Text Preprocessing I

From textual information to numerical vector

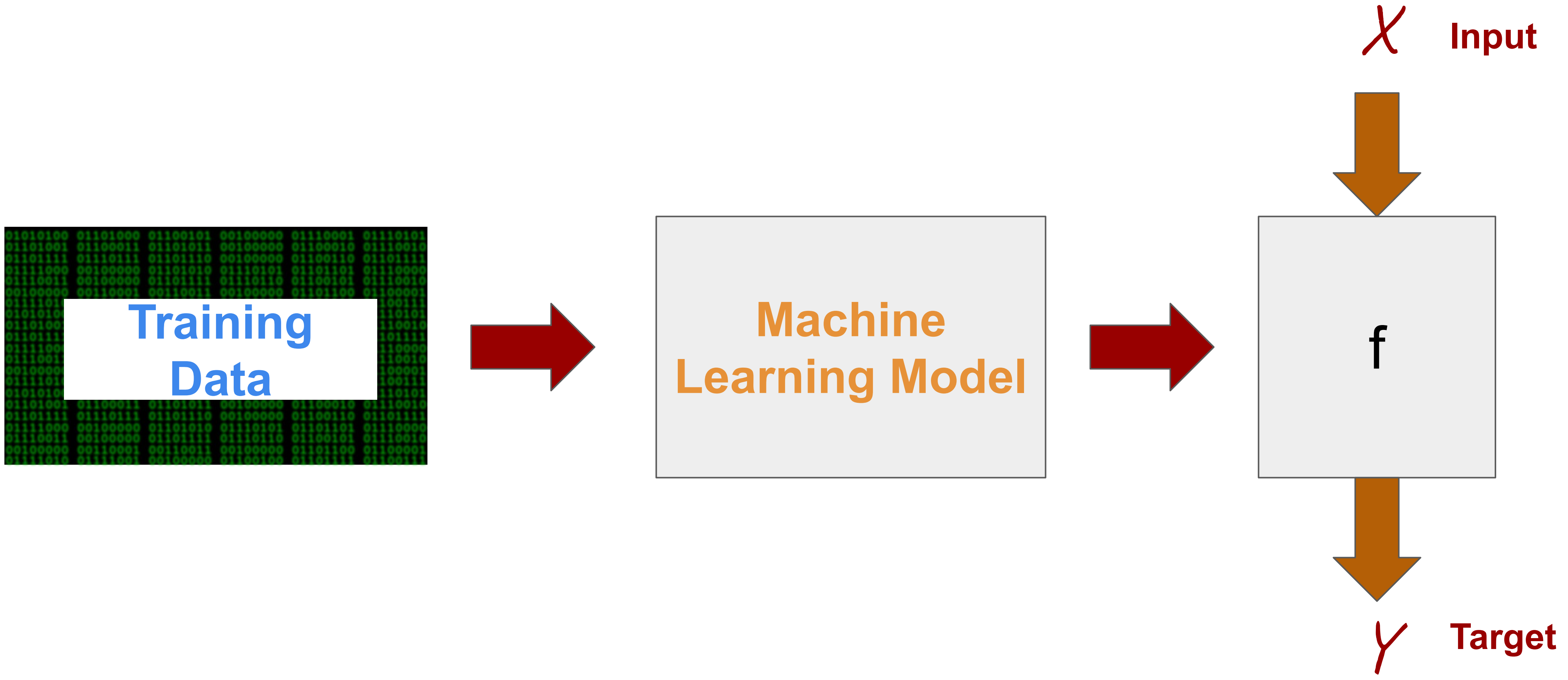
Late Policy

- Fill in the group information table (**group name**!) before 11:59 pm, Feb 1. **Penalty is 2 scores for late filing.**

- **Late Policy for all assignments:**
    - **Without any reasonable justification, penalty is 25% for each additional late day.**

A Simple Text Mining Case

Framework (supervised)



Our Task

- Example task: predict y, whether a string x is an email address
  - x: "rui.zhao@ntu.edu.sg" **y:1**
  - x: "ntuwkw" **y:0**
  - x: "@trump" **y:0**

- How do you address the problem?

Feature Extraction

- **Question**: what properties of x **might be** relevant for predicting y?

- **Feature extractor**: Given input x, output a set of (**feature name**, **feature value**) pairs.

“ntu@gmail.com” $\xrightarrow[\text{from top to down}]{\textbf{feature extractor}}$

Length > 10	**1**
Length < 50	**1**
contain “@”	**1**
endwith “com”	**1**
endwith “sg”	**0**
length between @ and .	**5**
fraction of alpha	**0.85**

Feature Vector notation

- **Mathematically, feature vector does not need feature names:**

Length > 10	1
Length < 50	1
contain “@”	1
endwith “com”	1
endwith “sg”	0
length between @ and .	5
fraction of alpha	0.85

feature vector space

Weight Vector notation

- **Weight vector: for each feature j, have a specified parameter representing contribution of feature to prediction**

Length > 10	**-1.2**
Length < 50	**1.4**
contain “@”	**2.2**
endwith “com”	**0.6**
endwith “sg”	**0.5**
length between @ and .	**0.3**
fraction of alpha	**0.6**

Linear Model

- **Linear combine the features by the weight:**
  - **weighted combination of features**

$$\mathbf{w} \cdot \phi(x) = \sum_{j=1}^{d} w_j \phi(x)_j$$

output: -1.2*(1) + 1.4*(1) + 2.2*(1) + 0.6*(1) + 0.5*(0) + 0.3*(5) + 0.6*(0.85)

Linear Model

- **Weight vector** $\mathbf{w} \in R^d$
- **Feature vector** $\phi(x) \in R^d$
- **For binary classification:**

$$f_{\mathbf{w}}(x) = \text{sign}(\mathbf{w} \cdot \phi(x)) = \begin{cases} +1 & \text{if } \mathbf{w} \cdot \phi(x) > 0 \\ -1 & \text{if } \mathbf{w} \cdot \phi(x) < 0 \\ ? & \text{if } \mathbf{w} \cdot \phi(x) = 0 \end{cases}$$

How do we learn model parameters

- **From Data**
- **Define a loss function and then optimize**

Introduction to Text Preprocessing

From Text to Numerical Features

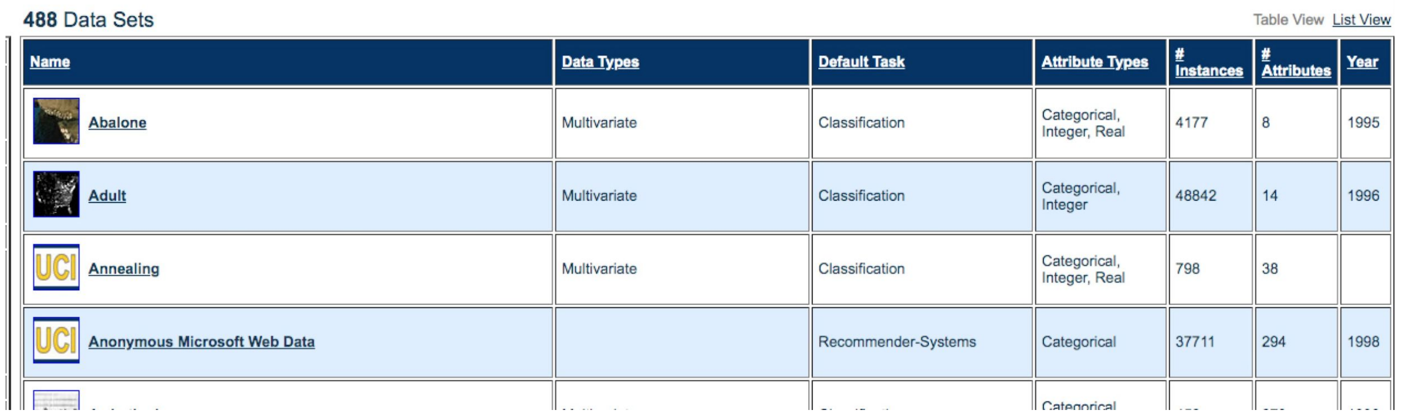
- To mine text, we first need to process it into a form that data mining procedures can use.
- First of all, we have to determine features (think it as the columns of the spreadsheet).
- Some useful features are easy to obtain.
    - the occurence of words
- Some semantic information are much more difficult.
    - The grammatical function of a word in a sentence such as subject, object, et.

Collecting Documents

- The first step in text mining is to collect the data (i.e., the relevant documents).
- In some applications, need to have a data collection process.
  - For a Web application, deploy a software tool such as a Web Crawler that collects the documents.
  - In another application, an email audit application may log all incoming and outgoing messages at a mail server for a period of time.
- For research and development of text-mining techniques, more generic data may be necessary, usually called a corpus
  - the collection of Reuters news stories, such as the Reuters 21578 corpus and RCV1 (Reuters Corpus Volume 1; about 810, 000 Reuters, English Language News stories; tagged with topics).
  - a corpus from the Gutenberg Project, a very large collection of literary and other texts put into machine-readable form as the material comes out of copyright.
  - The Linguistic Data Consortium (LDC) provides various data.

Collecting Documents

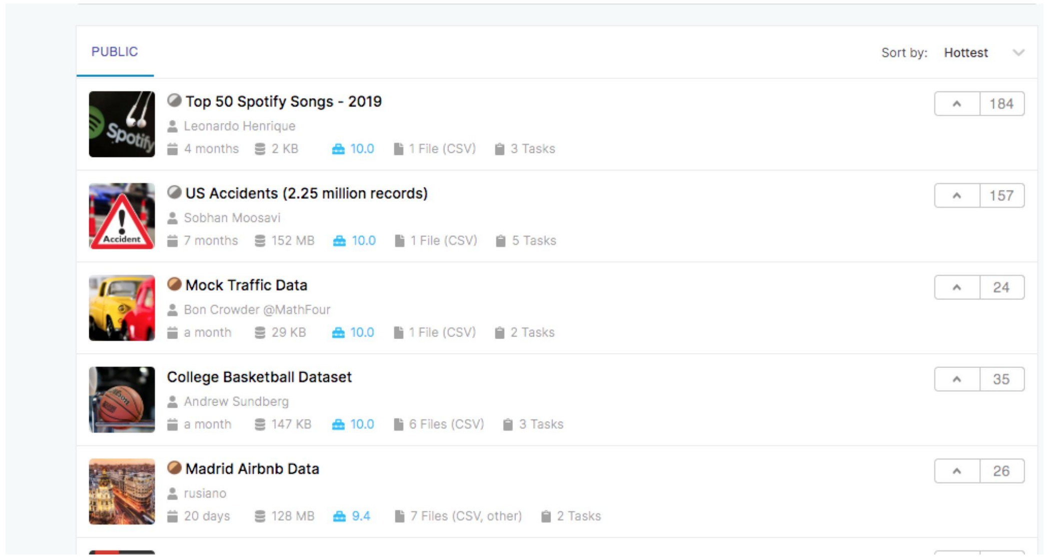
- For research and development of text-mining techniques, more generic data may be necessary, usually called a **corpus**.
  - **The UC Irvine Machine Learning Repository** currently maintain 468 datasets (e.g., amazon reviews, email spam and sentiment-labelled sentences) as a service to machine learning community.
  - **Kaggle** (data mining competition) also provides various data sets.



488 Data Sets

Table View List View

Name	Data Types	Default Task	Attribute Types	# Instances	# Attributes	Year
Abalone	Multivariate	Classification	Categorical, Integer, Real	4177	8	1995
Adult	Multivariate	Classification	Categorical, Integer	48842	14	1996
Annealing	Multivariate	Classification	Categorical, Integer, Real	798	38	
Anonymous Microsoft Web Data		Recommender-Systems	Categorical	37711	294	1998
			Categorical			



PUBLIC

Sort by: Hottest

Top 50 Spotify Songs - 2019 Leonardo Henrique 4 months · 2 KB · 10.0 · 1 File (CSV) · 3 Tasks		184
US Accidents (2.25 million records) Sobhan Moosavi 7 months · 152 MB · 10.0 · 1 File (CSV) · 5 Tasks		157
Mock Traffic Data Bon Crowder @MathFour a month · 29 KB · 10.0 · 1 File (CSV) · 2 Tasks		24
College Basketball Dataset Andrew Sundberg a month · 147 KB · 10.0 · 6 Files (CSV) · 3 Tasks		35
Madrid Airbnb Data rusiano 20 days · 128 MB · 9.4 · 7 Files (CSV, other) · 2 Tasks		26

Text Normalization

Text Normalization

- Every NLP tasks including text mining needs to do text normalization:
  - Segmenting/tokenizing words in running text
  - Normalizing word formats
    - convert to standard or common forms
  - Segmenting sentences in running text

Tokenization

Tokenization

- Breaks the stream of characters into **words** or **tokens**.
  - Trivial for a person familiar with the language structure.
- A computer program, though, being linguistically challenged, would find the task more complicated.
- The reason is that certain characters are sometimes **token delimiters** and sometimes not, depending on the application.
- The characters space, tab, and newline are always delimiters are not counted as tokens, often collectively called **white space**.
- The characters **( ) <> ! ? “** are always delimiters and may also be tokens.

