# CIS 530: Text Processing

MONDAYS AND WEDNESDAYS 1:30-3PM

~~3401 WALNUT, ROOM 401B~~

[COMPUTATIONAL-LINGUISTICS-CLASS.ORG](http://computational-linguistics-class.org)

PROFESSOR CALLISON-BURCH

# Reminders

HW1 IS DUE TONIGHT BEFORE 11:59PM.

IF YOU DON'T YET HAVE A PERMIT AND YOU ARE HOPING TO GET INTO THE CLASS, YOU **MUST** TURN THE HOMEWORK IN ON TIME.

READ TEXTBOOK CHAPTER 2 AND DEPRESSION AND SELF-HARM RISK ASSESSMENT IN ONLINE FORUMS

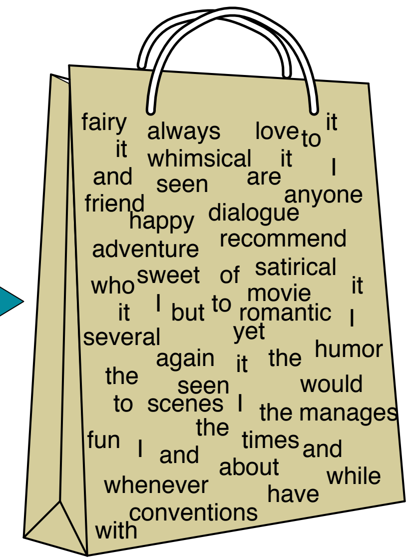
# Text Classification with Naïve Bayes

THE TASK OF TEXT CLASSIFICATION

# The Bag of Words Representation

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!

| | |
|---|---|
| it | 6 |
| I | 5 |
| the | 4 |
| to | 3 |
| and | 3 |
| seen | 2 |
| yet | 1 |
| would | 1 |
| whimsical | 1 |
| times | 1 |
| sweet | 1 |
| satirical | 1 |
| adventure | 1 |
| genre | 1 |
| fairy | 1 |
| humor | 1 |
| have | 1 |
| great | 1 |
| … | … |



# Multinomial Naïve Bayes Independence Assumptions

$$P(x_1, x_2, \ldots, x_n \mid c)$$

**Bag of Words assumption**: Assume position doesn't matter

**Conditional Independence**: Assume the feature probabilities $P(x_i | c_j)$ are independent given the class $c$.

$$P(x_1, \ldots, x_n \mid c) = P(x_1 \mid c) \bullet P(x_2 \mid c) \bullet P(x_3 \mid c) \bullet \ldots \bullet P(x_n \mid c)$$

# Multinomial Naïve Bayes Classifier

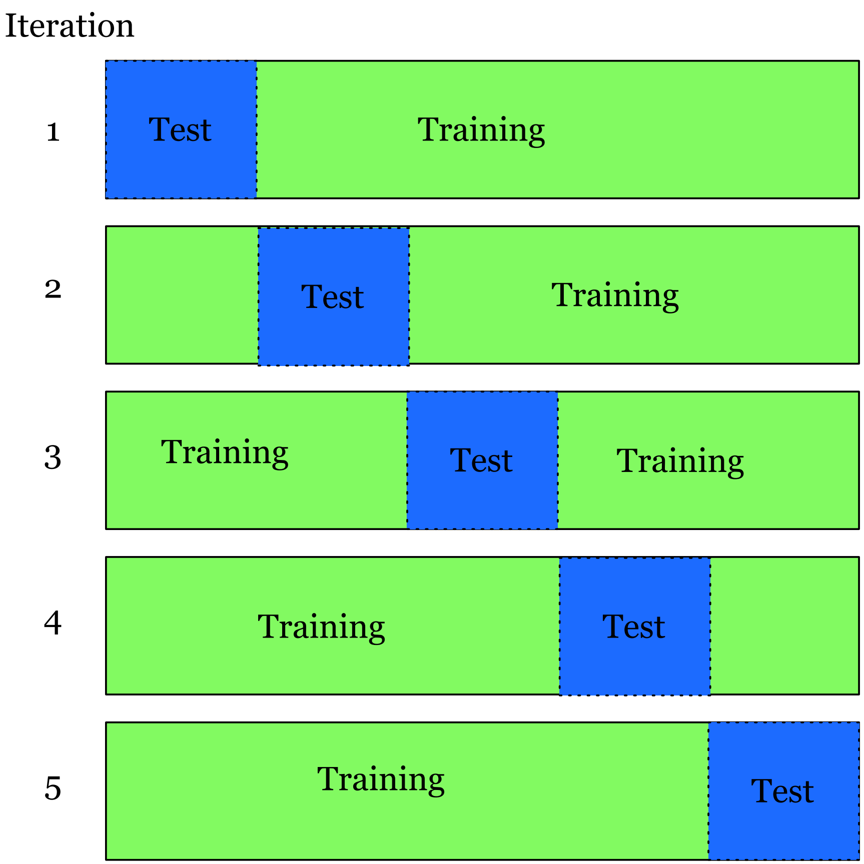
$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(x_1, x_2, \ldots, x_n \mid c) P(c)$$

