# Natural Language Processing

## Part of Speech Tagging and Named Entity Recognition

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## NLP: why?

| | | | | |
|---|---|---|---|---|
| 's | center-right | have | matteo | silvio |
| (pd) | chamber | he | minister | since |
| . | changing | him | more | stable |
| 2013 | clear | important | of | the |
| a | constitutional | in | on | to |
| abolish | cumbersome | institutional | pact | voting |
| ally | democratic | it | party | wants |
| also | elected | italia | prime | wednesday |
| an | elections | italian | priority | when |
| and | ended | its | reforms | winner |
| as | ensure | lawmaking | renzi | with |
| at | for | leader | rules | |
| became | forza | less | ruling | |
| been | government | lost | said | |
| berlusconi | had | make | senate | |

## NLP: why?

Italian Prime Minister Matteo Renzi lost an important ally on Wednesday when Silvio Berlusconi's center-right Forza Italia party said it had ended its pact with him on institutional and constitutional reforms.

Changing voting rules to ensure a clear winner at elections and more stable government have been a priority for Renzi since he became leader of the ruling Democratic Party (PD) in 2013. He also wants to abolish the Senate as an elected chamber to make lawmaking less cumbersome.

## NLP: why?

Texts are objects with inherent complex structure. A simple BoW model is not good enough for text understanding.

***Natural Language Processing*** provides models that go deeper to uncover the meaning.

- Part-of-speech tagging, NER
- Syntactic analysis
- Semantic analysis
- Discourse structure

## Upcoming lectures & labs

- Part-of-speech tagging, NER
- Parsing
- Coreference
- Using Tree Kernels for Syntactic/Semantic modeling
- Question Answering with NLP
- Pipelines and complex architectures
- Neural Nets for NLP tasks

## Labs

New repository with all the upcoming labs material:

**https://github.com/mnicosia/anlpir-2016**

Please download the current lab's material before the lab!

## Parts of Speech

- 8 traditional parts of speech for IndoEuropean languages
  - Noun, verb, adjective, preposition, adverb, article, interjection, pronoun, conjunction, etc
  - Around for over 2000 years (Dionysius Thrax of Alexandria, c. 100 B.C.)
  - Called: parts-of-speech, lexical category, word classes, morphological classes, lexical tags, POS

## POS examples for English

| | | |
|---|---|---|
| N | noun | *chair, bandwidth, pacing* |
| V | verb | *study, debate, munch* |
| ADJ | adj | *purple, tall, ridiculous* |
| ADV | adverb | *unfortunately, slowly* |
| P | preposition | *of, by, to* |
| PRO | pronoun | *I, me, mine* |
| DET | determiner | *the, a, that, those* |
| CONJ | conjunction | *and, or* |

## Open vs. Closed classes

- Closed:
  - determiners: ***a, an, the***
  - pronouns: ***she, he, I***
  - prepositions: ***on, under, over, near, by, …***
- Open:
  - Nouns, Verbs, Adjectives, Adverbs.

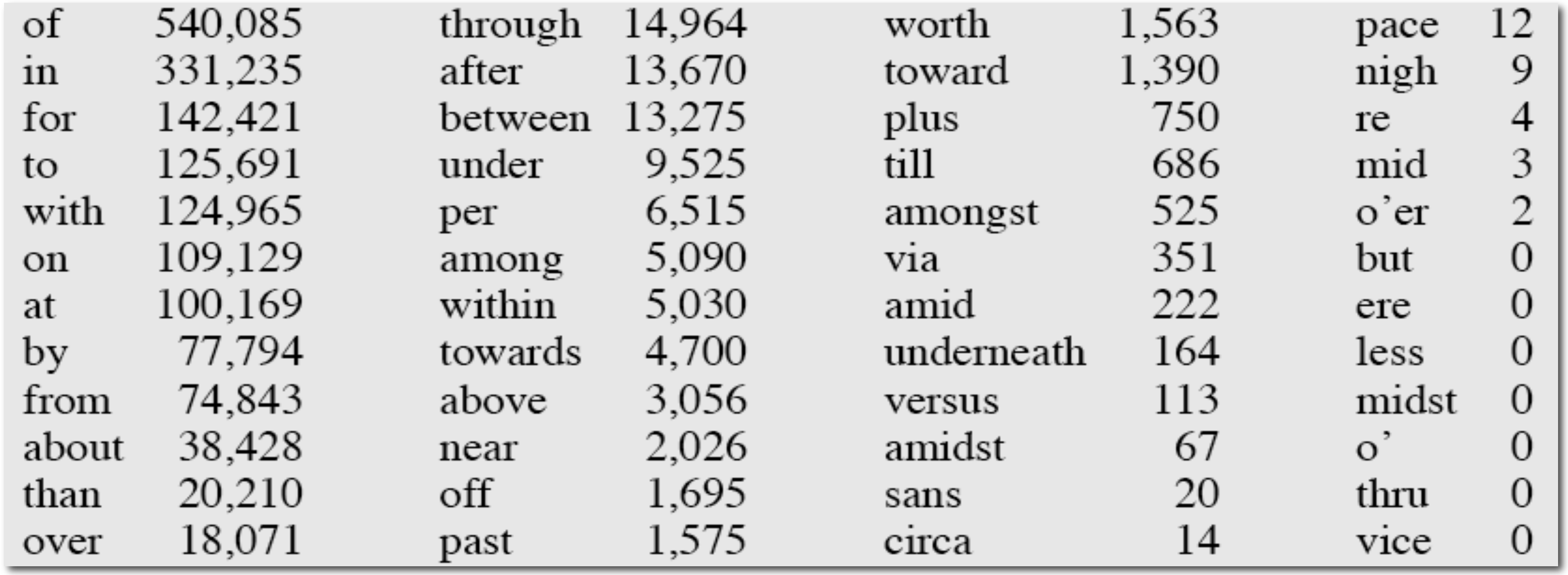
# Open Class Words

- Nouns
  - Proper nouns (Penn, Philadelphia, Davidson)
    - English capitalizes these.
  - Common nouns (the rest).
  - Count nouns and mass nouns
    - Count: have plurals, get counted: goat/goats, one goat, two goats
    - Mass: don' t get counted (snow, salt, communism) (*two snows)
- Adjectives/Adverbs: tend to modify nouns/verbs
  - Unfortunately, John walked home extremely slowly yesterday
  - Directional/locative adverbs (here,home, downhill)
  - Degree adverbs (extremely, very, somewhat)
  - Manner adverbs (slowly, slinkily, delicately)
- Verbs
  - In English, have morphological affixes (eat/eats/eaten)

## Closed Class Words

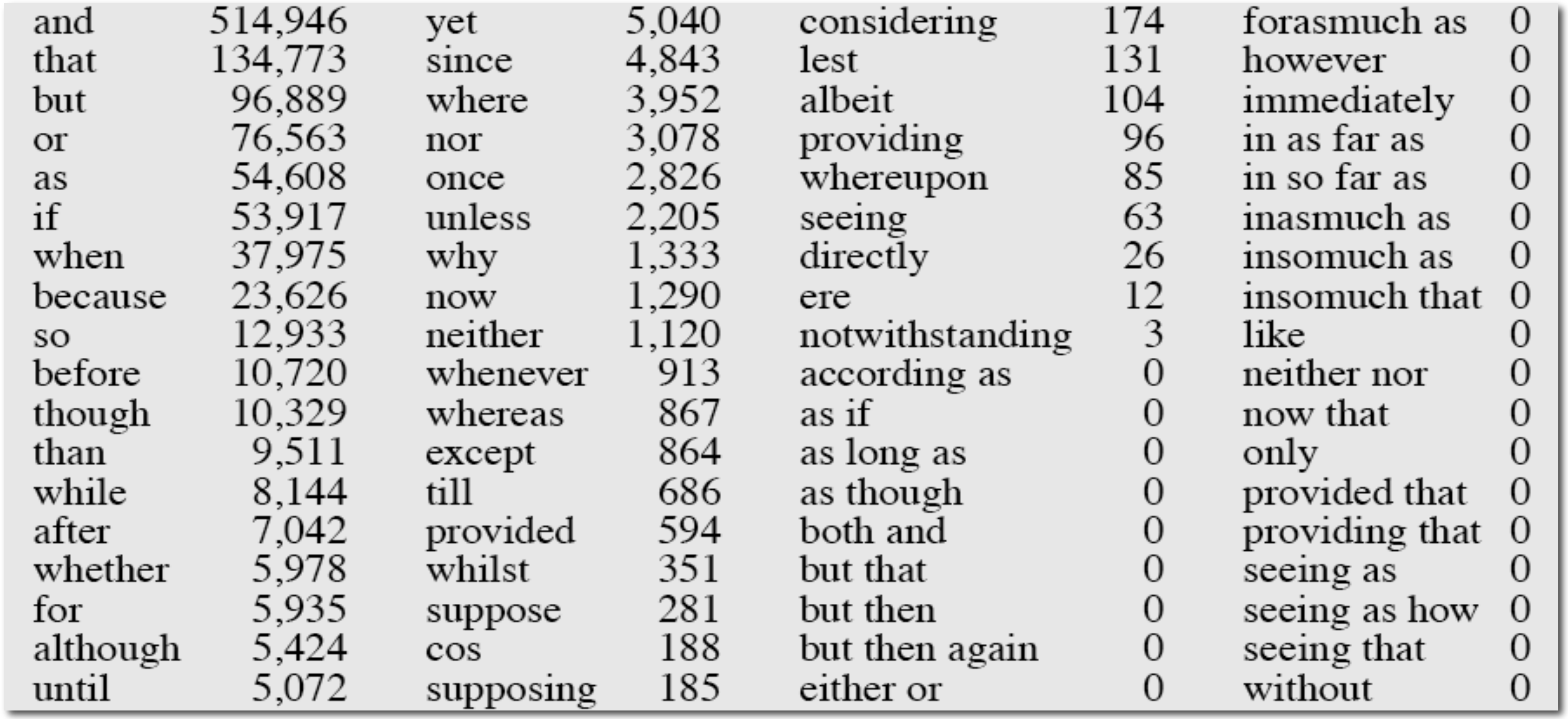
- Differ more from language to language than open class words
- Examples:
  - prepositions: *on, under, over, …*
  - particles: *up, down, on, off, …*
  - determiners: *a, an, the, …*
  - pronouns: *she, who, I, ..*
  - conjunctions: *and, but, or, …*
  - auxiliary verbs: *can, may should, …*
  - numerals: *one, two, three, third, …*