Tokenization

- The characters . , : - ’ may or may not be delimiters, depending on their environment.
- Example cases
  - Numbers: 100,000 or 333-1221
  - Abbreviations: Dr.
  - Part of the current token: isn’t or D’angelo
  - Possessive: Tess’
- To get the best possible features, one may need to customize the tokenizer for the available text.
  - E.g., part: 123-4567
- The tokenization process is language-dependent.

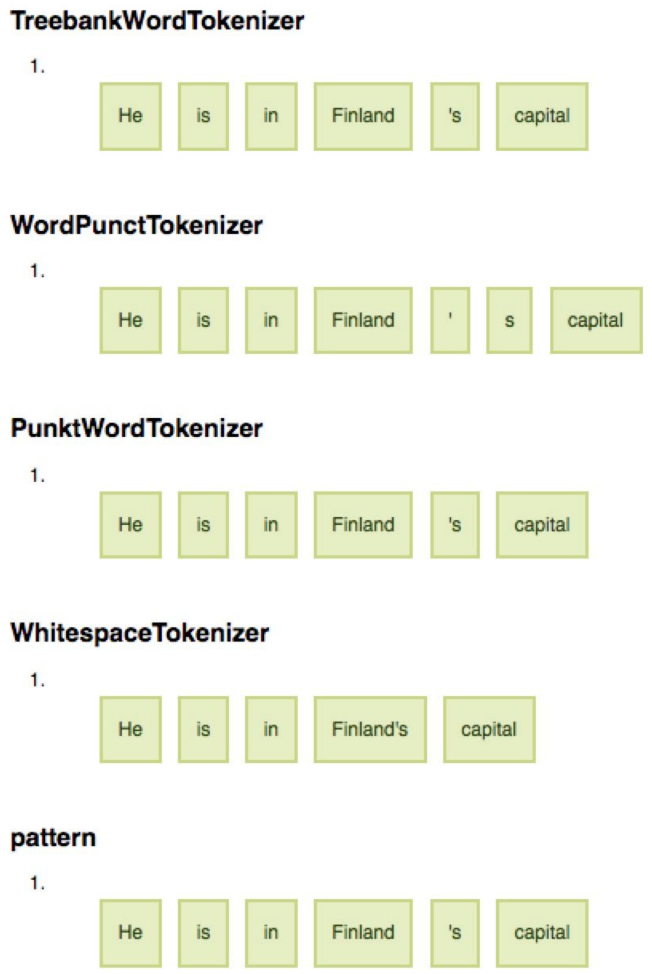
Example Issues in Tokenization

Raw Text

- Finland’s capital
- What’re, I’m, isn’t
- Hewlett-Packard
- state-of-the-art
- San Francisco

Tokenized Text

- ➢ Finland Finlands Finland’s ?
- ➢ what are, I am, is not ?
- ➢ Hewlett Packard ?
- ➢ state of the art ?
- ➢ one token or two?



TreebankWordTokenizer

1. He | is | in | Finland | 's | capital

WordPunctTokenizer

1. He | is | in | Finland | ' | s | capital

PunktWordTokenizer

1. He | is | in | Finland | 's | capital

WhitespaceTokenizer

1. He | is | in | Finland's | capital

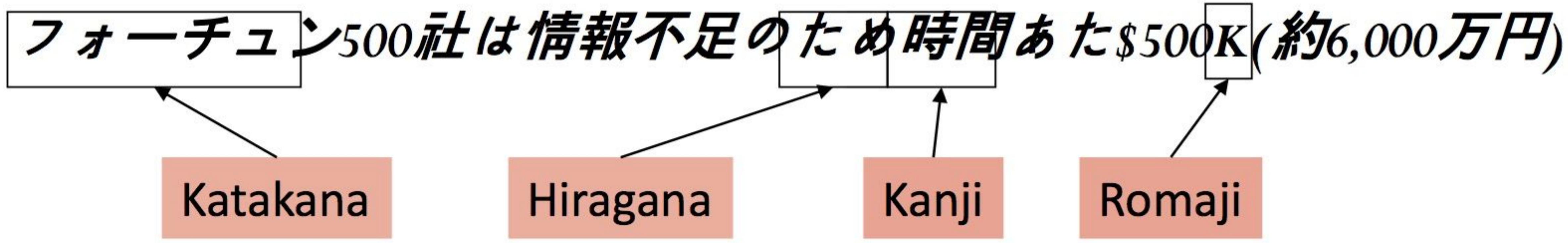
pattern

1. He | is | in | Finland | 's | capital

- Online Word Tokenization with python NLTK
  - http://text-processing.com/demo/tokenize/
  - E.g., “He is in Finland’s capital”

Tokenization: language issues

- Chinese and Japanese have no spaces between words:
  - 孙燕姿现在居住在新加坡东南部
  - 孙燕姿　　　　现在　居住 在　新加坡 东南部
  - Stefanie Sun　now　lives in　Singapore southeastern
- Further complicated in Japanese, with multiple alphabets intermingled.



Word Tokenization in Chinese

- Also called **Word Segmentation**
- Chinese words are composed of characters.
  - average length is 2.4 char. long.
- Standard baseline segmentation algorithm
  - **Maximum Matching** (also called Greedy)

Maximum Matching Word Segmentation Algorithm

- Given a wordlist of Chinese (i.e. dictionary), 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

    - 孙燕姿现在居住在新加坡东南部
    - 孙燕姿 现在 居住 在 新加坡 东南部
    - Stefanie Sun now lives in Singapore southeastern

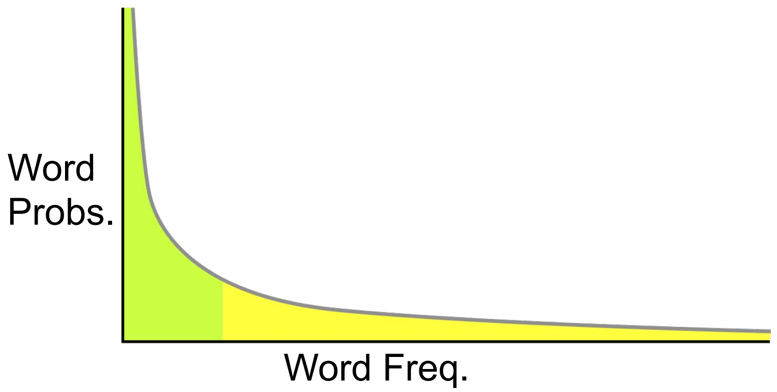
Max-match segmentation illustration

○ Thecatinthehat	the cat in the hat
○ Thetabledownthere	the table down there
	theta bled own there

- Doesn’t generally work in English!
- But works well in Chinese
    - 孙燕姿现在居住在新加坡东南部
    - 孙燕姿 现在 居住 在 新加坡 东南部
    - Stefanie Sun now lives in Singapore southeastern
- Moder probabilistic segmentation algorithms even better.
    - E.g., *“the table”* has a higher chance than *“theta bled”.*

Words Properties

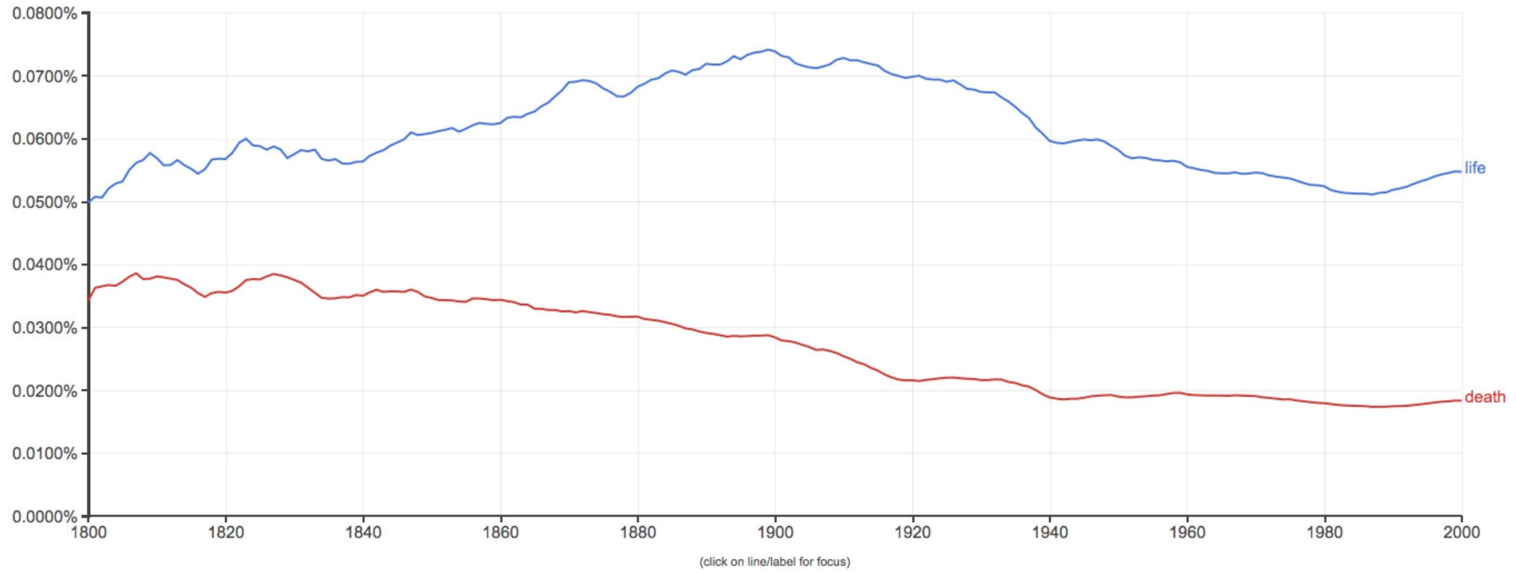
- Relations among word surface forms and their senses:
  - **Homonymy**: same form, but different meaning
    - E.g., bank: river bank and financial institution
  - **Polysemy**: same form, related meaning
    - E.g., man: the human species, male of the human species, and adult males of the human species.
  - **Synonymy**: different form, same meaning
    - E.g., singer and vocalist
- Word frequencies in texts have **power law distribution**:
  - …small number of very frequent words
  - ...big number of low frequent words
  - Also called Zipf's Law



How many words?

- N= number of tokens
- V= vocabulary=set of types

|v| is the size of the vocabulary



https://books.google.come/ngrams

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

Stop Words

- Stop-words are words that from non-linguistic view do not carry information
  - They have mainly functional role.
  - Usually we remove them to help the methods to perform better.
- Natural language dependent - examples:
  - English: A, ABOUT, ABOVE, ACROSS, AFTER, FROM, AGAIN,.....
  - Chinese: 的, 一, 不，在，有，。。。。

https://www.ranks.nl/stopwords

Stop Words

- Example Stop words

    - Information System Asia Web - provides research, IS-related commercial materials, interaction, **and even** research sponsorship **by** interested corporations **with a** focus **on** Asia Pacific region.

    - Survey **of** Information Retrieval - guide **to** IR, **with an** emphasis **on** web-based projects. Includes **a** glossary, **and** pointers **to** interesting papers.