$$c_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c_j) \prod_{x \in X} P(x \mid c)$$

# Text Classification and Naïve Bayes

TEXT CLASSIFICATION: EVALUATION

# Cross-Validation




Break up data into 10 folds

- (Equal positive and negative inside each fold?)

For each fold

- Choose the fold as a temporary test set
- Train on 9 folds, compute performance on the test fold

Report average performance of the 10 runs

# Development Test Sets and Cross-validation

Training set

Development Test Set

Test Set

## Metric: P/R/F1 or Accuracy

Development test set

- avoid overfitting to the unseen test set
- Use dev set to select the "best" model

- Cross-validation over multiple splits
  - Handle sampling errors from different datasets
- Compute pooled dev set performance
- This way we can use all data for validation

Training Set | Dev Test

Training Set | Dev Test

Dev Test | Training Set

Test Set

# Precision and Recall

*gold standard labels*

| | | gold positive | gold negative | |
|---|---|---|---|---|
| *system output labels* | system positive | **true positive** | **false positive** | $\textbf{precision} = \frac{\text{tp}}{\text{tp+fp}}$ |
| | system negative | **false negative** | **true negative** | |
| | | $\textbf{recall} = \frac{\text{tp}}{\text{tp+fn}}$ | | $\textbf{accuracy} = \frac{\text{tp+tn}}{\text{tp+fp+tn+fn}}$ |

# Precision and Recall

*gold labels*

| *system output* | | urgent | normal | spam | |
|---|---|---|---|---|---|
| | urgent | 8 | 10 | 1 | **precision**$_u = \frac{8}{8+10+1}$ |
| | normal | 5 | 60 | 50 | **precision**$_n = \frac{60}{5+60+50}$ |
| | spam | 3 | 30 | 200 | **precision**$_s = \frac{200}{3+30+200}$ |
| | | **recall**$_u = \frac{8}{8+5+3}$ | **recall**$_n = \frac{60}{10+60+30}$ | **recall**$_s = \frac{200}{1+50+200}$ | |

# Precision and Recall

**Class 1: Urgent**

| | true urgent | true not |
|---|---|---|
| system urgent | 8 | 11 |
| system not | 8 | 340 |

$$\text{precision} = \frac{8}{8+11} = .42$$

**Class 2: Normal**

| | true normal | true not |
|---|---|---|
| system normal | 60 | 55 |
| system not | 40 | 212 |

$$\text{precision} = \frac{60}{60+55} = .52$$

**Class 3: Spam**

| | true spam | true not |
|---|---|---|
| system spam | 200 | 33 |
| system not | 51 | 83 |

$$\text{precision} = \frac{200}{200+33} = .86$$

**Pooled**

| | true yes | true no |
|---|---|---|
| system yes | 268 | 99 |
| system no | 99 | 635 |

$$\text{microaverage precision} = \frac{268}{268+99} = \mathbf{.73}$$

$$\text{macroaverage precision} = \frac{.42+.52+.86}{3} = \mathbf{.60}$$

# 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 | 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^]` | Either e or ^ | `Look here` |
| `2^3` | The pattern 2 carat 3 | `The value of 2^3 is 8.` |