## Prepositions from CELEX



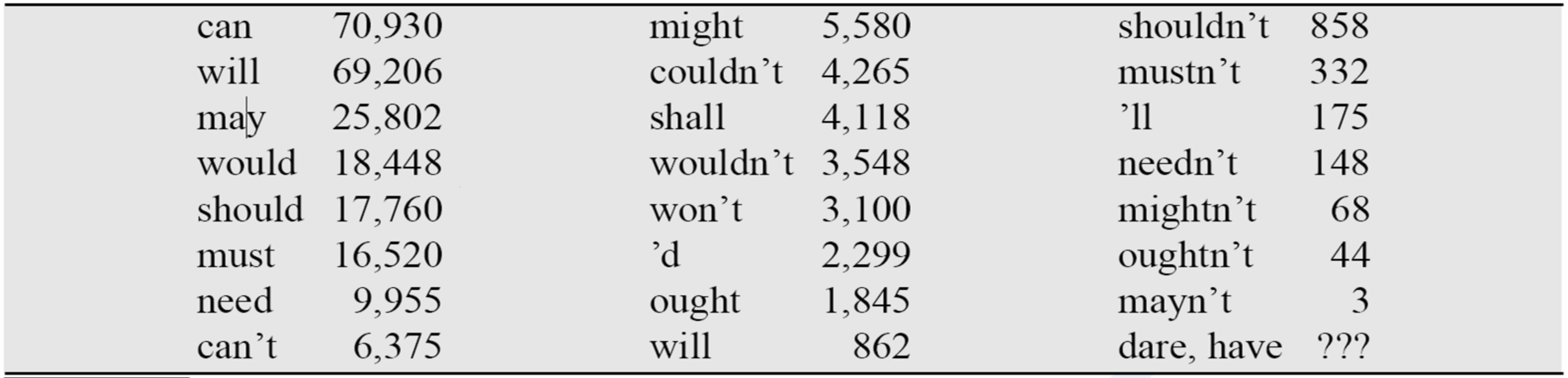
| | | | | | | | |
|---|---|---|---|---|---|---|---|
| of | 540,085 | through | 14,964 | worth | 1,563 | pace | 12 |
| in | 331,235 | after | 13,670 | toward | 1,390 | nigh | 9 |
| for | 142,421 | between | 13,275 | plus | 750 | re | 4 |
| to | 125,691 | under | 9,525 | till | 686 | mid | 3 |
| with | 124,965 | per | 6,515 | amongst | 525 | o’er | 2 |
| on | 109,129 | among | 5,090 | via | 351 | but | 0 |
| at | 100,169 | within | 5,030 | amid | 222 | ere | 0 |
| by | 77,794 | towards | 4,700 | underneath | 164 | less | 0 |
| from | 74,843 | above | 3,056 | versus | 113 | midst | 0 |
| about | 38,428 | near | 2,026 | amidst | 67 | o’ | 0 |
| than | 20,210 | off | 1,695 | sans | 20 | thru | 0 |
| over | 18,071 | past | 1,575 | circa | 14 | vice | 0 |

# Conjunctions



| | | | | | | | |
|---|---|---|---|---|---|---|---|
| and | 514,946 | yet | 5,040 | considering | 174 | forasmuch as | 0 |
| that | 134,773 | since | 4,843 | lest | 131 | however | 0 |
| but | 96,889 | where | 3,952 | albeit | 104 | immediately | 0 |
| or | 76,563 | nor | 3,078 | providing | 96 | in as far as | 0 |
| as | 54,608 | once | 2,826 | whereupon | 85 | in so far as | 0 |
| if | 53,917 | unless | 2,205 | seeing | 63 | inasmuch as | 0 |
| when | 37,975 | why | 1,333 | directly | 26 | insomuch as | 0 |
| because | 23,626 | now | 1,290 | ere | 12 | insomuch that | 0 |
| so | 12,933 | neither | 1,120 | notwithstanding | 3 | like | 0 |
| before | 10,720 | whenever | 913 | according as | 0 | neither nor | 0 |
| though | 10,329 | whereas | 867 | as if | 0 | now that | 0 |
| than | 9,511 | except | 864 | as long as | 0 | only | 0 |
| while | 8,144 | till | 686 | as though | 0 | provided that | 0 |
| after | 7,042 | provided | 594 | both and | 0 | providing that | 0 |
| whether | 5,978 | whilst | 351 | but that | 0 | seeing as | 0 |
| for | 5,935 | suppose | 281 | but then | 0 | seeing as how | 0 |
| although | 5,424 | cos | 188 | but then again | 0 | seeing that | 0 |
| until | 5,072 | supposing | 185 | either or | 0 | without | 0 |

## Auxiliaries



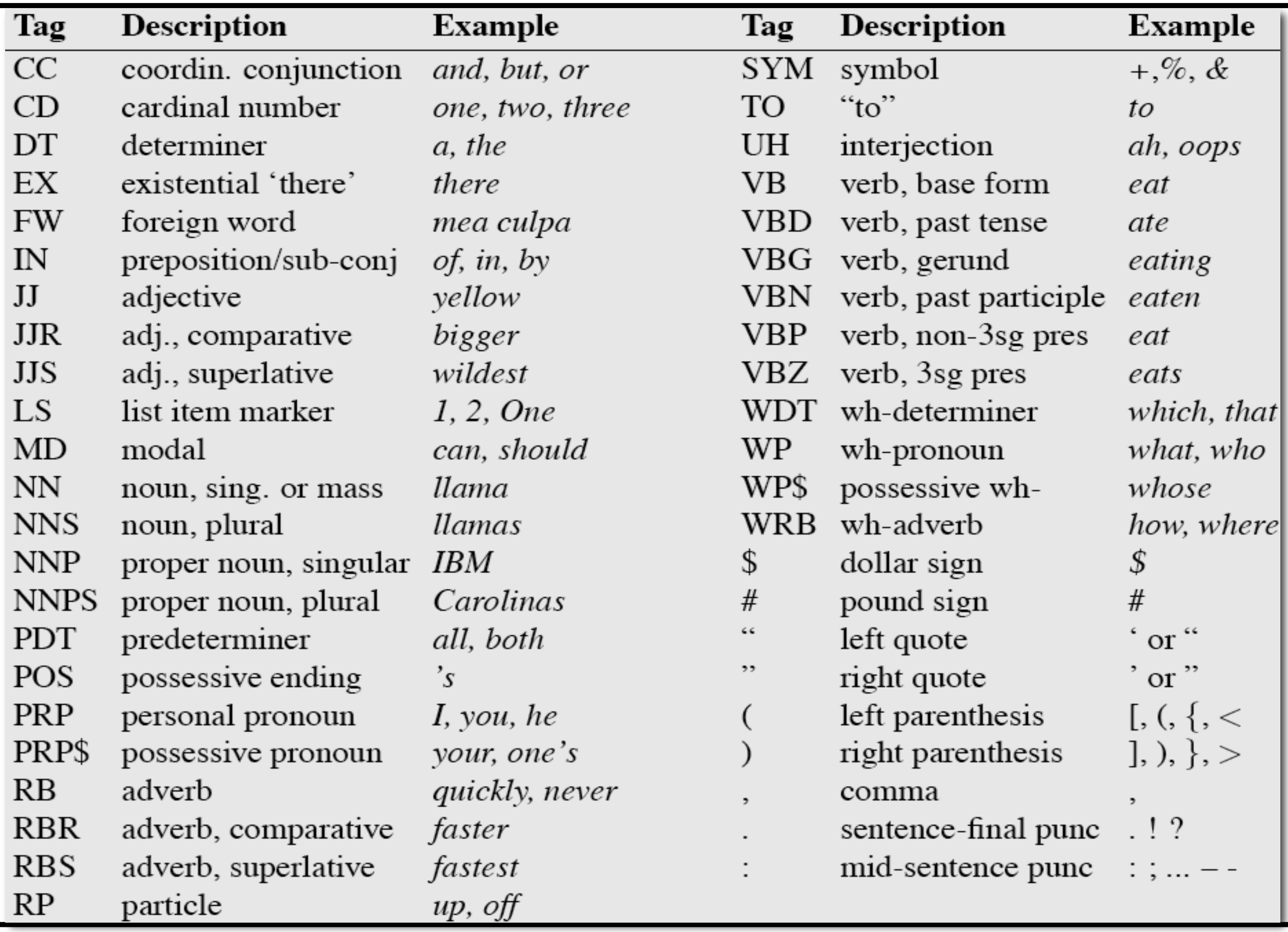
| | | | | | |
|---|---|---|---|---|---|
| can | 70,930 | might | 5,580 | shouldn’t | 858 |
| will | 69,206 | couldn’t | 4,265 | mustn’t | 332 |
| may | 25,802 | shall | 4,118 | ’ll | 175 |
| would | 18,448 | wouldn’t | 3,548 | needn’t | 148 |
| should | 17,760 | won’t | 3,100 | mightn’t | 68 |
| must | 16,520 | ’d | 2,299 | oughtn’t | 44 |
| need | 9,955 | ought | 1,845 | mayn’t | 3 |
| can’t | 6,375 | will | 862 | dare, have | ??? |

**Figure 5.5** English modal verbs from the CELEX on-line dictionary. Frequency counts are from the COBUILD 16 million word corpus.

## POS Tagging: Choosing a Tagset

- There are so many parts of speech, potential distinctions we can draw
- To do POS tagging, we need to choose a standard set of tags to work with
- Could pick very coarse tagsets
  - N, V, Adj, Adv.
- More commonly used set is finer grained, the "Penn TreeBank tagset", 45 tags
  - PRP$, WRB, WP$, VBG
- Even more fine-grained tagsets exist
- "UNIVERSAL" tagset
- Task-specific tagsets (e.g. for Twitter)

# Penn TreeBank POS Tagset



| Tag | Description | Example | Tag | Description | Example |
|---|---|---|---|---|---|
| CC | coordin. conjunction | *and, but, or* | SYM | symbol | +,%, & |
| CD | cardinal number | *one, two, three* | TO | “to” | *to* |
| DT | determiner | *a, the* | UH | interjection | *ah, oops* |
| EX | existential ‘there’ | *there* | VB | verb, base form | *eat* |
| FW | foreign word | *mea culpa* | VBD | verb, past tense | *ate* |
| IN | preposition/sub-conj | *of, in, by* | VBG | verb, gerund | *eating* |
| JJ | adjective | *yellow* | VBN | verb, past participle | *eaten* |
| JJR | adj., comparative | *bigger* | VBP | verb, non-3sg pres | *eat* |
| JJS | adj., superlative | *wildest* | VBZ | verb, 3sg pres | *eats* |
| LS | list item marker | *1, 2, One* | WDT | wh-determiner | *which, that* |
| MD | modal | *can, should* | WP | wh-pronoun | *what, who* |
| NN | noun, sing. or mass | *llama* | WP$ | possessive wh- | *whose* |
| NNS | noun, plural | *llamas* | WRB | wh-adverb | *how, where* |
| NNP | proper noun, singular | *IBM* | $ | dollar sign | *$* |
| NNPS | proper noun, plural | *Carolinas* | # | pound sign | # |
| PDT | predeterminer | *all, both* | “ | left quote | ‘ or “ |
| POS | possessive ending | *’s* | ” | right quote | ’ or ” |
| PRP | personal pronoun | *I, you, he* | ( | left parenthesis | [, (, {, < |
| PRP$ | possessive pronoun | *your, one’s* | ) | right parenthesis | ], ), }, > |
| RB | adverb | *quickly, never* | , | comma | , |
| RBR | adverb, comparative | *faster* | . | sentence-final punc | . ! ? |
| RBS | adverb, superlative | *fastest* | : | mid-sentence punc | : ; ... – - |
| RP | particle | *up, off* | | | |

## Using the Penn Tagset

- The/DT grand/JJ jury/NN commmented/VBD on/IN a/DT number/NN of/IN other/JJ topics/NNS ./.