Normalization

Normalization

- Need to **normalize** terms
  - Information Retrieval (IR): indexed text & query terms must have the same form.
    - we want to match ***U.S.A*** and ***USA***
- We define equivalence class of terms
- Alternative: query expansion
  - Enter: ***window*** Search: *window, windows*
  - Enter: ***windows*** Search: *Windows, windows, window*
- Potentially more powerful, but less efficient

Normalization

- Converts each of the tokens to **a standard form**, a process usually referred to as ***stemming*** or ***lemmatization***.
- Whether or not this step is necessary is application-dependent.
- One effect of normalization is to *reduce the number of distinct types* (i.e. unique terms) in a text corpus and to *increase the frequency of occurrence of some individual types*.
  - E.g., types and typed -> type
- For classification algorithms that take frequency into account, this can sometimes make a difference.

Case Folding

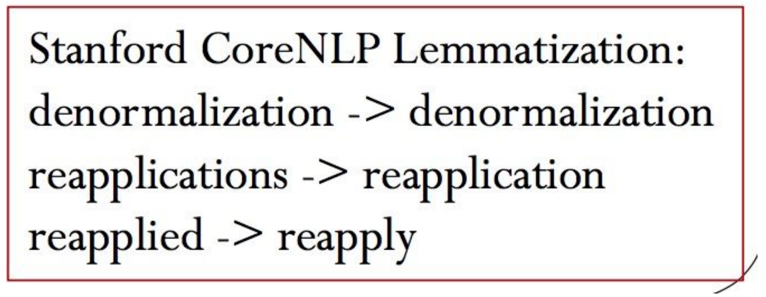
- Applications like IR: reduce all letters to lower case
  - Since users tend to use lower case, such as Car, CAR -> car
  - Possible exception: upper case in mid-sentence?
    - E.g.:
      - ***General Motors vs. general motors***
      - ***Fed vs. fed***
        - Fed: Federal Reserve
      - ***SAIL vs. sail***
        - SAIL: Stanford Artificial Intelligence Language, etc
- For Sentiment Analysis and Information Extraction
  - Case is helpful (***US*** versus ***us*** is important)
  - E.g., “*US won a gold medal*”; “*They like US*.” Vs. “*They like us*.”

Lemmatization - Stemming to a Root

- Converts to a **root form** with no inflectional or derivational prefixes and suffixes.
  - **Inflectional suffixes** are endings such as “-ed”, “-ing”, “s”, etc.
    - Create different forms of the same word (different grammatical forms)
  - **Derivational suffixes** are endings such as “-ism”, “-ful”, “-fy”, etc.
    - Change the meaning of the word
  - E.g., “denormalization’ is reduced to the stem “norm”.
  - E.g., “reapplied”, “applications” -> “apply”
- Words with the same core meaning are coalesced.
- The end result of such **aggressive stemming** is to reduce the number of types in a text collection very drastically, thereby making distributional statistics more reliable.

Lemmatization

- Additional examples
  - Reduce variant forms to base form
    - am, are, is -> *be*
    - *car, cars, car's, cars'* -> *car*
  - *the boy's cars are different colors* -> *the boy car be different color*
- Lemmatization: have to find correct dictionary headword form (i.e. root or lemma form).
- E.g., Stanford CoreNLP (http://stanfordnlp.github.io/CoreNLP/) supports lemmatization.
  - http://nlp.stanford.edu:8080/corenlp/



Stanford CoreNLP Lemmatization:
denormalization -> denormalization
reapplications -> reapplication
reapplied -> reapply

Some Terms: Morphology

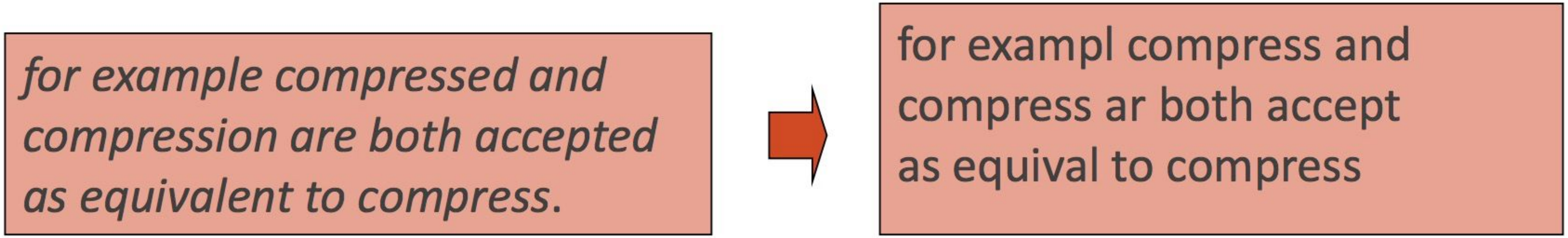
- **Morphemes**:
  - The small meaningful units that make up words.
  - E.g., un-like-ly contains three.
  - Stems: the main part of a word that stays the same when endings are added to it.
    - E.g., writ is the stem of writes, writing, and written.
  - Affixes: Bits and pieces that adhere to stems (i.e. the prefix and suffix)
    - Often with grammatical functions
    - E.g., likes.

Stemming

- When the normalization is confined to **regularizing grammatical variants** such as singular/plural and present/past, the process is called “**inflectional stemming**.”
  - This is called “morphological analysis”
- For a language such as English, with may irregular word forms and non-intuitive spelling, it is more difficult.
  - E.g., sought -> seek
- In English, an algorithm for inflectional stemming must be part rule-based and part dictionary-based.
- Any stemming algorithm for English that operates only on tokens, without more grammatical information such as part-of-speech, will make some mistakes because of ambiguity.
  - For example, is “bored” the adjective as in “he is bored” or is it the past tense of the verb “bore”?
  - He bored her with his stories about military life.

Stemming

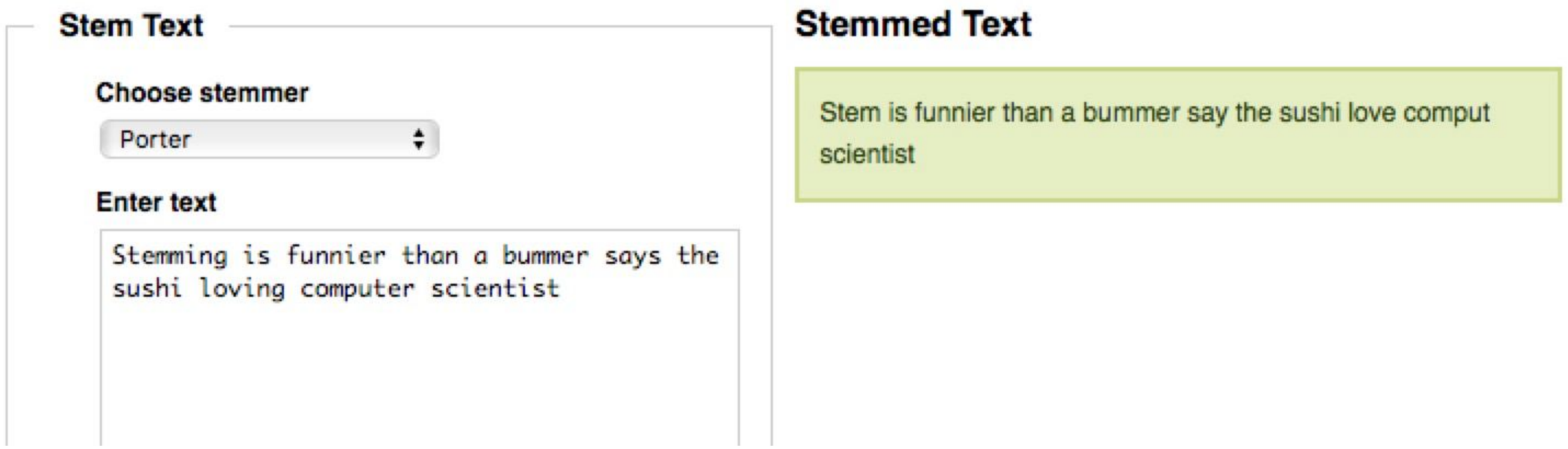
- Reduces terms to their stems.
  - E.g., used in information retrieval and text mining applications.
- Stemming is **crude chopping of affixes**.
  - Language dependent
  - e.g., *automates*, *automatic*, *automation* all reduced to automat.



for example compressed and compression are both accepted as equivalent to compress.

for exampl compress and compress ar both accept as equival to compress

Stemming with Python NLTK



Stem Text

Choose stemmer

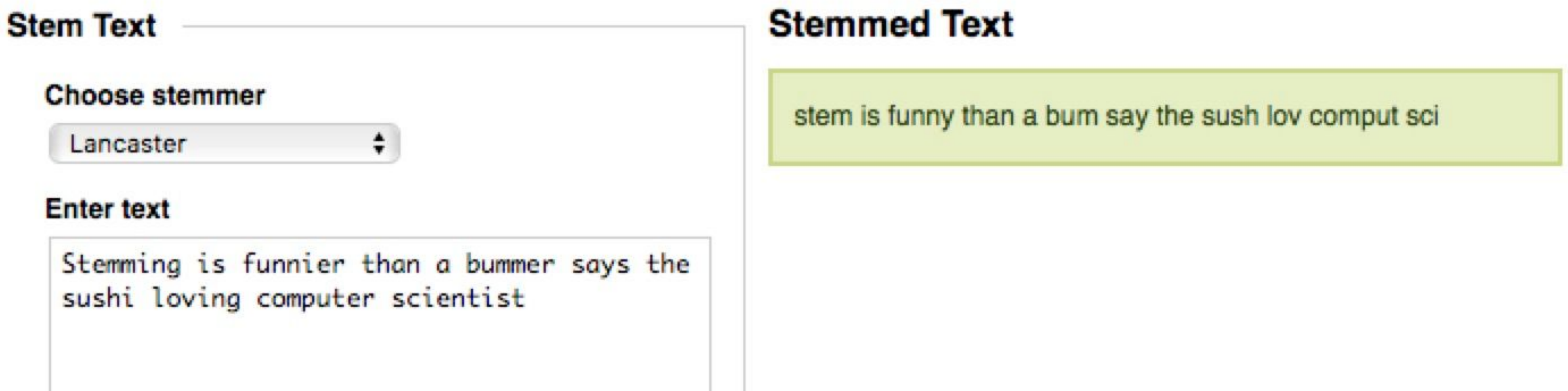
Porter

Enter text

```
Stemming is funnier than a bummer says the
sushi loving computer scientist
```

Stemmed Text

Stem is funnier than a bummer say the sushi love comput scientist



Stem Text

Choose stemmer

Lancaster

Enter text

```
Stemming is funnier than a bummer says the
sushi loving computer scientist
```

