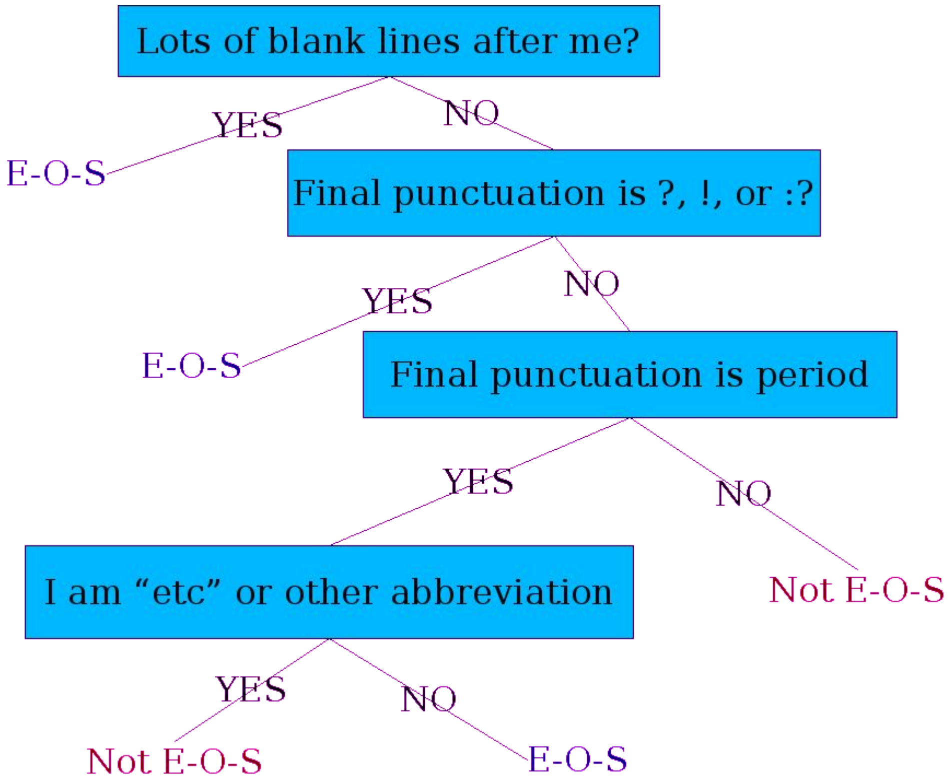
Basic Text Processing

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
  - etc.

Final Thoughts on Normalization

- Typically tl
- It's import … e text was processed

sisted of XML files marked up with inline named entity tags. In order to generate machine learning features, this data has to be tokenised, possibly cleaned up and the named entity markup had to be converted to a token-based scheme. Each of these steps can be carried out in several ways, and choices made here can have great influence on the rest of the pipeline.

Fokkens et al., 2013