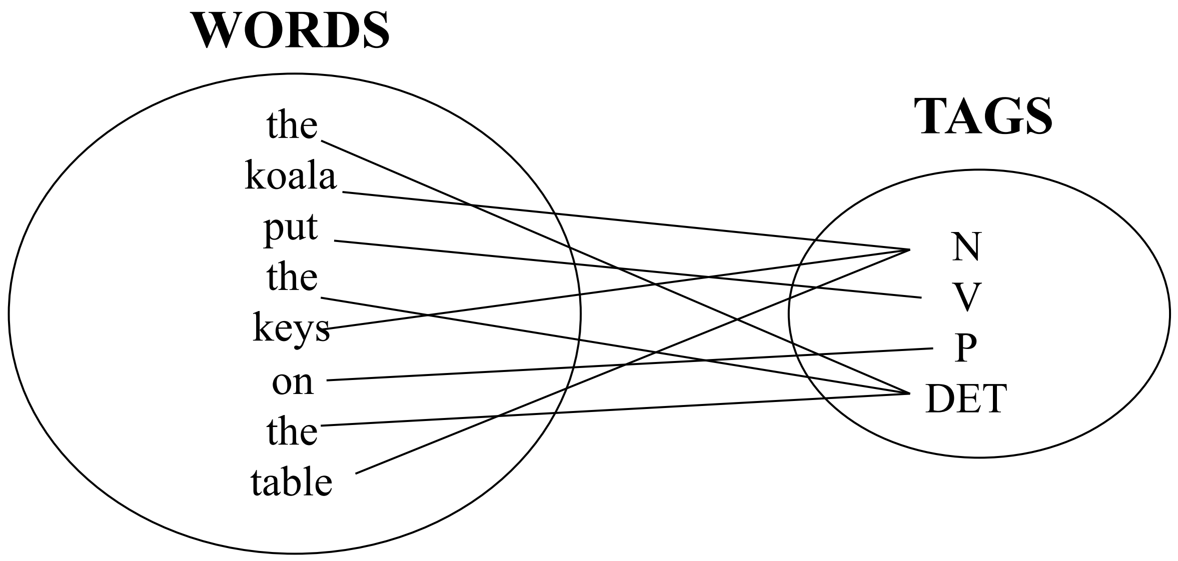
- Prepositions and subordinating conjunctions marked IN (“although/IN I/PRP..”)
- Except the preposition/complementizer “to” is just marked “TO”.

## Deciding on the correct part of speech can be difficult even for people

- Mrs/NNP Shaefer/NNP never/RB got/VBD around/RP to/TO joining/VBG
- All/DT we/PRP gotta/VBN do/VB is/VBZ go/VB around/IN the/DT corner/NN
- Chateau/NNP Petrus/NNP costs/VBZ around/RB 250/CD

## POS Tagging: Definition

- The process of assigning a part-of-speech or lexical class marker to each word in a corpus:



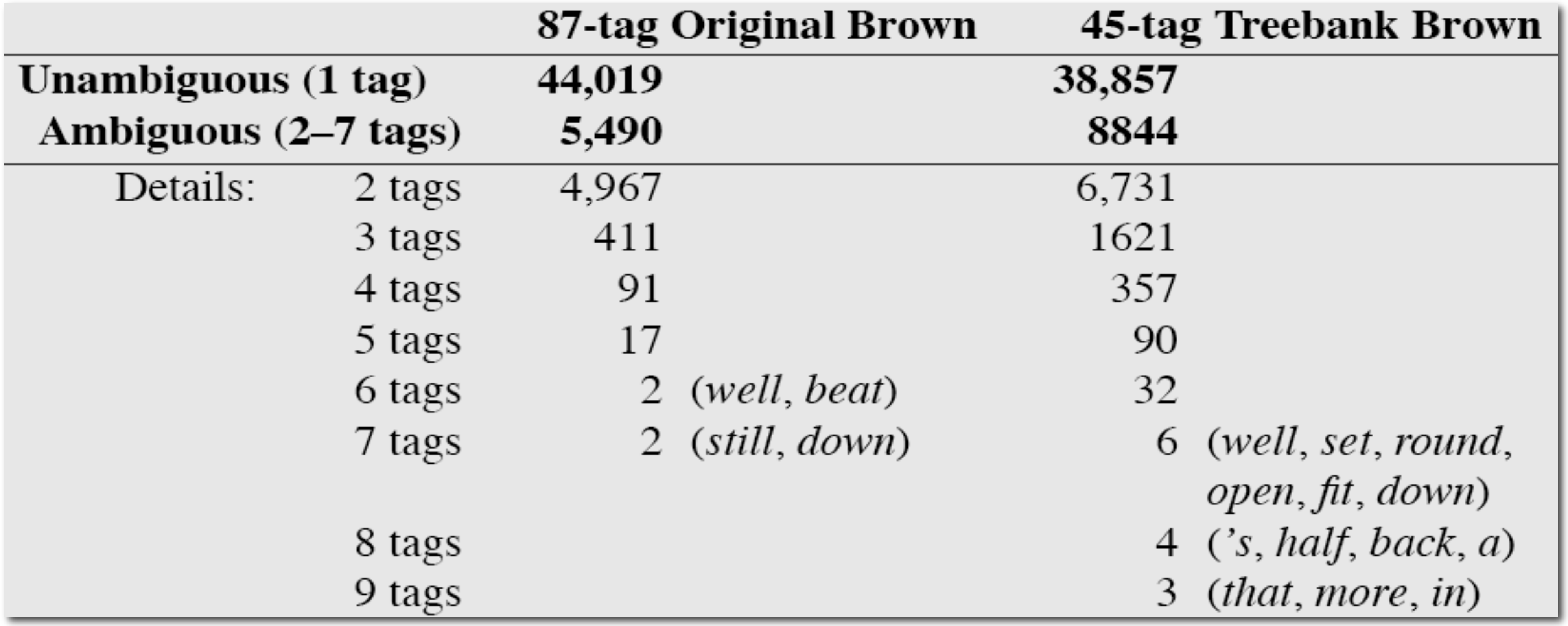
## POS Tagging example

| WORD | tag |
|---|---|
| **the** | **DET** |
| **koala** | **N** |
| **put** | **V** |
| **the** | **DET** |
| **keys** | **N** |
| **on** | **P** |
| **the** | **DET** |
| **table** | **N** |

## POS Tagging

- Words often have more than one POS: *back*
  - The *back* door = JJ
  - On my *back* = NN
  - Win the voters *back* = RB
  - Promised to *back* the bill = VB
- The POS tagging problem is to determine the POS tag for a particular instance of a word.

## How Hard is POS Tagging? Measuring Ambiguity



| | | 87-tag Original Brown | | 45-tag Treebank Brown | |
|---|---|---|---|---|---|
| **Unambiguous (1 tag)** | | **44,019** | | **38,857** | |
| **Ambiguous (2–7 tags)** | | **5,490** | | **8844** | |
| Details: | 2 tags | 4,967 | | 6,731 | |
| | 3 tags | 411 | | 1621 | |
| | 4 tags | 91 | | 357 | |
| | 5 tags | 17 | | 90 | |
| | 6 tags | 2 | (*well*, *beat*) | 32 | |
| | 7 tags | 2 | (*still*, *down*) | 6 | (*well*, *set*, *round*, *open*, *fit*, *down*) |
| | 8 tags | | | 4 | (*’s*, *half*, *back*, *a*) |
| | 9 tags | | | 3 | (*that*, *more*, *in*) |

## How difficult is POS tagging?

- About 11% of the word types in the Brown corpus are ambiguous with regard to part of speech
- But they tend to be very common words
- 40% of the word tokens are ambiguous

## Rule-Based Tagging

- Start with a dictionary
- Assign all possible tags to words from the dictionary
- Write rules by hand to selectively remove tags
- Leaving the correct tag for each word.

## Start With a Dictionary

| | |
|---|---|
| she: | PRP |
| promised: | VBN,VBD |
| to | TO |
| back: | VB, JJ, RB, NN |
| the: | DT |
| bill: | NN, VB |

- Etc… for the ~100,000 words of English with more than 1 tag

## Assign Every Possible Tag and apply rules

| | | | | | |
|---|---|---|---|---|---|
| | | | NN | | |
| | | | RB | | |
| | VBN | | JJ | | VB |
| PRP | VBD | TO | VB | DT | NN |
| **She** | **promised** | **to** | **back** | **the** | **bill** |

## Assign Every Possible Tag and apply rules

| | | | | | |
|---|---|---|---|---|---|
| | | | NN | | |
| | | | RB | | |
| | VBN | | JJ | | ~~VB~~ |
| PRP | VBD | TO | VB | **DT** | NN |
| **She** | **promised** | **to** | **back** | **the** | **bill** |

# Assign Every Possible Tag and apply rules

| | | | | | |
|---|---|---|---|---|---|
| | | | NN | | |
| | | | RB | | |
| | VBN | | ~~JJ~~ | | |
| PRP | VBD | TO | VB | **DT** | NN |
| **She** | **promised** | **to** | **back** | **the** | **bill** |

## Simple Statistical Approaches: Idea 1

Simply assign each word its most likely POS.

Success rate: 91%!

| Word | POS listings in Brown | | |
|---|---|---|---|
| heat | noun/89 | **verb/5** | |
| oil | **noun/87** | | |
| in | **prep/20731** | noun/1 | adv/462 |
| a | **det/22943** | noun/50 | noun-proper/30 |
| large | **adj/354** | noun/2 | adv/5 |
| pot | **noun/27** | | |

## Simple Statistical Approaches: Idea 2

For a string of words

$$W = w_1 w_2 w_3 \ldots w_n$$

find the string of POS tags

$$T = t_1\, t_2\, t_3 \ldots t_n$$

which maximizes $P(T|W)$

- i.e., the probability of tag string T given that the word string was W
- i.e., that W was tagged T

## The Sparse Data Problem

A Simple, Impossible Approach to Compute P(T|W):

Count up instances of the string "heat oil in a large pot" in the training corpus, and pick the most common tag assignment to the string..

## A Practical Statistical Tagger

**By Bayes' Rule:**

$$\mathbf{P(T|W)} = \frac{P(W|T) * P(T)}{P(W)}$$

so to maximize $P(T|W)$, need to maximize $P(W|T) * P(T)$.