Stemmed Text

stem is funny than a bum say the sush lov comput sci

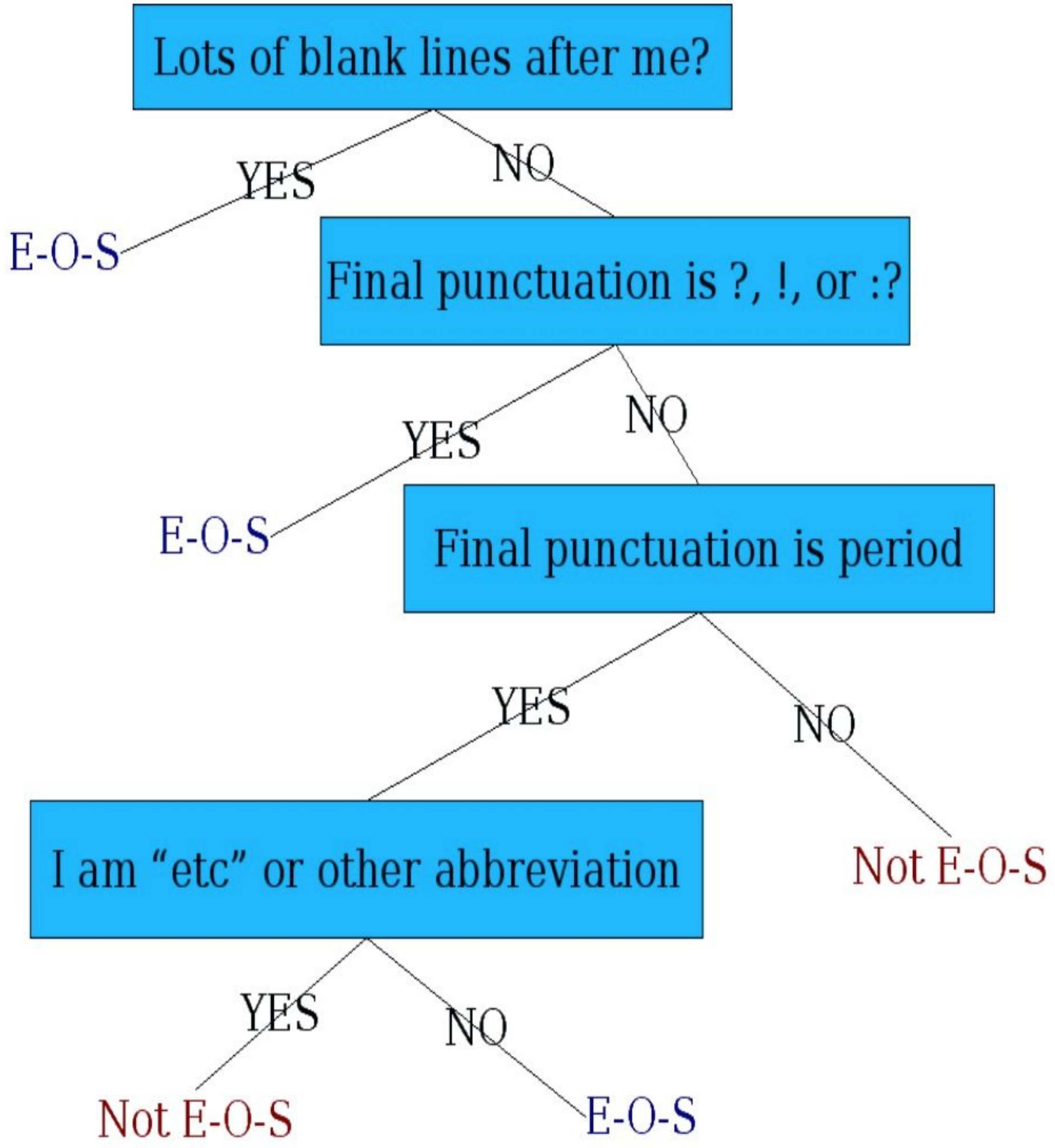
Sentence Boundary Detection

Sentence Boundary Determination

- For more sophisticated linguistic parsing, the algorithms often require **a complete sentence as input**.
  - E.g., sentence-level sentiment analysis
- We shall also see other information extraction algorithms that operate on a sentence at a time.
- Sentence boundary determination is essentially the problem of deciding *which instances of a period (**.**) followed by whitespace are sentence delimiters and which are not* since we assume that the characters **?** and **!** are unambiguous sentence boundaries.

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


Lots of blank lines after me?
YES
NO
E-O-S
Final punctuation is ?, !, or :?
YES
NO
E-O-S
Final punctuation is period
YES
NO
I am "etc" or other abbreviation
Not E-O-S
YES
NO
Not E-O-S
E-O-S

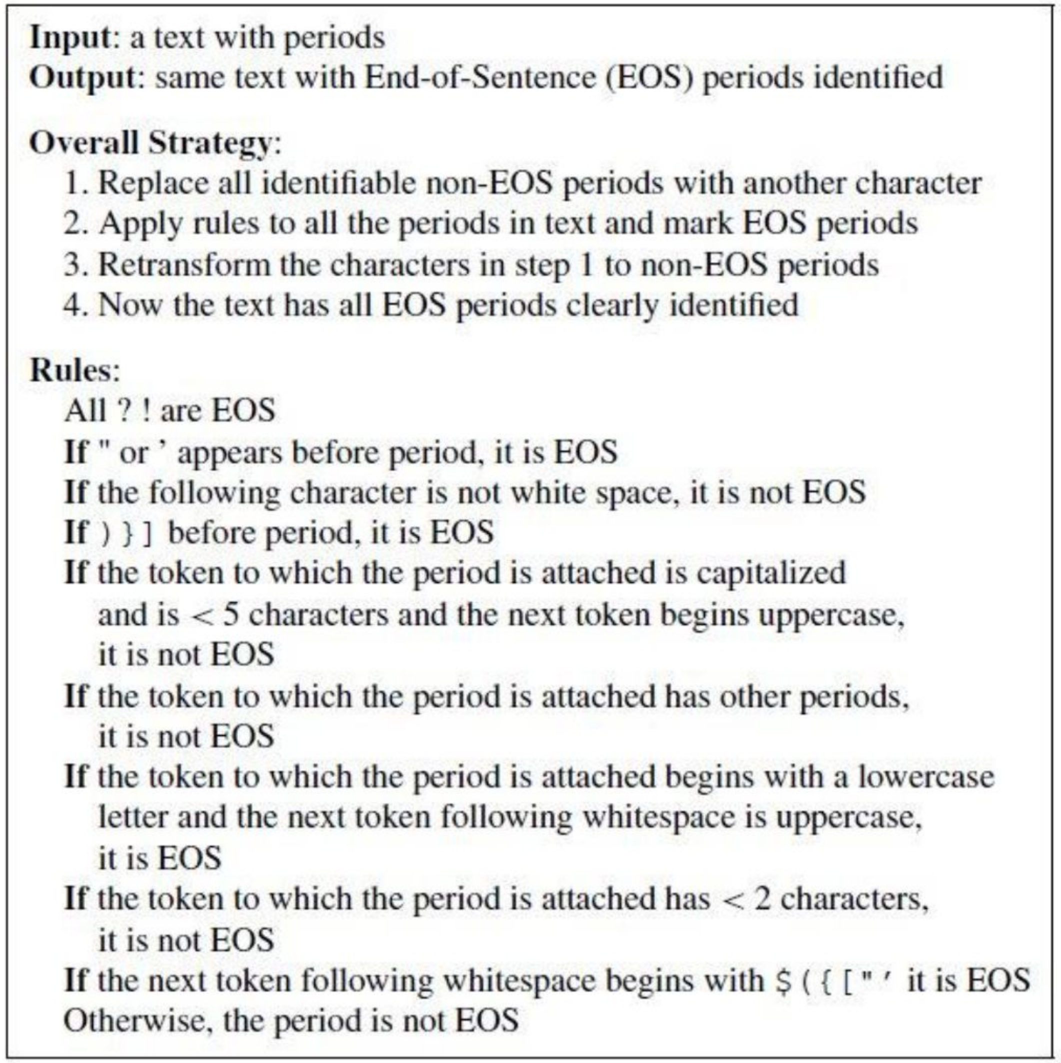
Implementing Decision Trees

- A decision tree is just an if-then-else statement.
  - We can think of the questions in a decision tree.
- The interesting research is choosing the features.
- Setting up the structure is often too hard to do by hand.
  - Hand-building only possible for every simple features, domains.
    - For numeric features, it is too hard to pick each threshold.
  - Instead, structure usually learned by machine learning from a training corpus.
- The features could be exploited by any kind of classifier
  - SVM, Neural Networks, Logistic Regression, etc.

Sentence Boundary Determination

Sentence Detection Algorithm.

- **Hand-written rule**
- Examples of EOS
  - …”.   …’.
  - …).   …}.
  - …].   …x.Y
  - . $. (
  - . {   . [
  - . “   . ‘
- Examples of not EOS
  - Ph.D.
  - www.google.com
  - i.e.



```
Input: a text with periods
Output: same text with End-of-Sentence (EOS) periods identified

Overall Strategy:
   1. Replace all identifiable non-EOS periods with another character
   2. Apply rules to all the periods in text and mark EOS periods
   3. Retransform the characters in step 1 to non-EOS periods
   4. Now the text has all EOS periods clearly identified

Rules:
   All ? ! are EOS
   If " or ' appears before period, it is EOS
   If the following character is not white space, it is not EOS
   If ) } ] before period, it is EOS
   If the token to which the period is attached is capitalized
      and is < 5 characters and the next token begins uppercase,
      it is not EOS
   If the token to which the period is attached has other periods,
      it is not EOS
   If the token to which the period is attached begins with a lowercase
      letter and the next token following whitespace is uppercase,
      it is EOS
   If the token to which the period is attached has < 2 characters,
      it is not EOS
   If the next token following whitespace begins with $ ( { [ " ' it is EOS
   Otherwise, the period is not EOS
```

End-of-sentence detection algorithm

Syntactic Analysis

Syntactic Analysis

- Part-of-Speech Tagging
- Word Sense Disambiguation
- Parsing

Part-of-Speech Tagging

- If no further linguistic analysis is necessary, one might proceed directly to feature generation, in which the features will be obtained from the tokens (E.g., *linguistic* and *analysis* from this sentence).
- However, if the goal is more specific, say recognizing names of people, places, and organizations, it is usually desirable to perform additional linguistic analyses of the text and extract more sophisticated features.
  - E.g., San Francisco
- In English, some analyses may use as few as six or seven categories and others nearly one hundred.
- Most English grammars would have a minimum noun, verb, adjective, adverb, preposition, and conjunction.

Part-of-Speech Tagging

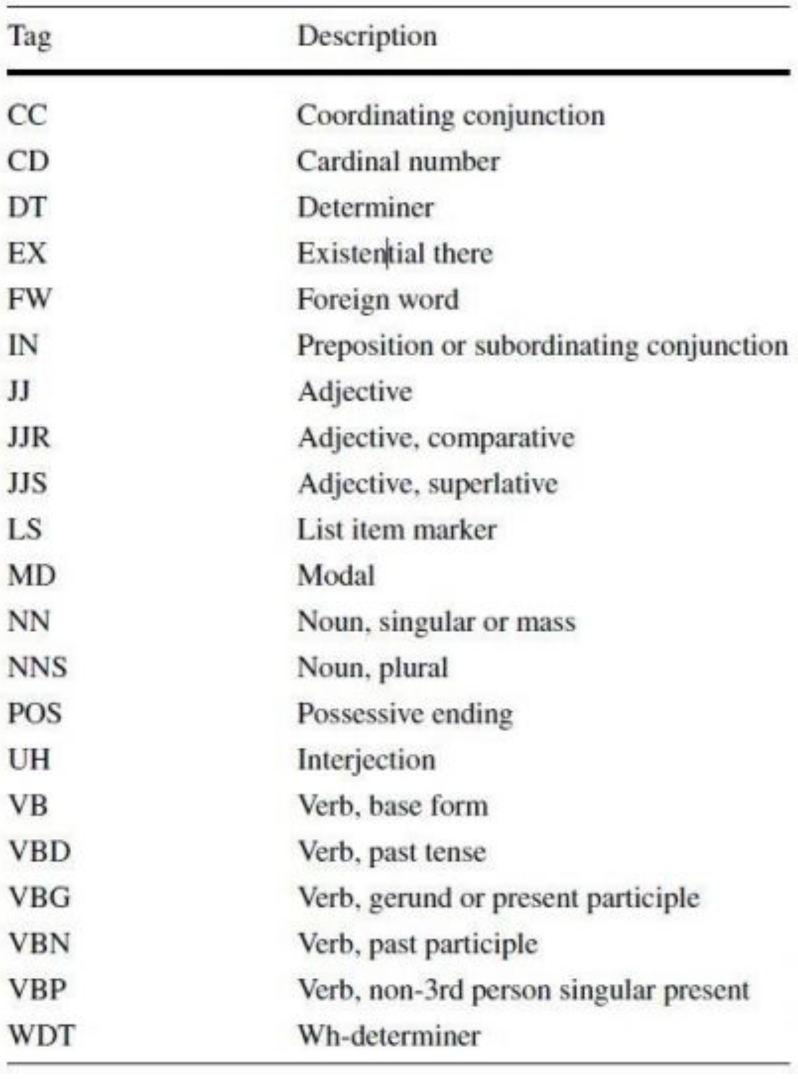
- POS can be used for feature reduction, e.g., use only verb, adjective, and adverb for sentiment classification.