# Regular Expressions: More Disjunction

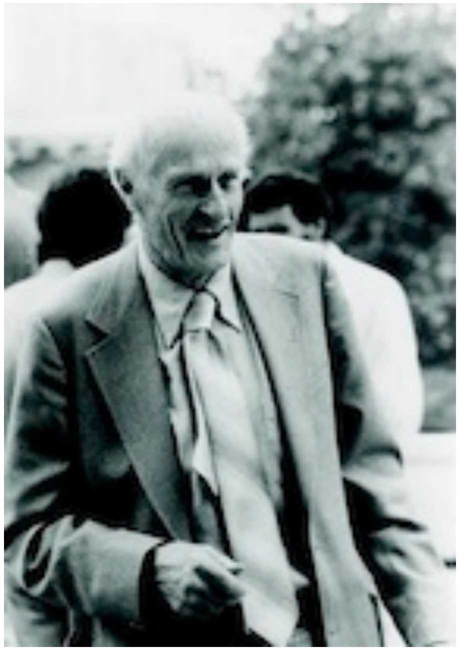
Woodchucks is another name for groundhog!

The pipe | for disjunction

| Pattern | Matches |
|---|---|
| groundhog\|woodchuck | woodchuck |
| yours\|mine | yours<br>mine |
| a\|b\|c | = [abc] |
| [gG]roundhog\|[Ww]oodchuck | Woodchuck |

# 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 |



# Regular Expressions: Anchors ^ $

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

Find me all instances of the word “the” in a text.

`the`

Misses capitalized examples

`[tT]he`

Incorrectly returns o**the**r or **the**ology

`[^a-zA-Z][tT]he[^a-zA-Z]`

Is correct

# Example

# 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
- Not matching things that we should have matched (The)
  - False negatives

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).

# Errors


# Role of Regular Expressions

Regular expressions play a surprisingly large role

- Sophisticated sequences of regular expressions are often the first model for any text processing text

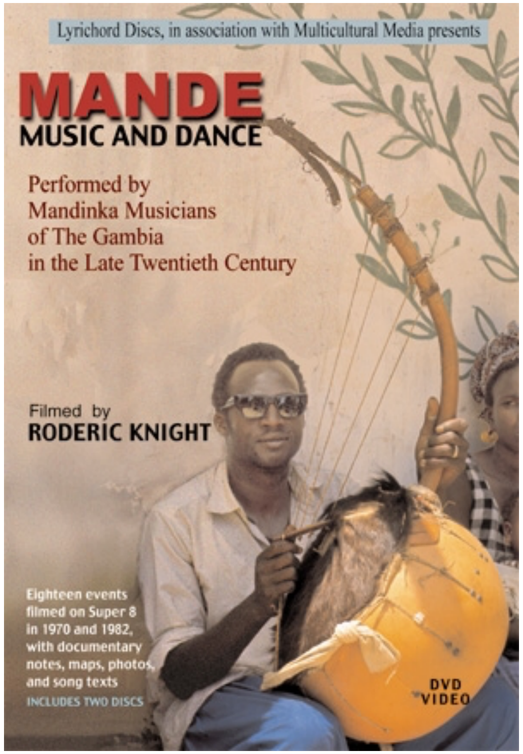
For many hard tasks, we use machine learning classifiers

- But regular expressions are used as features in the classifiers
- Can be very useful in capturing generalizations

# Hearst Patterns

In her seminal 1992 paper, entitled Automatic Acquisition of Hyponyms from Large Text Corpora, Marti Hearst defined a set of patterns for identifying *hypernym/hyponym* relations (also known as *is-a)*

The bow lute, **such as** the Bambara ndang, is plucked and has an individual curved neck for each string



## Hearst's Patterns for extracting IS-A relations

| Hearst pattern | Example occurrences |
|---|---|
| X and other Y | ...temples, treasuries, and other important civic buildings. |
| X or other Y | Bruises, wounds, broken bones or other injuries... |
| Y such as X | The bow lute, such as the Bambara ndang... |
| Such Y as X | ...such authors as Herrick, Goldsmith, and Shakespeare. |
| Y including X | ...common-law countries, including Canada and England... |
| Y , especially X | European countries, especially France, England, and Spain... |