**To compute** $\mathbf{P(T)}$**:** By the chain rule,

$$P(T) = P(t_1) * P(t_2|t_1) * P(t_3|t_1 t_2) * \ldots * P(t_n|t_1 \ldots t_{n-1})$$

## A Practical Statistical Tagger II

But we can't accurately estimate more than tag bigrams or so…

Again, we change to a model that we CAN estimate:

**A Markov Assumption:** $\mathrm{P}(\mathrm{t_i}|\mathrm{t_1}\ldots\mathrm{t_{i-1}}) = \mathrm{P}(\mathrm{t_i}|\mathrm{t_{i-1}})$

By which

$$P(T) = P(t_1)*P(t_2|t_1)*P(t_3|t_2)*\ldots*P(t_n|t_{n-1})$$

## A Practical Statistical Tagger III

**To compute $\mathrm{P(W|T)}$, similarly assume**

$$\mathrm{P(w_i|t_1 \ldots t_n) = P(w_i|t_i)}$$

By which

$$\boldsymbol{P(W|T) = P(w_1|t_1) * P(w_2|t_2) * \ldots * P(w_n|t_n)}$$

So, for a given string W = $w_1w_2w_3 \ldots w_{n,}$ the tagger needs to *find the string of tags T which maximizes*

$$\begin{aligned} P(T) * P(W|T) \ = & \\ & P(t_1) * P(t_2|t_1) * P(t_3|t_2) * \ldots * P(t_n|t_{n-1}) * \\ & P(w_1|t_1) * P(w_2|t_2) * \ldots * P(w_n|t_n) \end{aligned}$$

## Training and Performance

- To estimate the parameters of this model, given an annotated training corpus:

To estimate $\mathrm{P}(\mathrm{t_i}|\mathrm{t_{i-1}})$:

$$\frac{Count(t_{i-1}t_i)}{Count(t_{i-1})}$$

To estimate $\mathrm{P}(\mathrm{w_i}|\mathrm{t_i})$:

$$\frac{Count(\ w_i \text{ tagged } t_i)}{Count(\text{ all words tagged } t_i)}$$

- Because many of these counts are small, *smoothing* is necessary for best results…
- Such taggers typically achieve about 95-96% correct tagging, **for tag sets of 40-80 tags.**

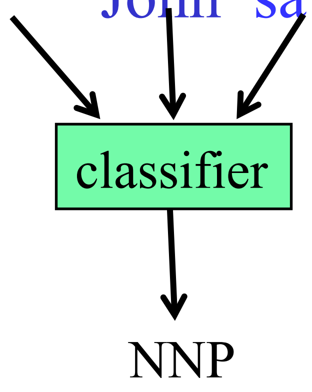
## Assigning tags to unseen words

- Pretend that each unknown word is ambiguous among all possible tags, with equal probability
- Assume that the probability distribution of tags over unknown words is like the distribution of tags over words seen only once
- Morphological clues
- Combination

## Sequence Labeling as Classification

- Classify each token independently but use as input features, information about the surrounding tokens (sliding window).

John saw the saw and decided to take it to the table.



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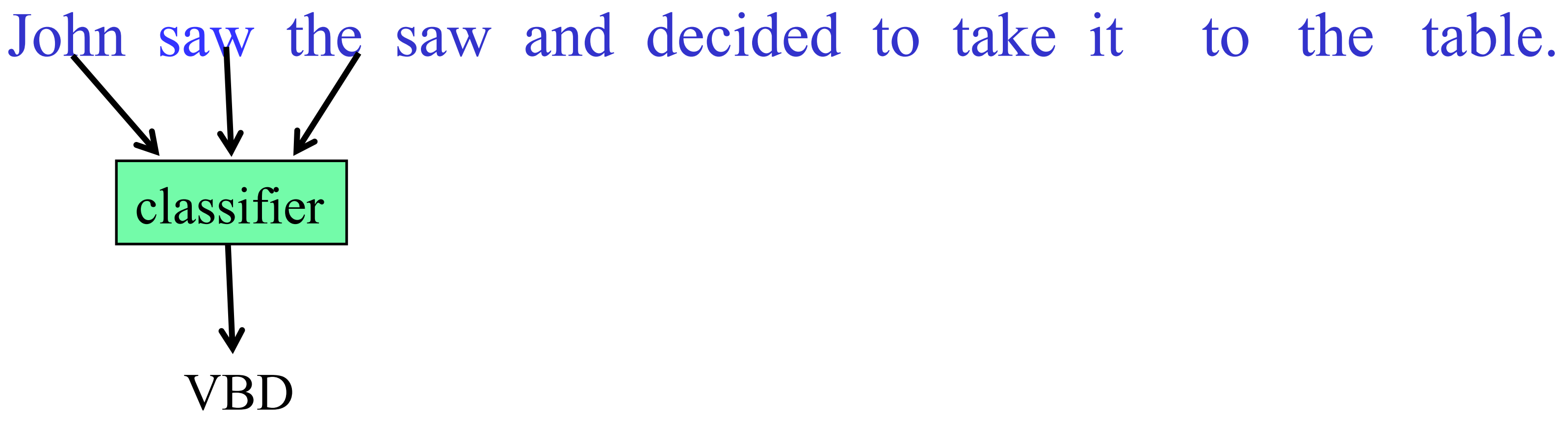

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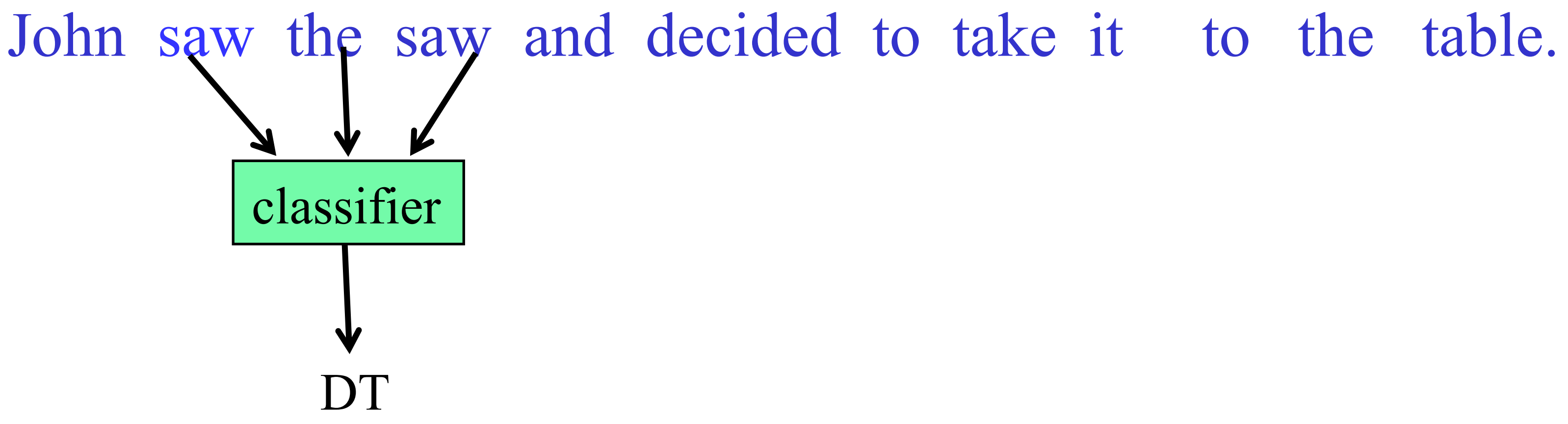

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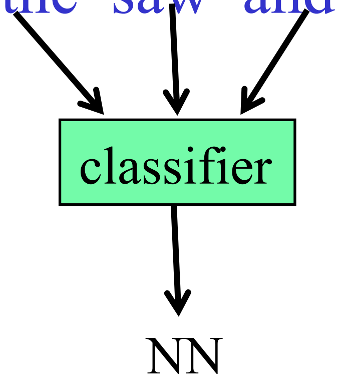

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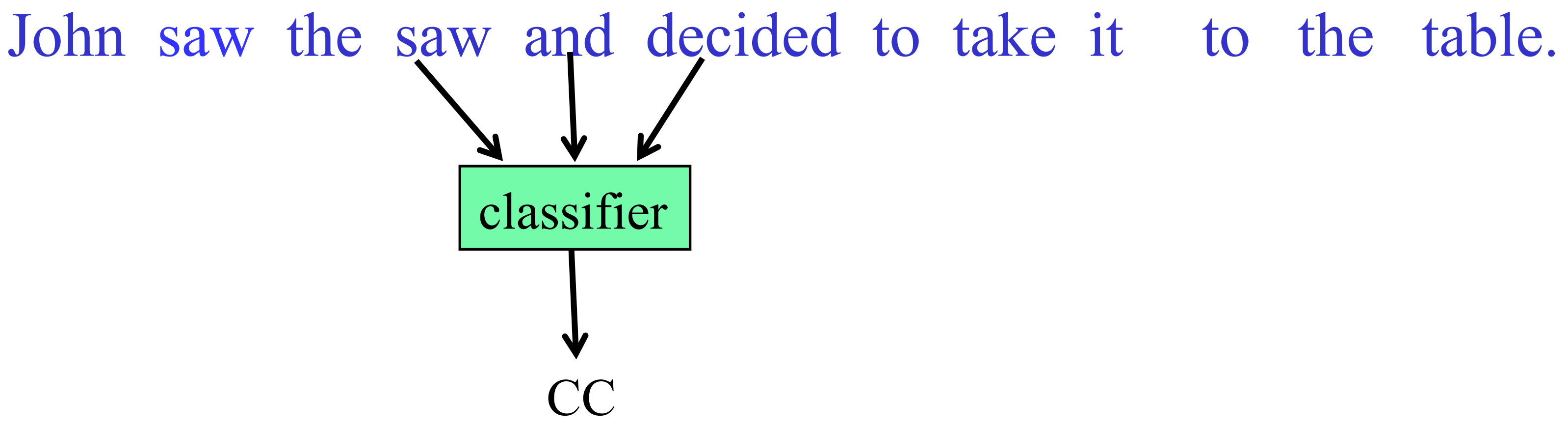