- Distribution of POS can be used for author, gender, and document genre (formal vs. informal) classification

Part-of-Speech Tagging

- A set of 36 categories is used in the **PennTree Bank** (https://catalog.ldc.upenn.edu/docs/LDC95T7/cl93.html) constructed from the Wall Street Journal corpus (see next page)
  - A **tree bank** is a parsed text corpus that annotates sentence structure, such as POS and phrases.
- Almost all POS taggers have been trained on the Wall Street Journal corpus available from LDC (linguistic Data Consortium, www.ldc.upenn.edu)
  - E.g., *I love you* -> *I* (**personal pronoun**) *love* (**verb**, not noun)
- The Brill tagger is in the public domain and is in wide use.
  - Online Brill tagger: https://nlpweb01.nors.ku.dk/online/pos_tagger/uk/index.html
- The Stanford Parser: a statistical parser
  - An implementation in Java: https://nlp.stanford.edu/software/lex-parser.shtml

Penn Tree Bank POS set

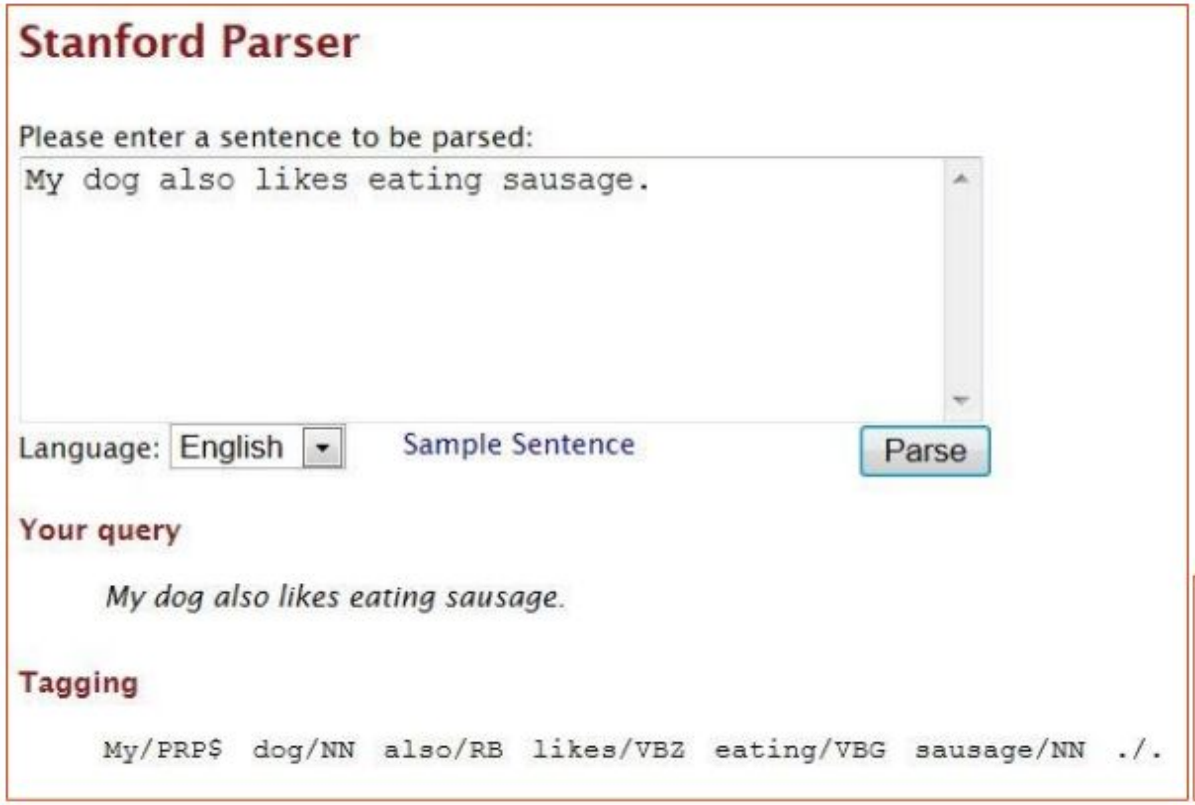


Tag	Description
CC	Coordinating conjunction
CD	Cardinal number
DT	Determiner
EX	Existential there
FW	Foreign word
IN	Preposition or subordinating conjunction
JJ	Adjective
JJR	Adjective, comparative
JJS	Adjective, superlative
LS	List item marker
MD	Modal
NN	Noun, singular or mass
NNS	Noun, plural
POS	Possessive ending
UH	Interjection
VB	Verb, base form
VBD	Verb, past tense
VBG	Verb, gerund or present participle
VBN	Verb, past participle
VBP	Verb, non-3rd person singular present
WDT	Wh-determiner

All the POS categories:
http://cs.nyu.edu/grishman/jet/guide/PennPOS.html

Part-of-Speech Tagging

- The Stanford Parser: online parser
  - http://nlp.stanford.edu:8080/parser/



```
My dog also likes eating sausage.
```

Your query

My dog also likes eating sausage.

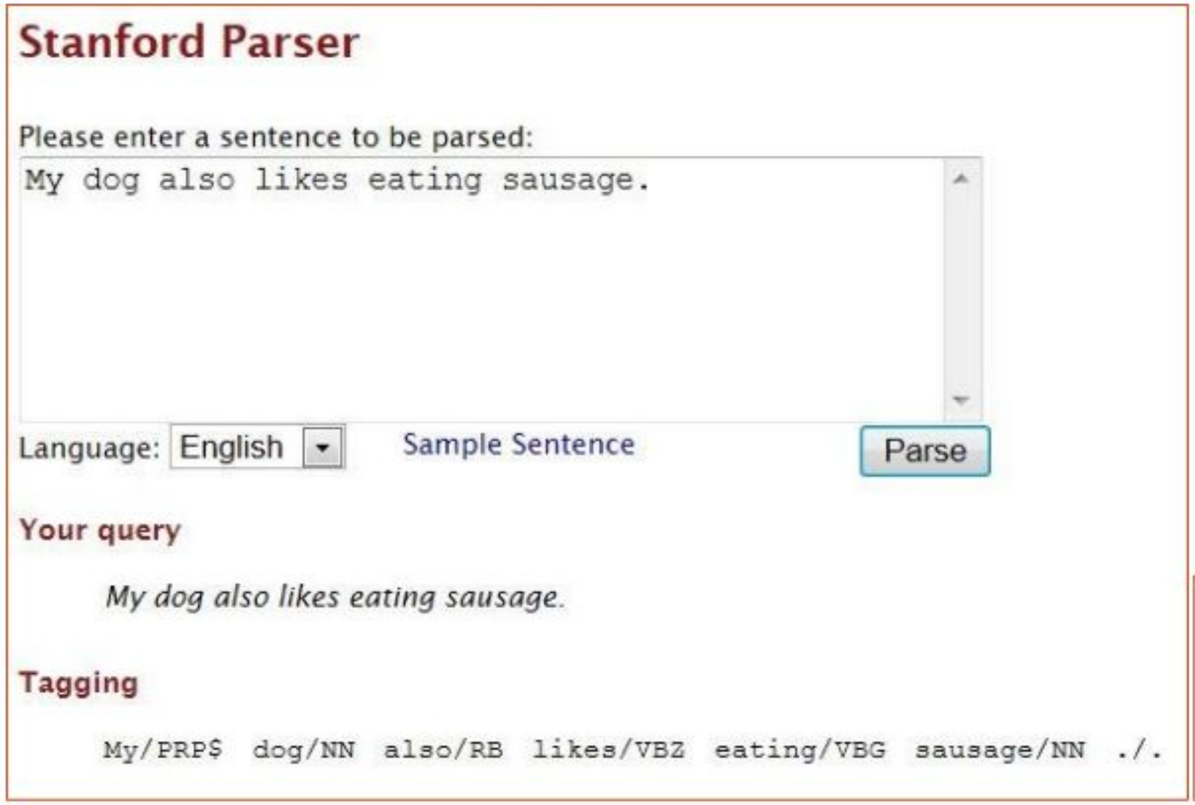
Tagging

```
My/PRP$  dog/NN  also/RB  likes/VBZ  eating/VBG  sausage/NN  ./.
```

Note:
PRP$: Possessive pronoun
RB: Adverb
VBZ: Verb, 3rd person singular present

Part-of-Speech Tagging

- The Stanford Parser: online parser
  - http://nlp.stanford.edu:8080/parser/



Stanford Parser

Please enter a sentence to be parsed:

```
My dog also likes eating sausage.
```

Your query

My dog also likes eating sausage.

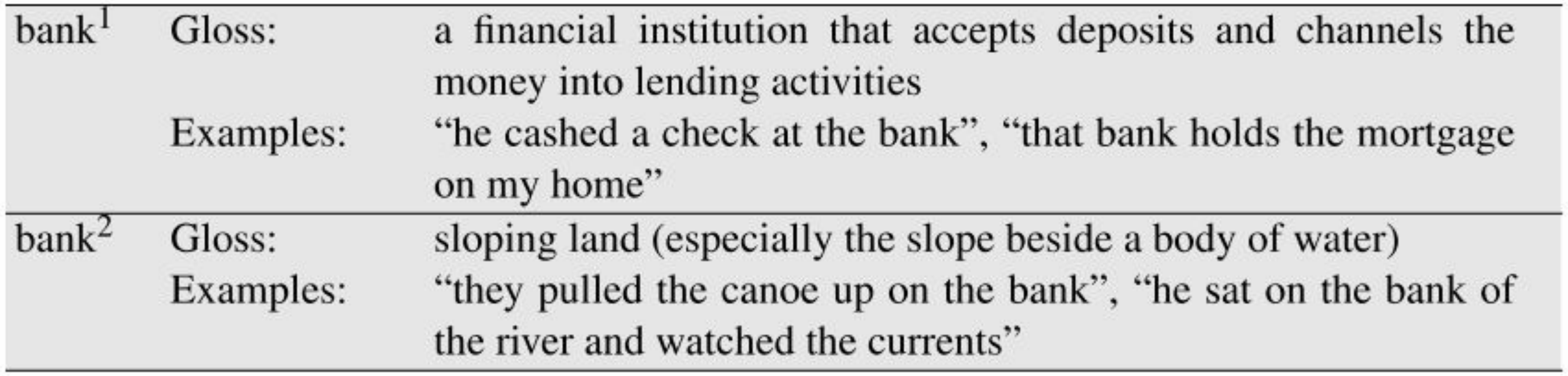
Tagging

```
My/PRP$  dog/NN  also/RB  likes/VBZ  eating/VBG  sausage/NN  ./.
```

Note:
PRP$: Possessive pronoun
RB: Adverb
VBZ: Verb, 3rd person singular present

Word Sense Disambiguation

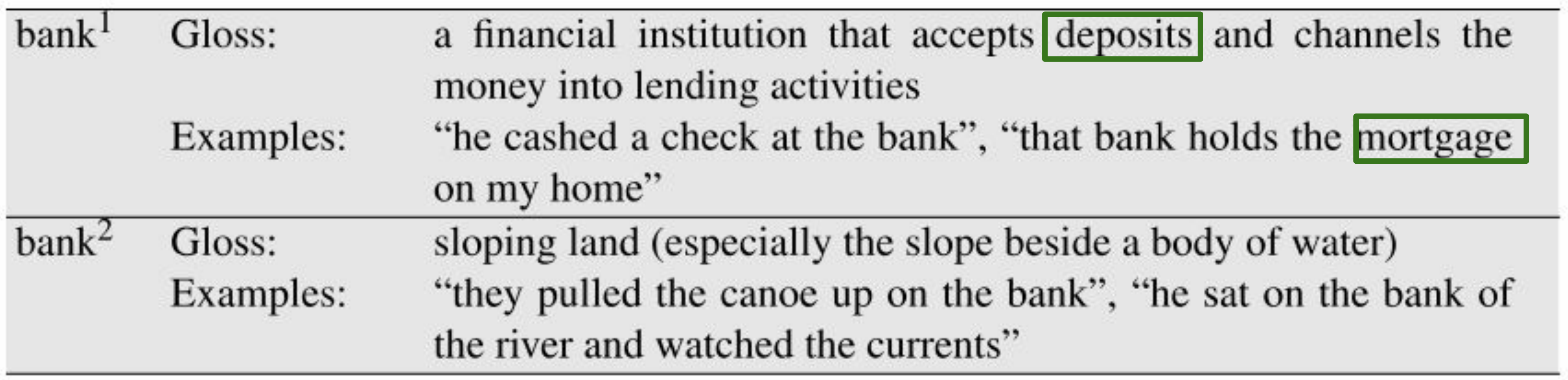
- Let’s disambiguate “bank” in this sentence:
  - The bank can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.
- Given the following two WordNet senses:



bank[1]	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	“he cashed a check at the bank”, “that bank holds the mortgage on my home”
bank[2]	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	“they pulled the canoe up on the bank”, “he sat on the bank of the river and watched the currents”