Slide from D. Jurafsky

# Unix utility: grep

zcat * | grep " such as " | more

management consultants **such as** McKinsey and CSC Index.
social evils **such as** prostitution, drug addiction and HIV
new set of potentially lucrative services, **such as** movies on demand
the students use canned chicken broth such as Swanson's
in treating medical conditions such as psoriasis, seasonal

zcat * | grep " and other " | more

sanitation problems, the endless red tape **and other** difficulties
Court records **and other** documents show that Angela Tene
providing dominoes, card games **and other** recreation to help asylum
malls, swap meets, colleges, barber shops and other popular haunts

# 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

*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 |

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

# How many words?

# 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
     | sort -nr
```

Change all non-alpha to newlines

Sort in alphabetical order

Merge and count each type

Sort numerically descending

# 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` | $\rightarrow$ | `Finland Finlands Finland's ?` |
| `what're, I'm, isn't` | $\rightarrow$ | `What are, I am, is not` |
| `Hewlett-Packard` | $\rightarrow$ | `Hewlett Packard ?` |
| `state-of-the-art` | $\rightarrow$ | `state of the art ?` |
| `Lowercase` | $\rightarrow$ | `lower-case lowercase lower case ?` |
| `San Francisco` | $\rightarrow$ | one token or two? |
| m.p.h., PhD. | $\rightarrow$ | ?? |

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

*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!

# Tokenization: language issues

# 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

the cat in the hat

Thetabledownthere

the table down there

theta bled own there

Doesn't generally work in English!

But works suprisingly 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* $\rightarrow$ *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
…
```

```
(*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
```

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

50

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’

# Dealing with complex morphology is sometimes necessary

# Basic Text Processing

SENTENCE SEGMENTATION AND DECISION TREES

# Sentence Segmentation

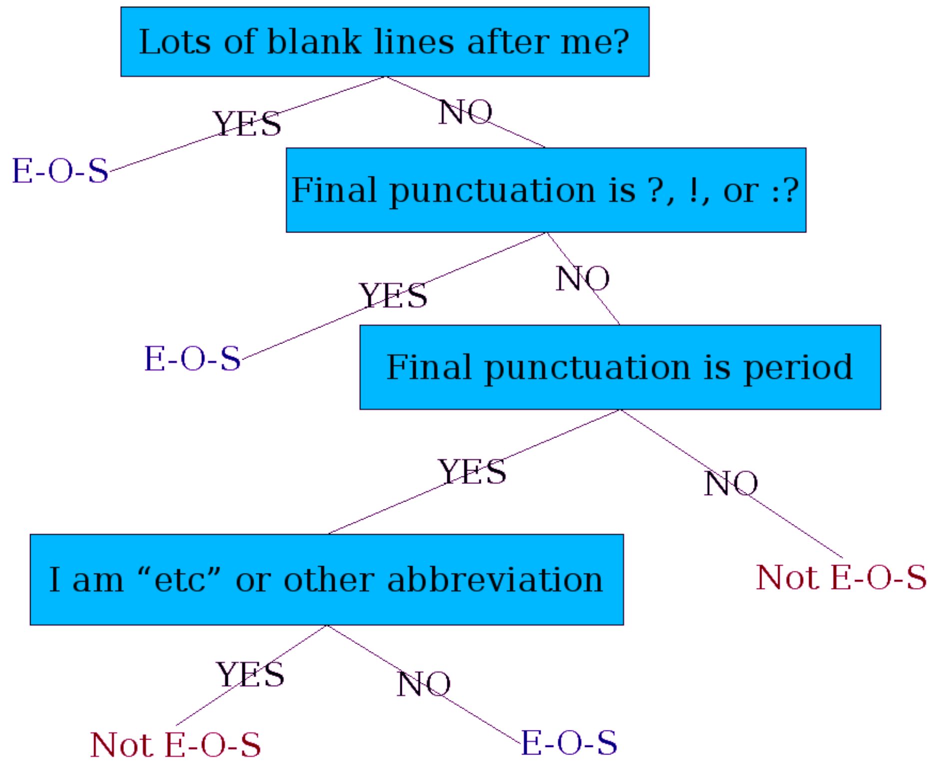
!, ? are relatively unambiguous

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

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)

# More sophisticated decision tree features

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

# Implementing Decision Trees

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.

# Decision Trees and other classifiers