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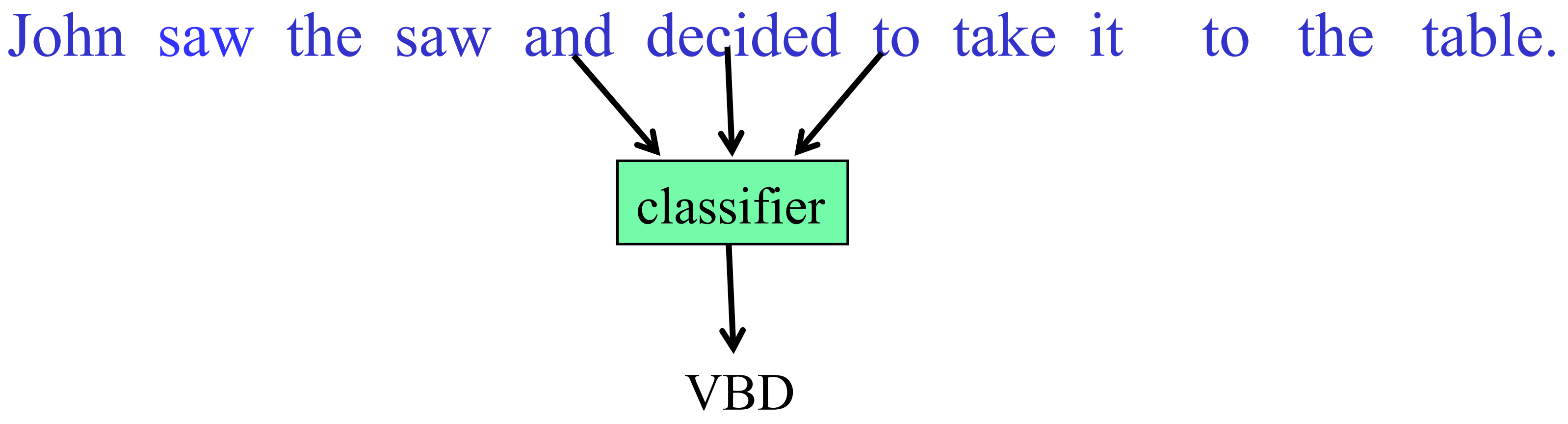

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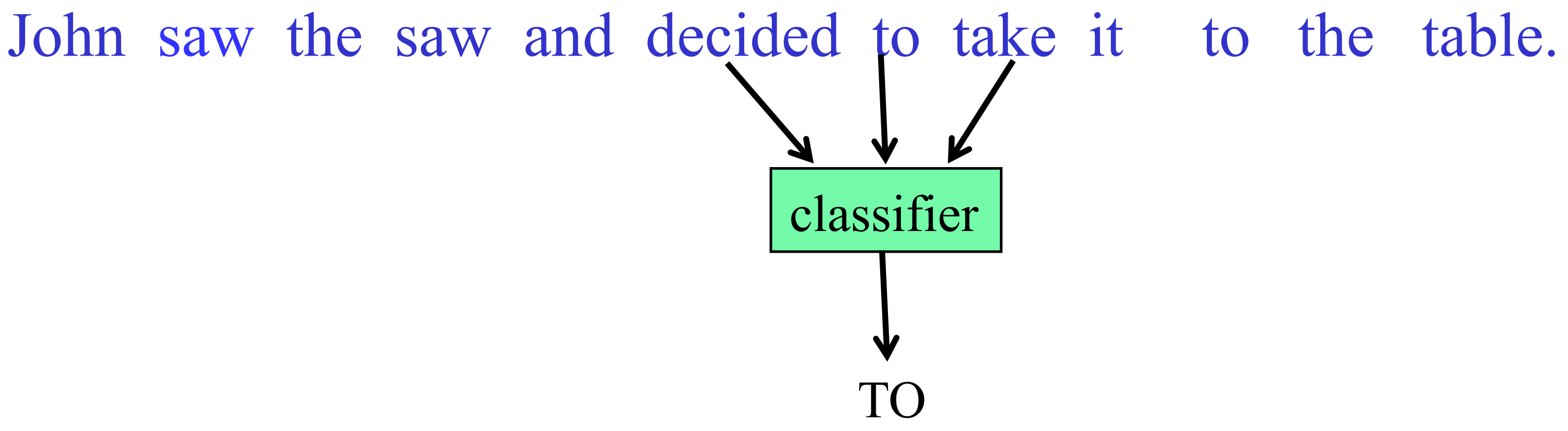

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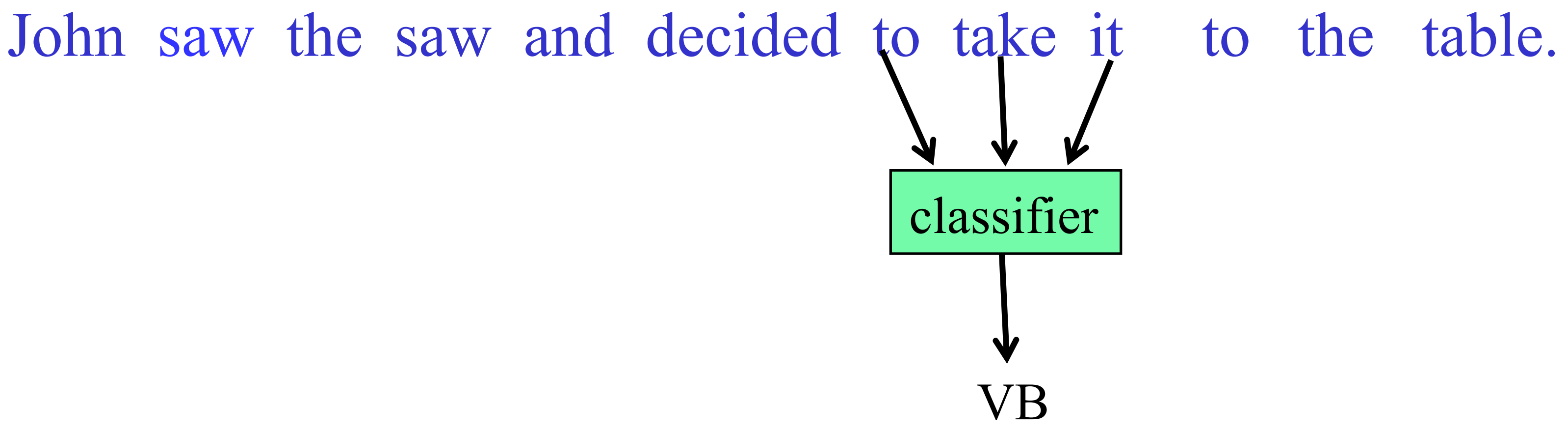

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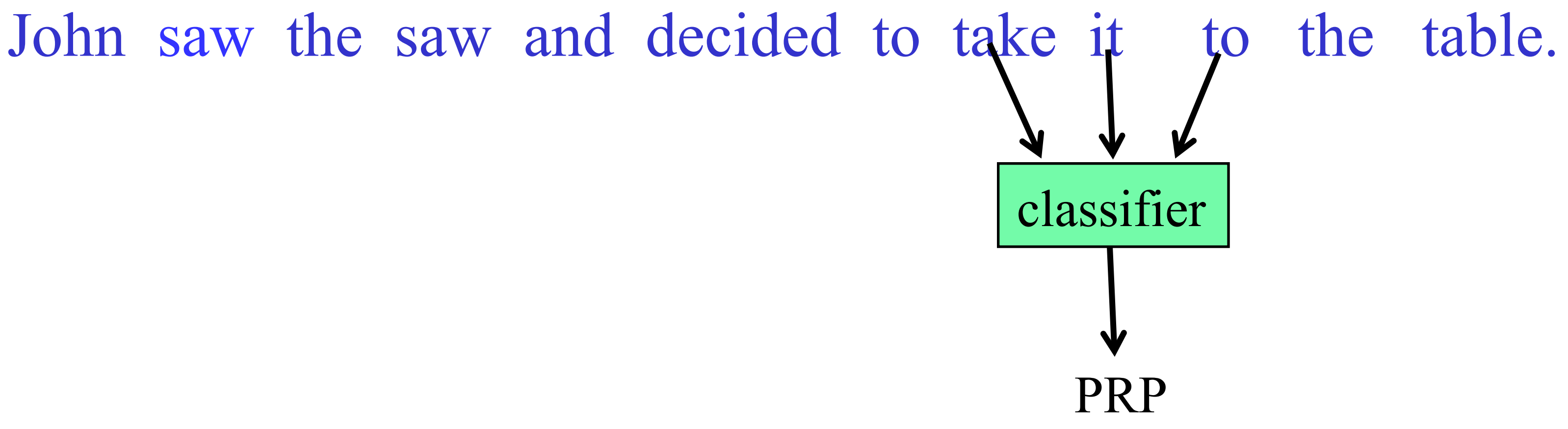

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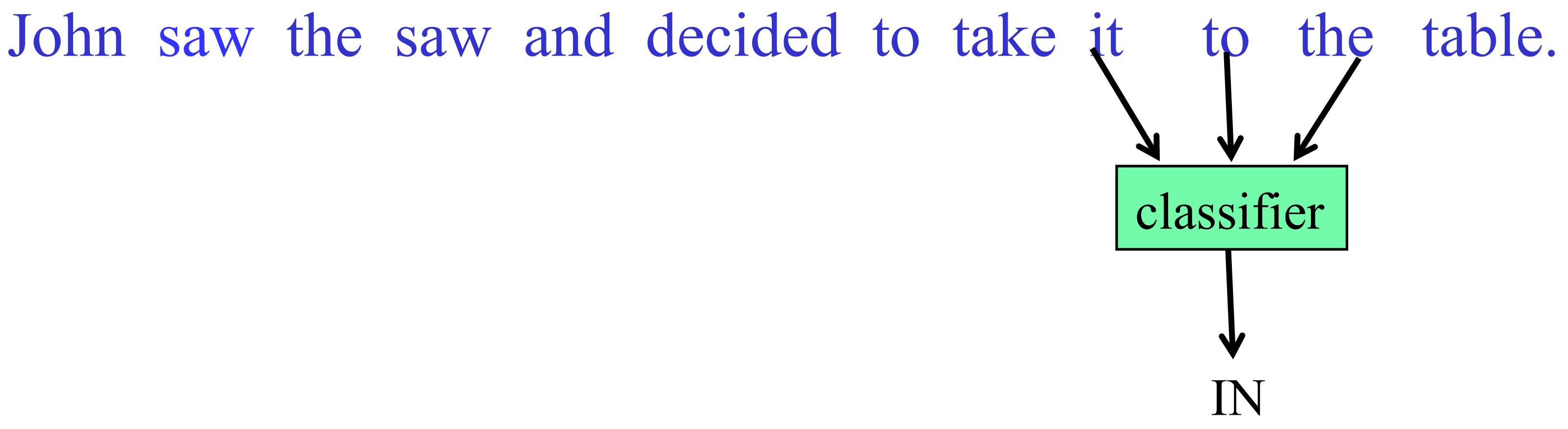