WSD: The Simplified Lesk Algorithm

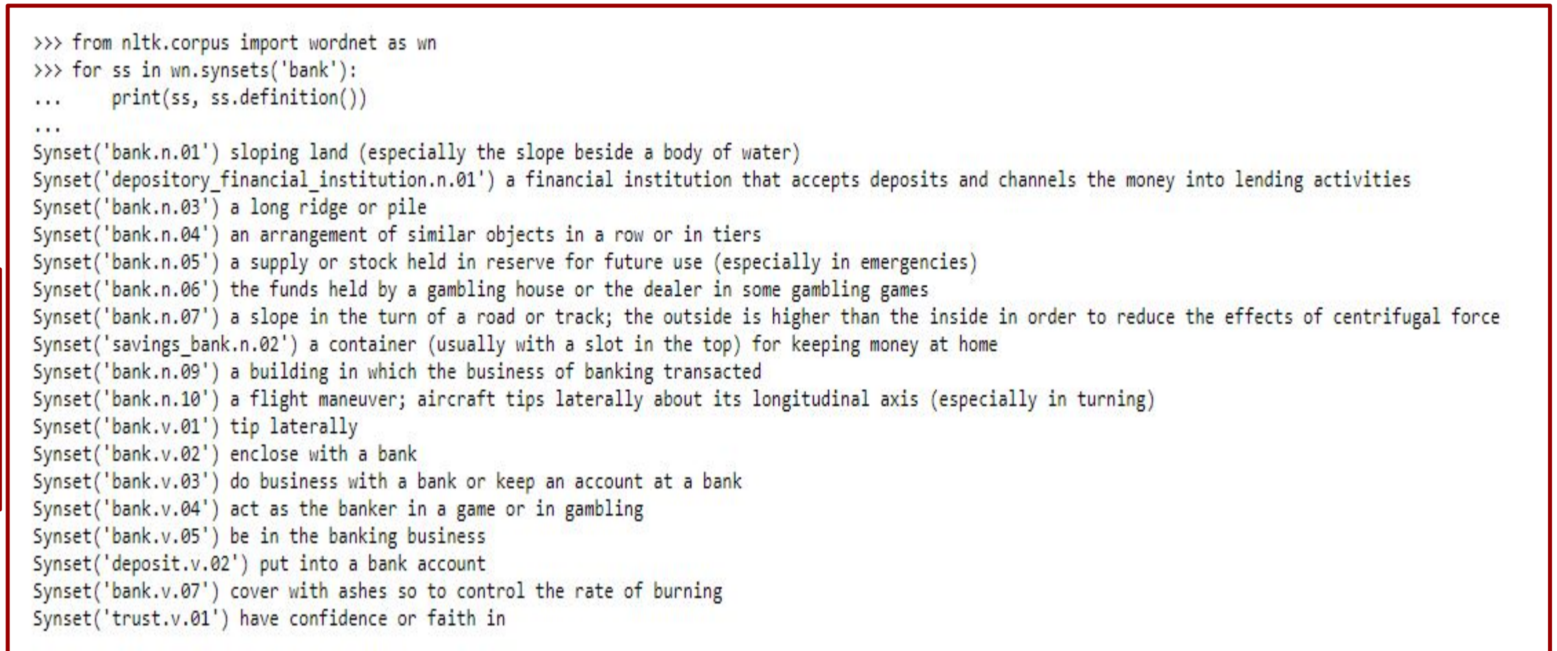
- Choose sense with **most word overlap** between gloss and context (not counting stop words)
  - The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.



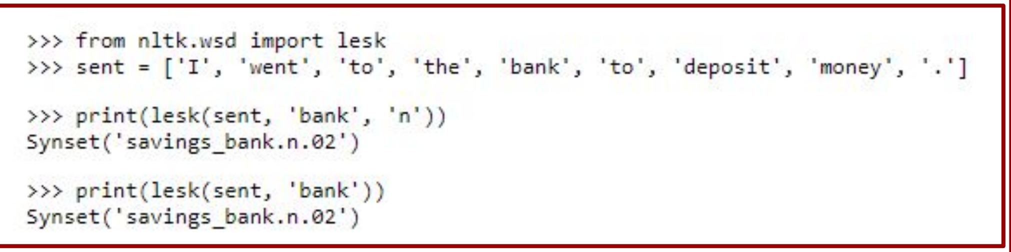
bank^1	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	“he cashed a check at the bank”, “that bank holds the mortgage on my home”
bank^2	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	“they pulled the canoe up on the bank”, “he sat on the bank of the river and watched the currents”

WSD

- Performs the classic Lesk algorithm for Word Sense Disambiguation (WSD)
  - Given an ambiguous word and the context in which the word occurs, Lesk returns a Synset with the highest number of overlapping words between the context sentence and different definitions from each Synset.
  - http://www.nltk.org/howto/wsd.html



```
>>> from nltk.corpus import wordnet as wn
>>> for ss in wn.synsets('bank'):
...     print(ss, ss.definition())
...
Synset('bank.n.01') sloping land (especially the slope beside a body of water)
Synset('depository_financial_institution.n.01') a financial institution that accepts deposits and channels the money into lending activities
Synset('bank.n.03') a long ridge or pile
Synset('bank.n.04') an arrangement of similar objects in a row or in tiers
Synset('bank.n.05') a supply or stock held in reserve for future use (especially in emergencies)
Synset('bank.n.06') the funds held by a gambling house or the dealer in some gambling games
Synset('bank.n.07') a slope in the turn of a road or track; the outside is higher than the inside in order to reduce the effects of centrifugal force
Synset('savings_bank.n.02') a container (usually with a slot in the top) for keeping money at home
Synset('bank.n.09') a building in which the business of banking transacted
Synset('bank.n.10') a flight maneuver; aircraft tips laterally about its longitudinal axis (especially in turning)
Synset('bank.v.01') tip laterally
Synset('bank.v.02') enclose with a bank
Synset('bank.v.03') do business with a bank or keep an account at a bank
Synset('bank.v.04') act as the banker in a game or in gambling
Synset('bank.v.05') be in the banking business
Synset('deposit.v.02') put into a bank account
Synset('bank.v.07') cover with ashes so to control the rate of burning
Synset('trust.v.01') have confidence or faith in
```



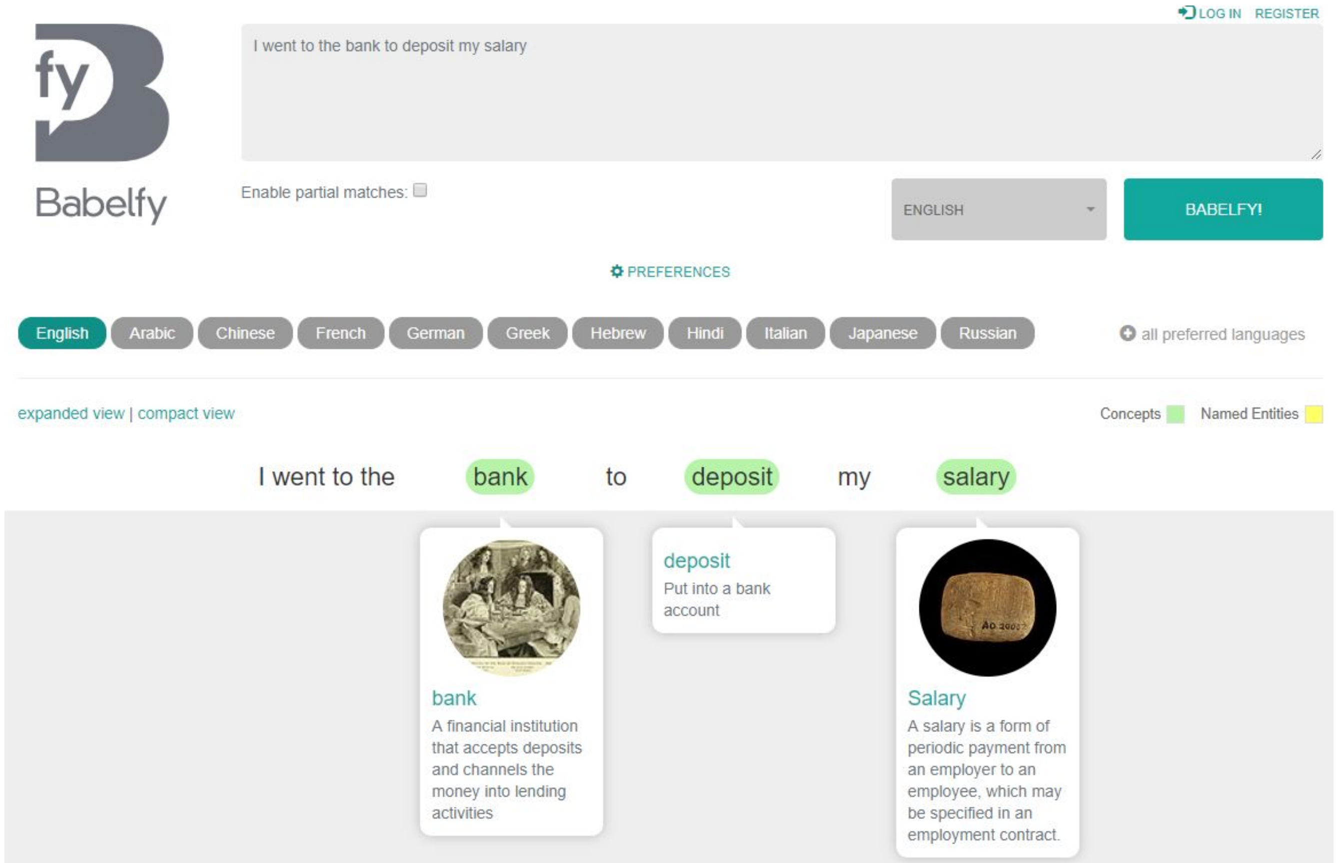
```
>>> from nltk.wsd import lesk
>>> sent = ['I', 'went', 'to', 'the', 'bank', 'to', 'deposit', 'money', '.']

>>> print(lesk(sent, 'bank', 'n'))
Synset('savings_bank.n.02')

>>> print(lesk(sent, 'bank'))
Synset('savings_bank.n.02')
```

WSD

- Use Babelfy for Word Sense Disambiguation (WSD)
  - Considered as a state-of-the-art system based on BabelNet Multilingual Semantic network for multilingual Word Sense Disambiguation and Entity Linking.
  - http://babelfy.org/



I went to the bank to deposit my salary

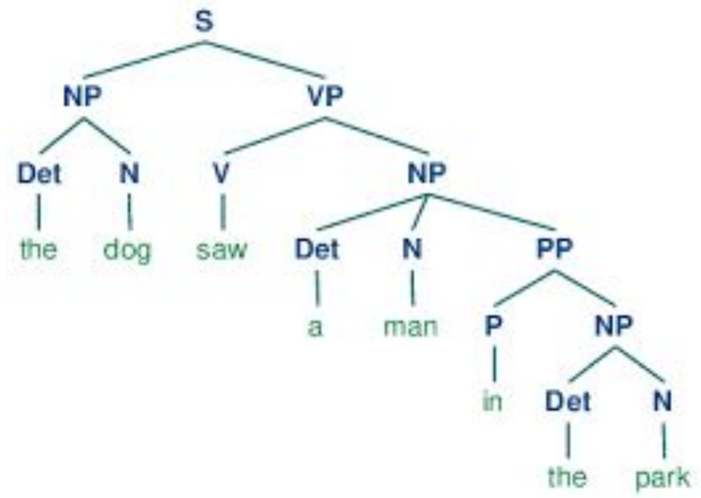
bank
A financial institution that accepts deposits and channels the money into lending activities

deposit
Put into a bank account

Salary
A salary is a form of periodic payment from an employer to an employee, which may be specified in an employment contract.

Parsing

- Is the step of producing **a full parse of a sentence**.
- Each word in a sentence is connected to a single structure, usually a tree.
- Considerable research has been done on constructing parasers from a statistical analysis of tree banks of sentences parsed by hand.
- The reason for considering such a comparatively expensive process is that it provides **detailed syntactic relationships information** that phrase identification cannot provide.



Parsing

- Consider a sentence such as “Johnson was replaced at XYZ Corp. by Smith” for which a simple parse tree is shown in the below.

- **Phrase structure tree**

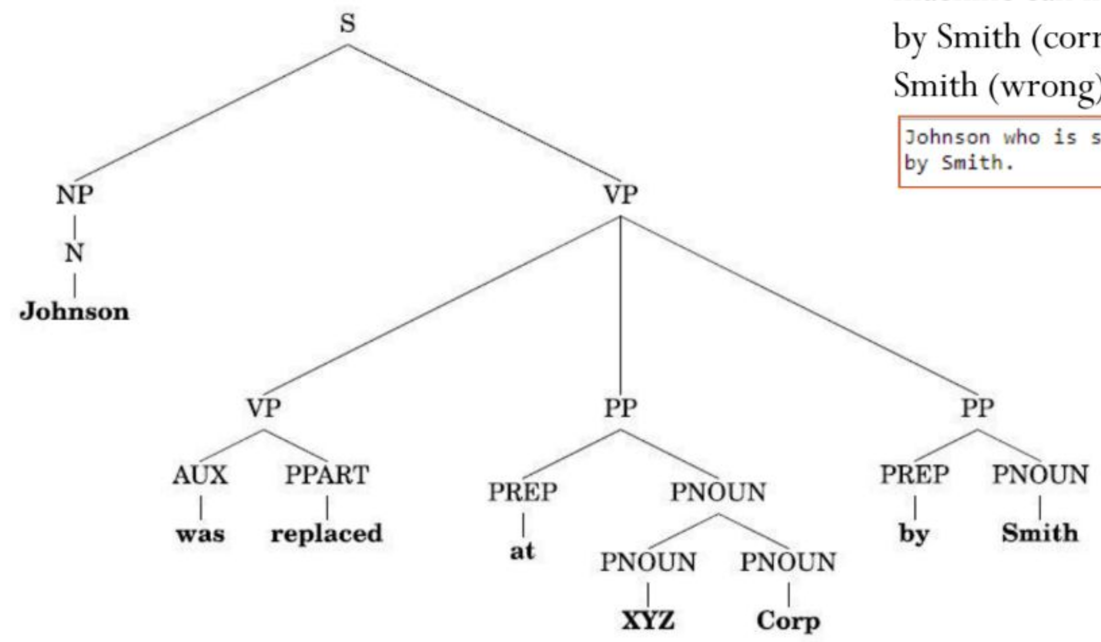
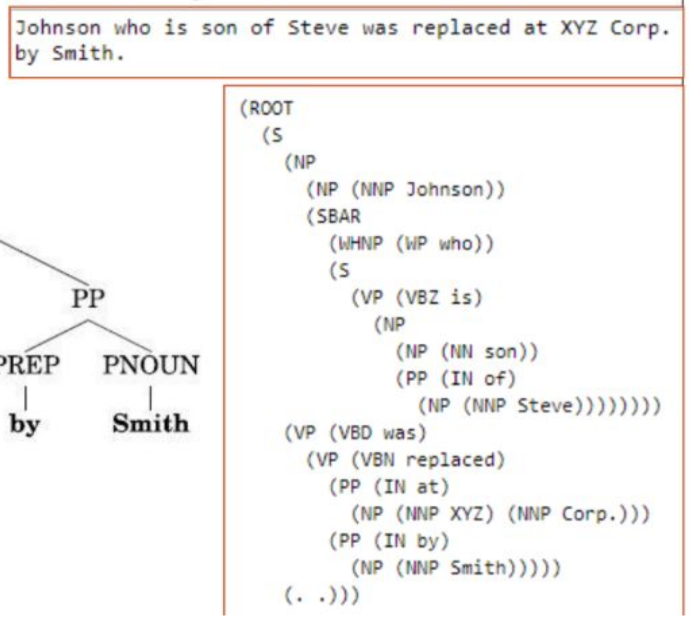


Fig. 2.9 Simple parse tree

For instance, by looking at the Parse Tree, machine can infer that Johnson was replaced by Smith (correct); Steve was replaced by Smith (wrong).

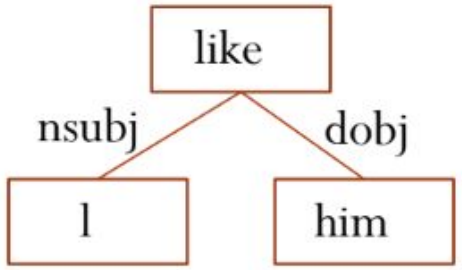


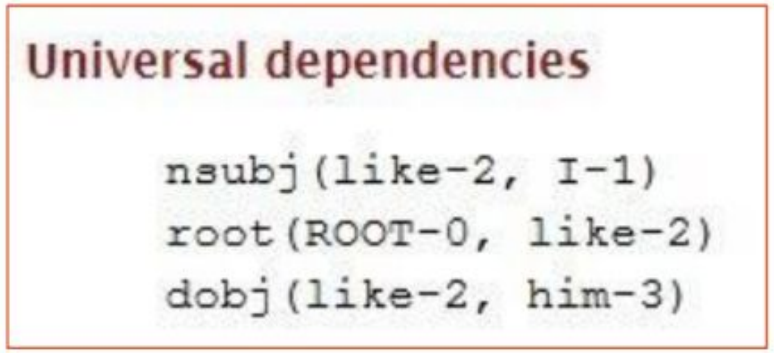
```
Johnson who is son of Steve was replaced at XYZ Corp.
by Smith.
```

```
(ROOT
  (S
    (NP
      (NP (NNP Johnson))
      (SBAR
        (WHNP (WP who))
        (S
          (VP (VBZ is)
            (NP
              (NP (NN son))
              (PP (IN of)
                (NP (NNP Steve))))))))
    (VP (VBD was)
      (VP (VBN replaced)
        (PP (IN at)
          (NP (NNP XYZ) (NNP Corp.)))
        (PP (IN by)
          (NP (NNP Smith)))))
    (. .)))
```

Parsing

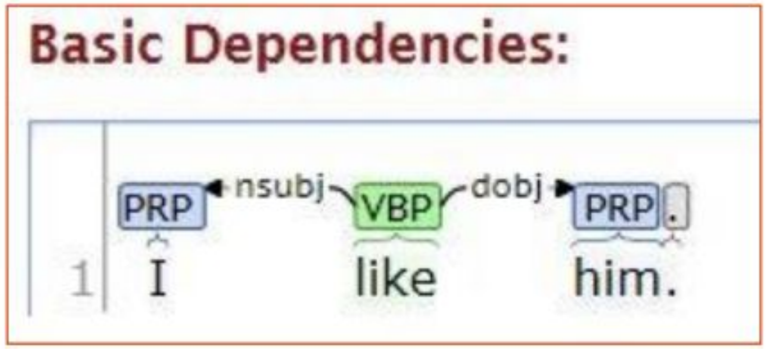
- Universal dependencies (i.e. grammatical relations; evolved out of Stanford Dependencies) from Stanford Parser: “I like him”.




Universal dependencies

```
nsubj(like-2, I-1)
root(ROOT-0, like-2)
dobj(like-2, him-3)
```

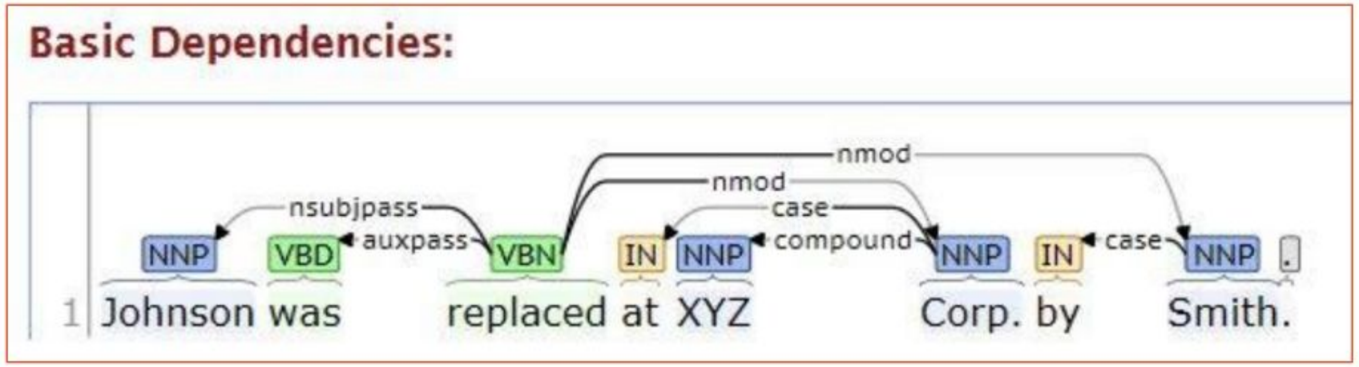
Output from Stanford Parser

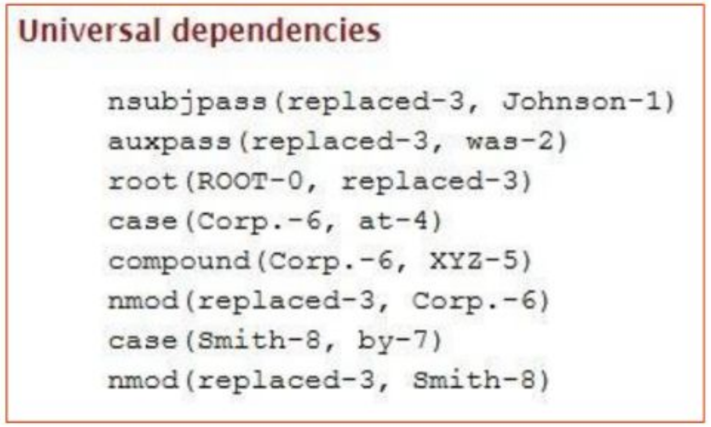

Basic Dependencies:

Output from Stanford CoreNLP

Parsing

- Universal dependencies (i.e. grammatical relations; evolved out of Stanford Dependencies) from Stanford CoreNLP: “Johnson was replaced at XYZ Corp. by Smith”.




Universal dependencies

```
nsubjpass(replaced-3, Johnson-1)
auxpass(replaced-3, was-2)
root(ROOT-0, replaced-3)
case(Corp.-6, at-4)
compound(Corp.-6, XYZ-5)
nmod(replaced-3, Corp.-6)
case(Smith-8, by-7)
nmod(replaced-3, Smith-8)
```

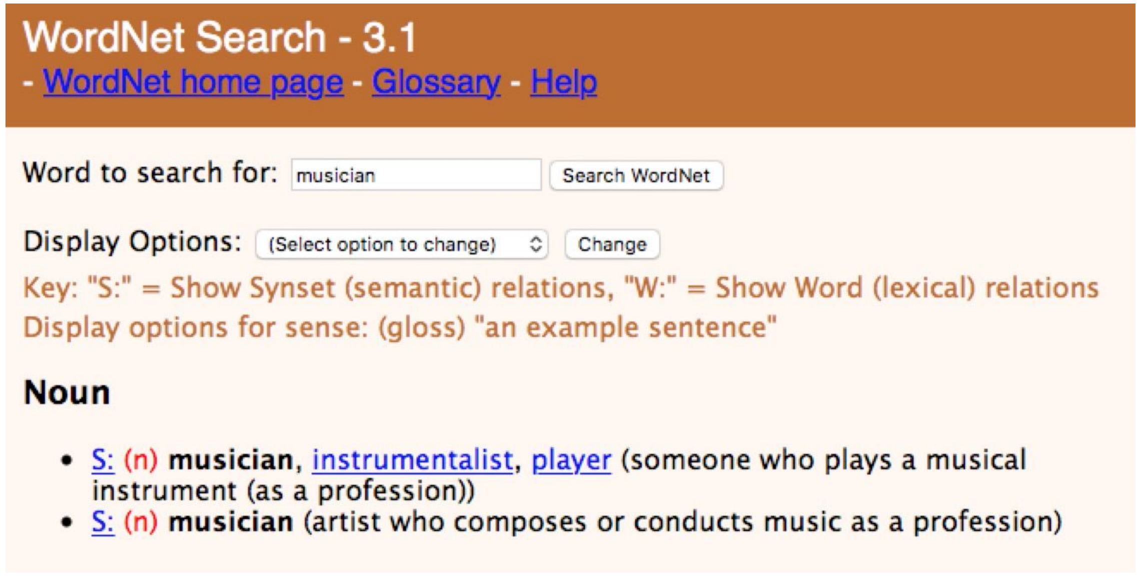
- For these above tasks such as tokenization, POS, Parsing and so on, we can build our machine learning models from scratch.