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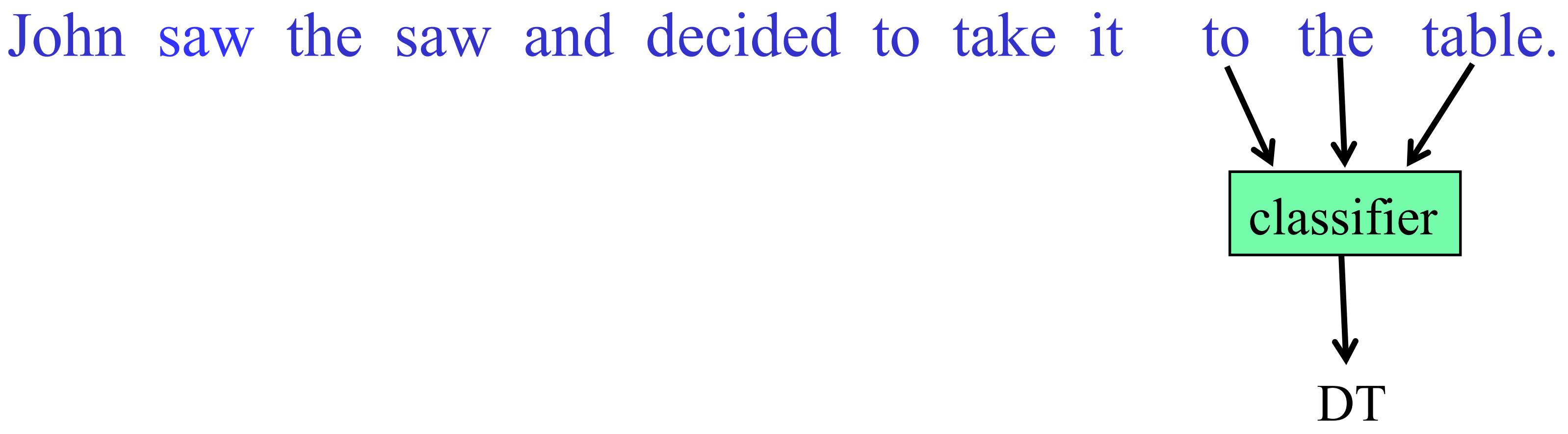

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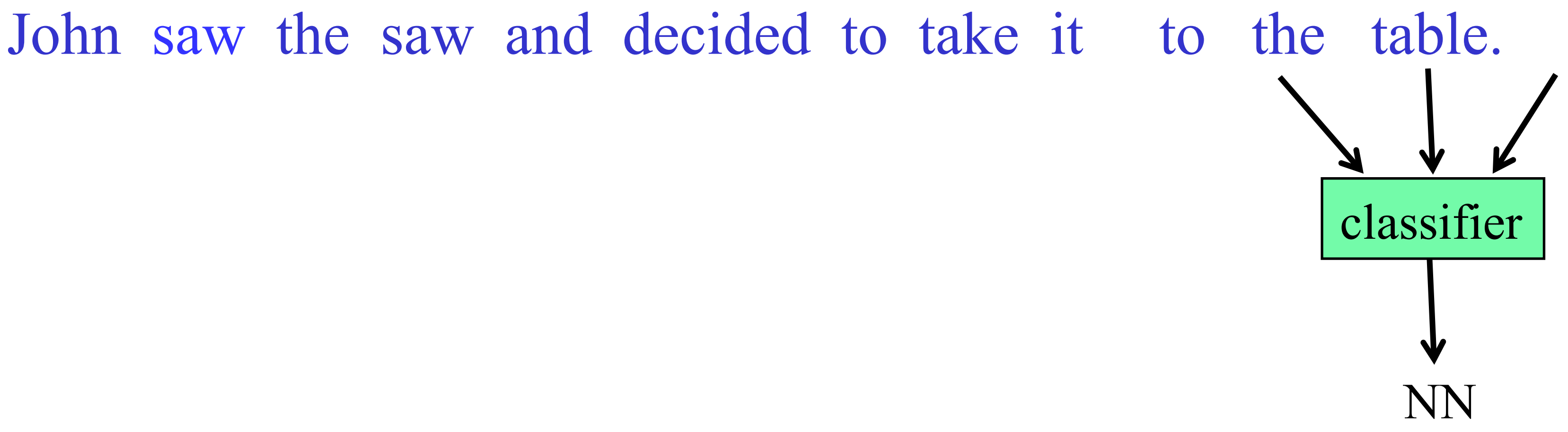


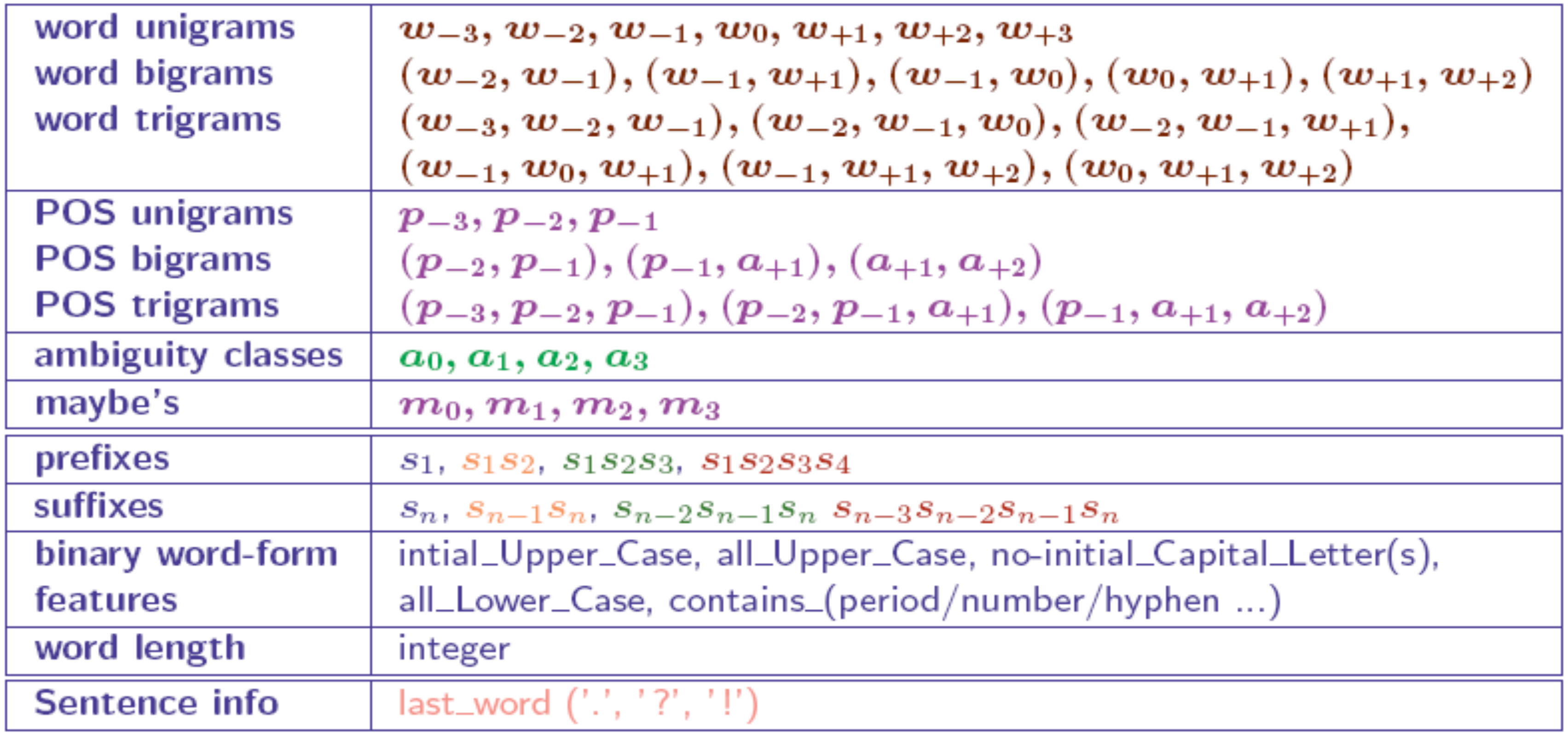
## Sequence Labeling as Classification Using Outputs as Inputs

- Better input features are usually the categories of the surrounding tokens, but these are not available yet.
- Can use category of either the preceding or succeeding tokens by going forward or back and using previous output.

## SVMs for tagging

- http://www.lsi.upc.edu/~nlp/SVMTool/SVMTool.v1.4.ps
- We can use SVMs in a similar way
- We can use a window around  the word
- 97.16 % on WSJ

# SVMs for tagging



| | |
|---|---|
| word unigrams<br>word bigrams<br>word trigrams | $w_{-3}, w_{-2}, w_{-1}, w_0, w_{+1}, w_{+2}, w_{+3}$<br>$(w_{-2}, w_{-1}), (w_{-1}, w_{+1}), (w_{-1}, w_0), (w_0, w_{+1}), (w_{+1}, w_{+2})$<br>$(w_{-3}, w_{-2}, w_{-1}), (w_{-2}, w_{-1}, w_0), (w_{-2}, w_{-1}, w_{+1}),$<br>$(w_{-1}, w_0, w_{+1}), (w_{-1}, w_{+1}, w_{+2}), (w_0, w_{+1}, w_{+2})$ |
| POS unigrams<br>POS bigrams<br>POS trigrams | $p_{-3}, p_{-2}, p_{-1}$<br>$(p_{-2}, p_{-1}), (p_{-1}, a_{+1}), (a_{+1}, a_{+2})$<br>$(p_{-3}, p_{-2}, p_{-1}), (p_{-2}, p_{-1}, a_{+1}), (p_{-1}, a_{+1}, a_{+2})$ |
| ambiguity classes | $a_0, a_1, a_2, a_3$ |
| maybe's | $m_0, m_1, m_2, m_3$ |
| prefixes | $s_1$, $s_1s_2$, $s_1s_2s_3$, $s_1s_2s_3s_4$ |
| suffixes | $s_n$, $s_{n-1}s_n$, $s_{n-2}s_{n-1}s_n$ $s_{n-3}s_{n-2}s_{n-1}s_n$ |
| binary word-form features | intial_Upper_Case, all_Upper_Case, no-initial_Capital_Letter(s), all_Lower_Case, contains_(period/number/hyphen ...) |
| word length | integer |
| Sentence info | last_word ('.', '?', '!') |

From Gimenez & Marquez

## No sequence modeling

- Can do surprisingly well just looking at a word by itself:

| | |
|---|---|
| Word | the: the → DT |
| Lowercased word | Importantly: importantly → RB |
| Prefixes | unfathomable: un- → JJ |
| Suffixes | Surprisingly: -ly → RB |
| Capitalization | Meridian: CAP → NNP |
| Word shapes | 35-year: d-x → JJ |

- Then build a maxent (or whatever) model to predict tag
- Maxent P(t|w): 93.7% / 82.6%

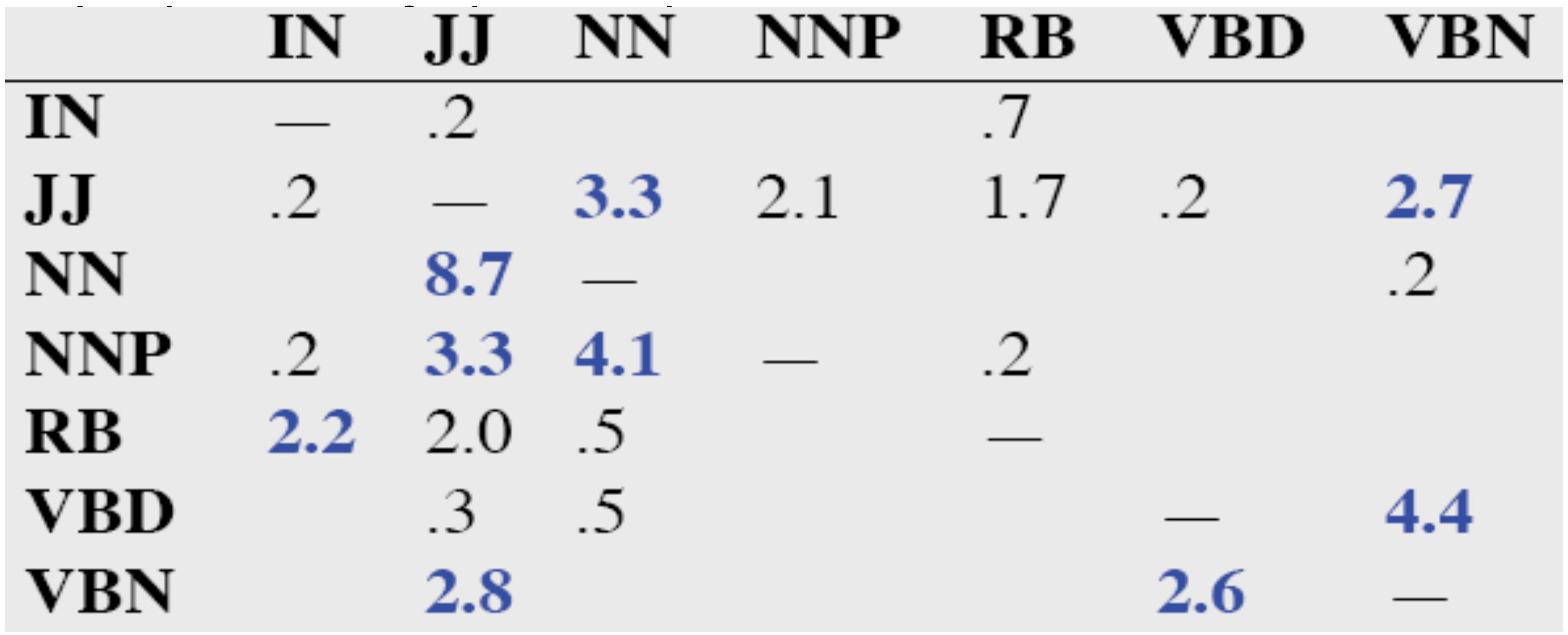
## Evaluation

- So once you have you POS tagger running how do you evaluate it?
  - Overall error rate with respect to a gold-standard test set.
  - Error rates on particular tags
  - Error rates on particular words
  - Tag confusions...

## Evaluation

- The result is compared with a manually coded “Gold Standard”
  - Typically accuracy reaches 96-97%
  - This may be compared with result for a baseline tagger (one that uses no context).
- Important: 100% is impossible even for human annotators.

# Error Analysis



| | IN | JJ | NN | NNP | RB | VBD | VBN |
|---|---|---|---|---|---|---|---|
| IN | — | .2 | | | .7 | | |
| JJ | .2 | — | 3.3 | 2.1 | 1.7 | .2 | 2.7 |
| NN | | 8.7 | — | | | | .2 |
| NNP | .2 | 3.3 | 4.1 | — | .2 | | |
| RB | 2.2 | 2.0 | .5 | | — | | |
| VBD | | .3 | .5 | | | — | 4.4 |
| VBN | | 2.8 | | | | 2.6 | — |

- See what errors are causing problems
  - Noun (NN) vs ProperNoun (NNP) vs Adj (JJ)
  - Past tense verb form (VBD) vs Participle (VBN) vs Adjective (JJ)

## Named Entity Recognition

# Linguistically Difficult Problem

- NE involves **identification** of *proper names* in texts, and **classification** into a set of predefined categories of interest.
- Three universally accepted categories: **person**, **location** and **organisation**
- Other common tasks: recognition of **date/time expressions**, **measures** (percent, money, weight etc), email addresses etc.
- Other domain-specific entities: names of drugs, medical conditions, names of ships, bibliographic references etc.

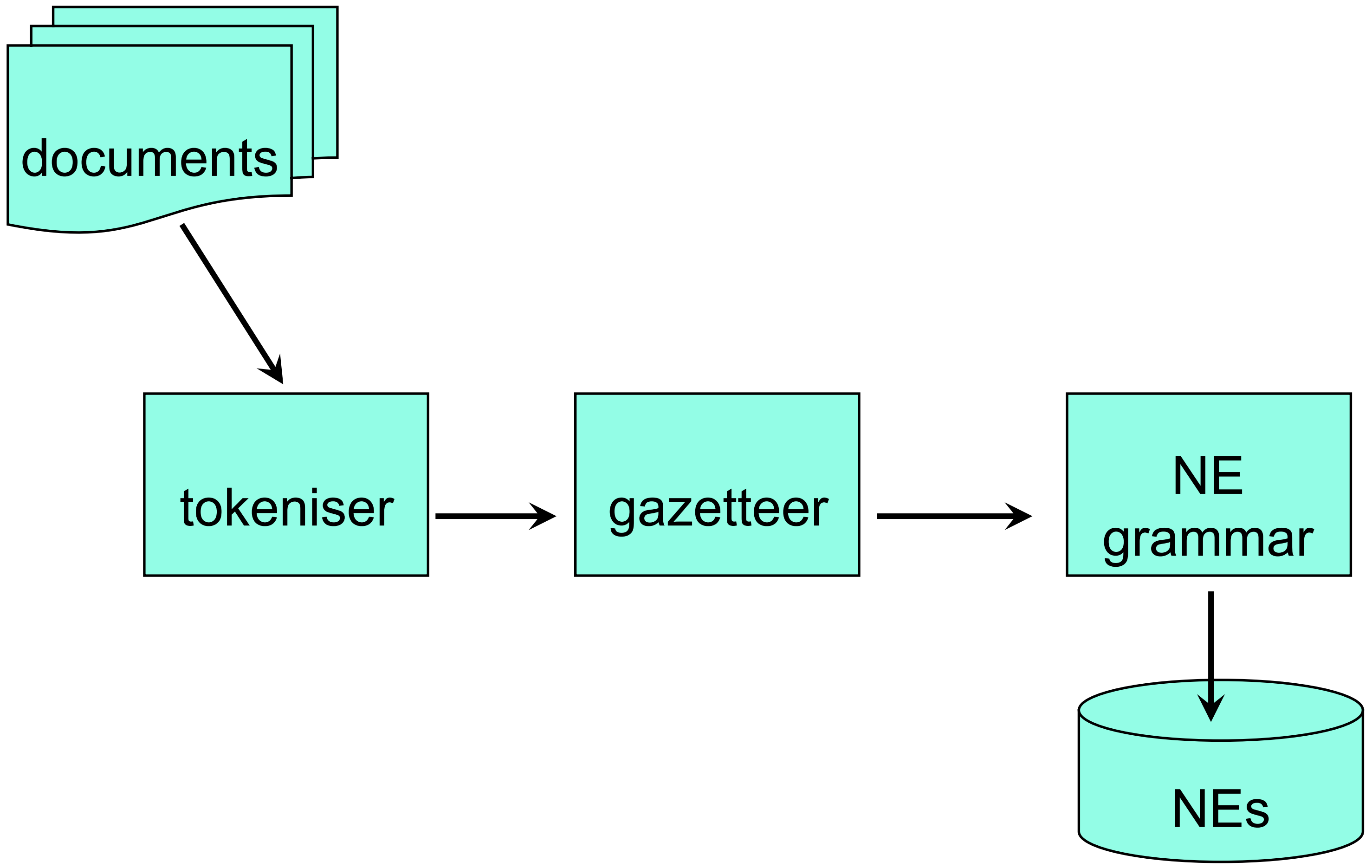
## Applications of NER

- Yellow pages with local search capabilities
- Monitoring trends and sentiment in textual social media
- Interactions between genes and cells in biology and genetics

## Problems in NE Task Definition

- Category definitions are intuitively quite clear, but there are many grey areas.
- Many of these grey area are caused by **metonymy**.
  - Organisation vs. Location : “**England** won the World Cup” vs. “The World Cup took place in **England**”.
  - Company vs. Artefact: “shares in **MTV**” vs. “watching **MTV**”
  - Location vs. Organisation: “she met him at **Heathrow**” vs. “the **Heathrow** authorities”

## NE System Architecture



## Approach con’t

- Again Text Categorization
- N-grams in a window centered on the NER
- Features similar to POS-tagging
  - **Gazetteer**
  - Capitalize
  - Beginning of the sentence
  - Is it all capitalized

## Approach con't

- NE task in two parts:
  - Recognising the entity boundaries
  - Classifying the entities in the NE categories
- Tokens in text are often coded with the IOB scheme
  - O – outside, B-XXX – first word in NE, I-XXX – all other words in NE
  - Easy to convert to/from inline MUC-style markup
  -