- However, in almost 80% of applications, the off-the-shelf tools (NLTK, Stanford CoreNLP, Spacy and Textblob) are used

WordNet: Linguistic Resources

WordNet - a database of lexical relations

- **WordNet** is the most well developed and widely used lexical database for English
  - It consists from 4 databases (nouns, verbs, adjectives, and adverbs)
  - On-line version: http://wordnetweb.princeton.edu/perl/webwn
- Each database consists of sense entries consisting from a set of synonyms (synsets), e.g.,:
  - musician, instrumentalist, player
  - person, individual, someone
  - life form, organism, being


WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: musician [Search WordNet]

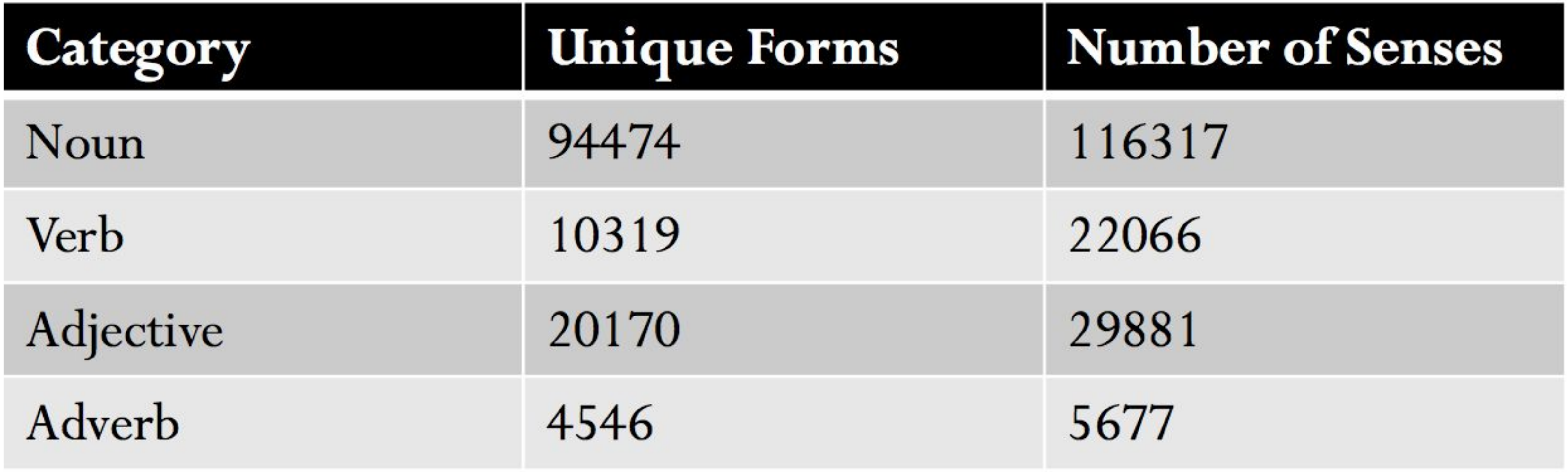
Display Options: (Select option to change) [Change]

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations
Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **musician**, instrumentalist, player (someone who plays a musical instrument (as a profession))
- S: (n) **musician** (artist who composes or conducts music as a profession)

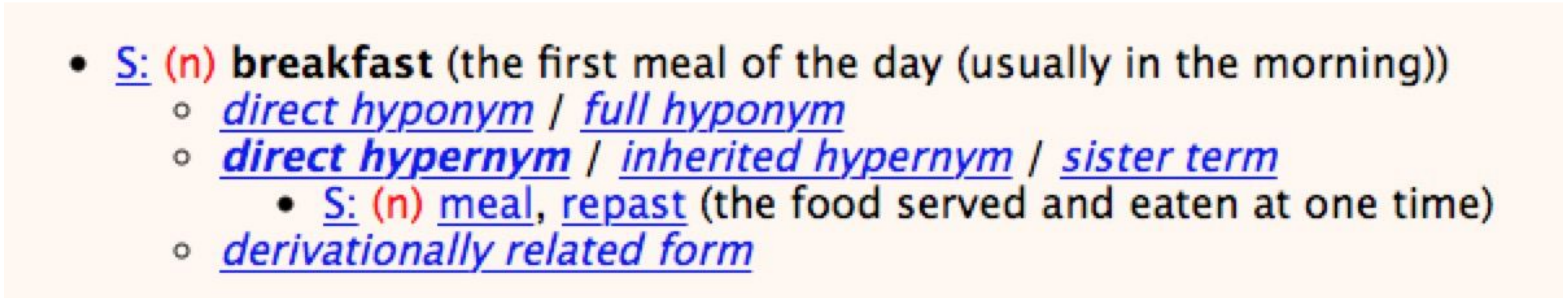
WordNet - a database of lexical relations



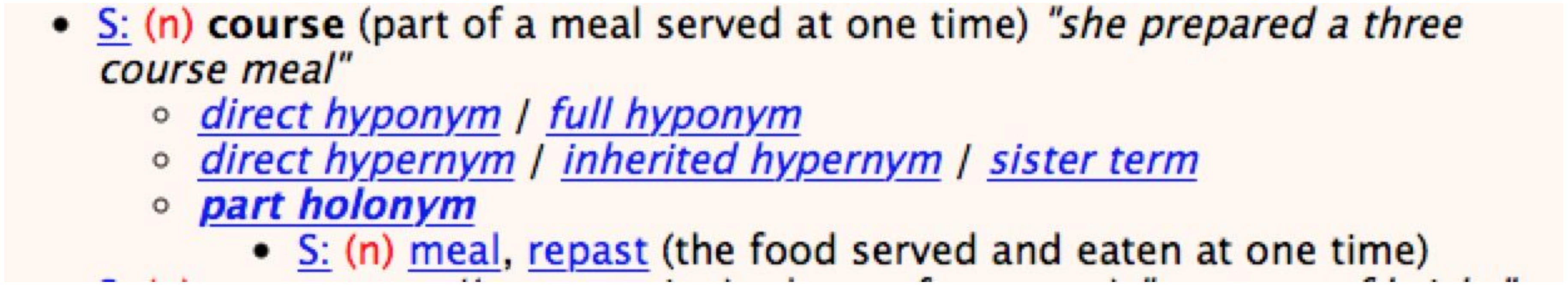
Category	Unique Forms	Number of Senses
Noun	94474	116317
Verb	10319	22066
Adjective	20170	29881
Adverb	4546	5677

WordNet relations

- Each WordNet entry is connected with other entries in a graph through relations.



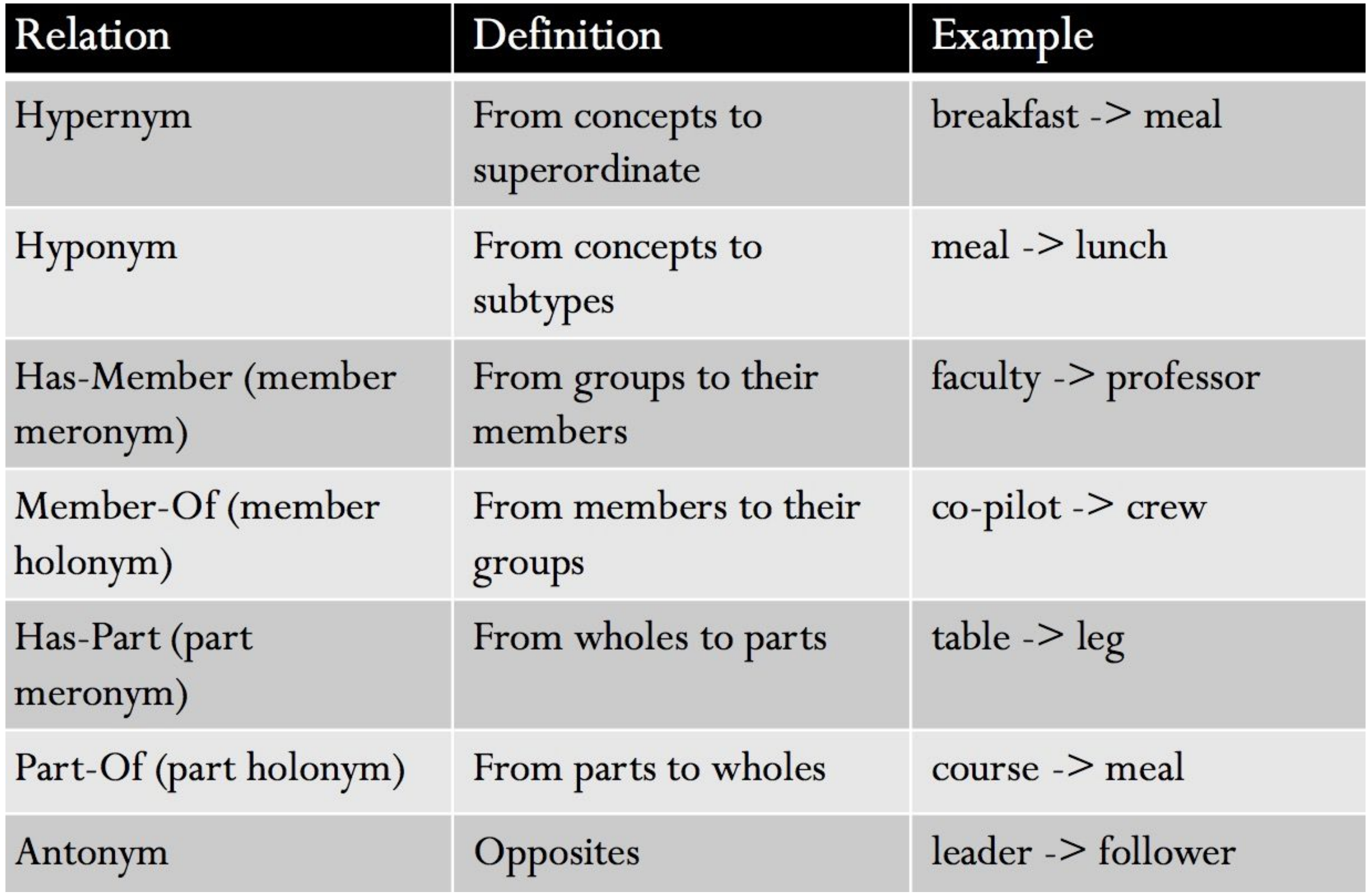
- S: (n) **breakfast** (the first meal of the day (usually in the morning))
  - *direct hyponym* / *full hyponym*
  - ***direct hypernym*** / *inherited hypernym* / *sister term*
    - S: (n) meal, repast (the food served and eaten at one time)
  - *derivationally related form*



- S: (n) **course** (part of a meal served at one time) *"she prepared a three course meal"*
  - *direct hyponym* / *full hyponym*
  - *direct hypernym* / *inherited hypernym* / *sister term*
  - ***part holonym***
    - S: (n) meal, repast (the food served and eaten at one time)

WordNet relations

- Relations in the database of **nouns**.



Relation	Definition	Example
Hypernym	From concepts to superordinate	breakfast -> meal
Hyponym	From concepts to subtypes	meal -> lunch
Has-Member (member meronym)	From groups to their members	faculty -> professor
Member-Of (member holonym)	From members to their groups	co-pilot -> crew
Has-Part (part meronym)	From wholes to parts	table -> leg
Part-Of (part holonym)	From parts to wholes	course -> meal
Antonym	Opposites	leader -> follower