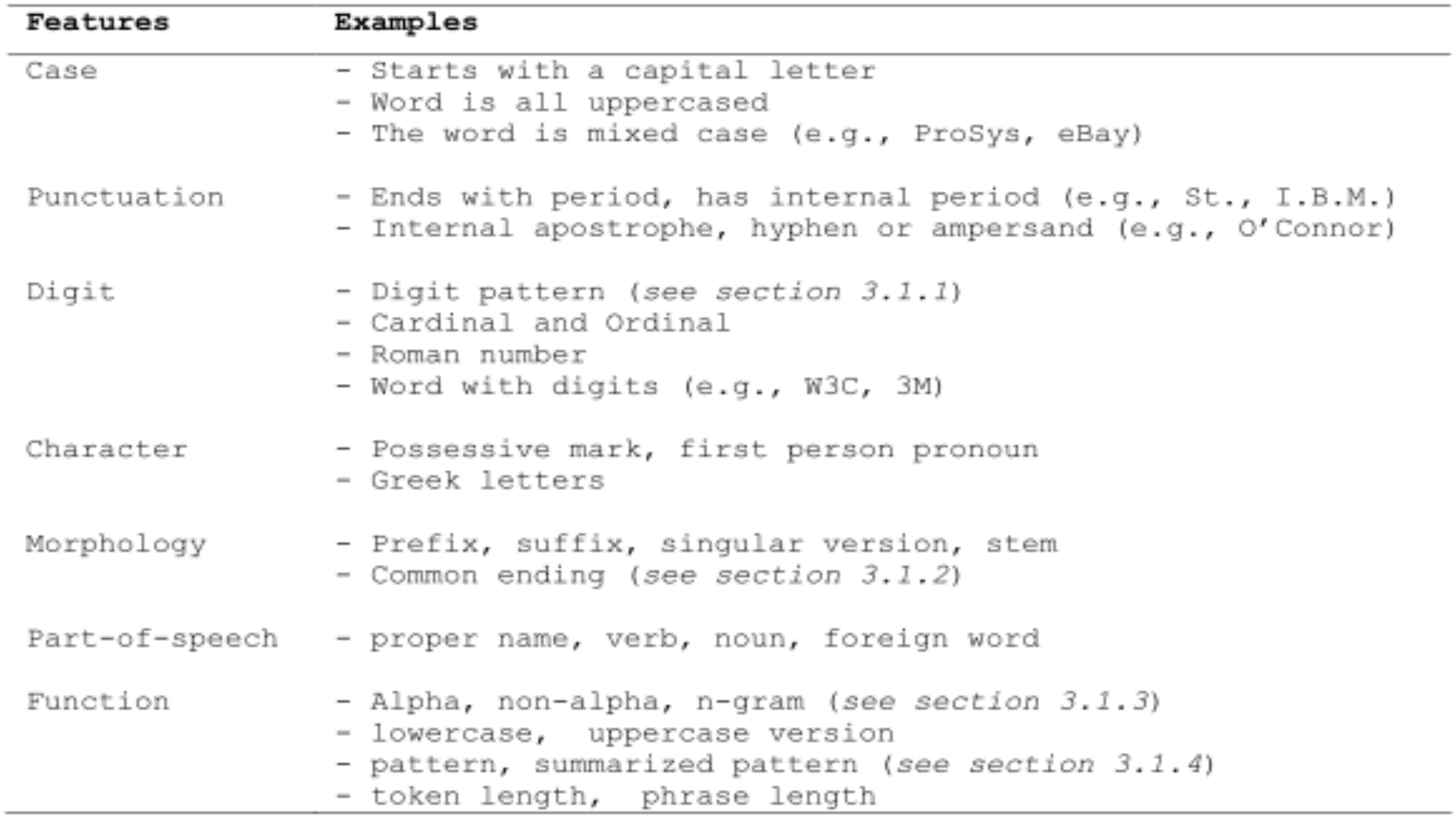
| | |
|---|---|
| Argentina | B-LOCATION |
| played | O |
| with | O |
| Del | B-PERSON |
| Bosque | I-PERSON |

## Feature types

- Word-level features
- List lookup features
- Document & corpus features

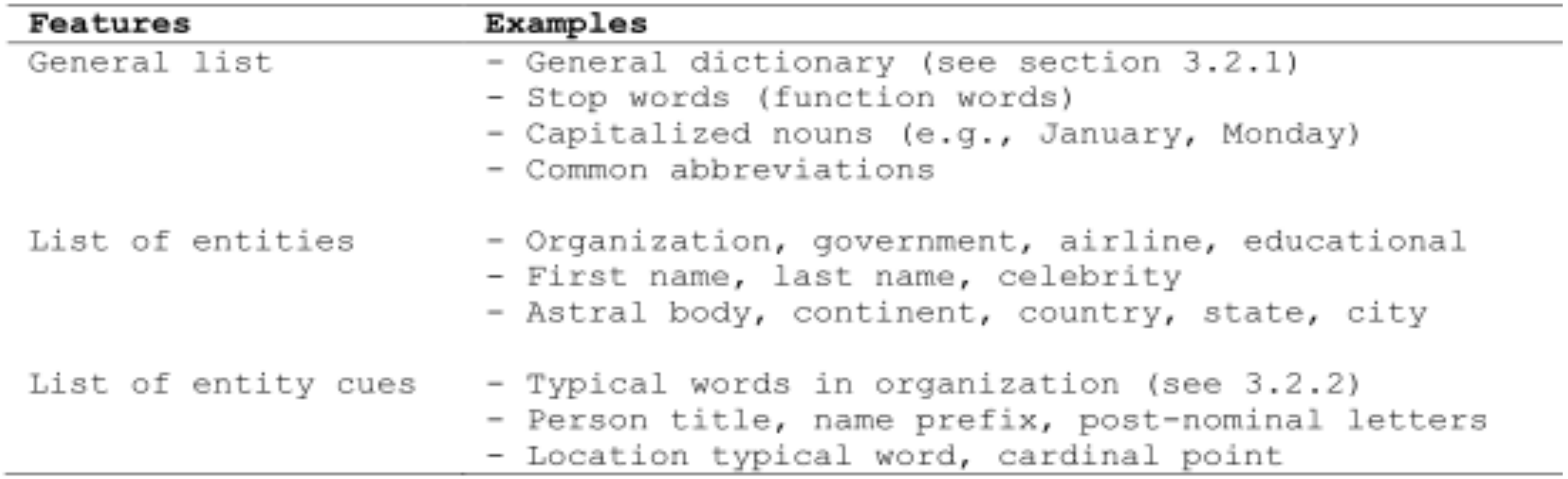
## Word-level features

Table 1: Word-level features



| Features | Examples |
|---|---|
| Case | - Starts with a capital letter<br>- Word is all uppercased<br>- The word is mixed case (e.g., ProSys, eBay) |
| Punctuation | - Ends with period, has internal period (e.g., St., I.B.M.)<br>- Internal apostrophe, hyphen or ampersand (e.g., O'Connor) |
| Digit | - Digit pattern (*see section 3.1.1*)<br>- Cardinal and Ordinal<br>- Roman number<br>- Word with digits (e.g., W3C, 3M) |
| Character | - Possessive mark, first person pronoun<br>- Greek letters |
| Morphology | - Prefix, suffix, singular version, stem<br>- Common ending (*see section 3.1.2*) |
| Part-of-speech | - proper name, verb, noun, foreign word |
| Function | - Alpha, non-alpha, n-gram (*see section 3.1.3*)<br>- lowercase, uppercase version<br>- pattern, summarized pattern (*see section 3.1.4*)<br>- token length, phrase length |

## List lookup features



| Features | Examples |
|---|---|
| General list | - General dictionary (see section 3.2.1)<br>- Stop words (function words)<br>- Capitalized nouns (e.g., January, Monday)<br>- Common abbreviations |
| List of entities | - Organization, government, airline, educational<br>- First name, last name, celebrity<br>- Astral body, continent, country, state, city |
| List of entity cues | - Typical words in organization (see 3.2.2)<br>- Person title, name prefix, post-nominal letters<br>- Location typical word, cardinal point |

Exact match vs. flexible match

Stems (remove inflectional and derivational suffixes)

Lemmas (remove inflectional suffixes only)

Small lexical variations (small edit distance)

Normalize words to their Soundex codes

# Document and corpus features

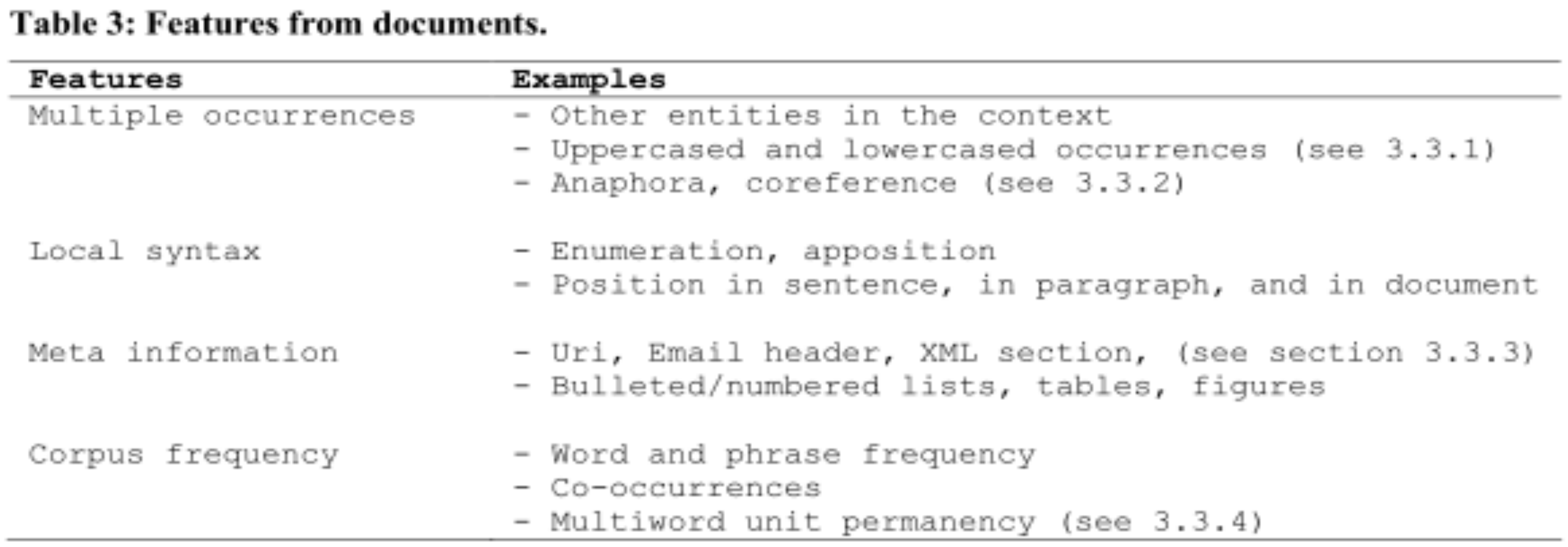


Table 3: Features from documents.

| Features | Examples |
|---|---|
| Multiple occurrences | - Other entities in the context<br>- Uppercased and lowercased occurrences (see 3.3.1)<br>- Anaphora, coreference (see 3.3.2) |
| Local syntax | - Enumeration, apposition<br>- Position in sentence, in paragraph, and in document |
| Meta information | - Uri, Email header, XML section, (see section 3.3.3)<br>- Bulleted/numbered lists, tables, figures |
| Corpus frequency | - Word and phrase frequency<br>- Co-occurrences<br>- Multiword unit permanency (see 3.3.4) |

## Examples of uses of document and corpus features

- Meta-information (e.g. names in email headers)
- Multiword entities that do not contain rare lowercase words of a relatively long size are candidate NEs
- Frequency of a word (e.g. Life) divided by its frequency in case insensitive form

## Contributions on Italian Versions

- Annotation of 220 documents from “La Repubblica”
- Modification of some features, e.g. “date”
- Accent treatments, e.g Cinecittà

## English Results

```
                  ACT| REC PRE
--------------------+---------
SUBTASK SCORES      |
enamex              |
 organization    454|  85  84
 person          381|  90  88
 location        126|  94  82
timex               |
 date            109|  95  97
 time              0|   0   0
numex               |
 money            87|  97  85
 percent          26|  94  62
```

Precision = 91%
Recall = 87%
F1 = 88.61

# Italian Corpus from "La Repubblica"

## Training data

| Class | Subtype | N° | Total |
|---|---|---|---|
| ENAMEX | Person | 1825 | 3886 |
| | Organization | 769 | |
| | Location | 1292 | |
| TIMEX | Date | 511 | 613 |
| | Time | 102 | |
| NUMEX | Money | 105 | 223 |
| | Percent | 118 | |

## Italian Corpus from “La Repubblica”

### Test data

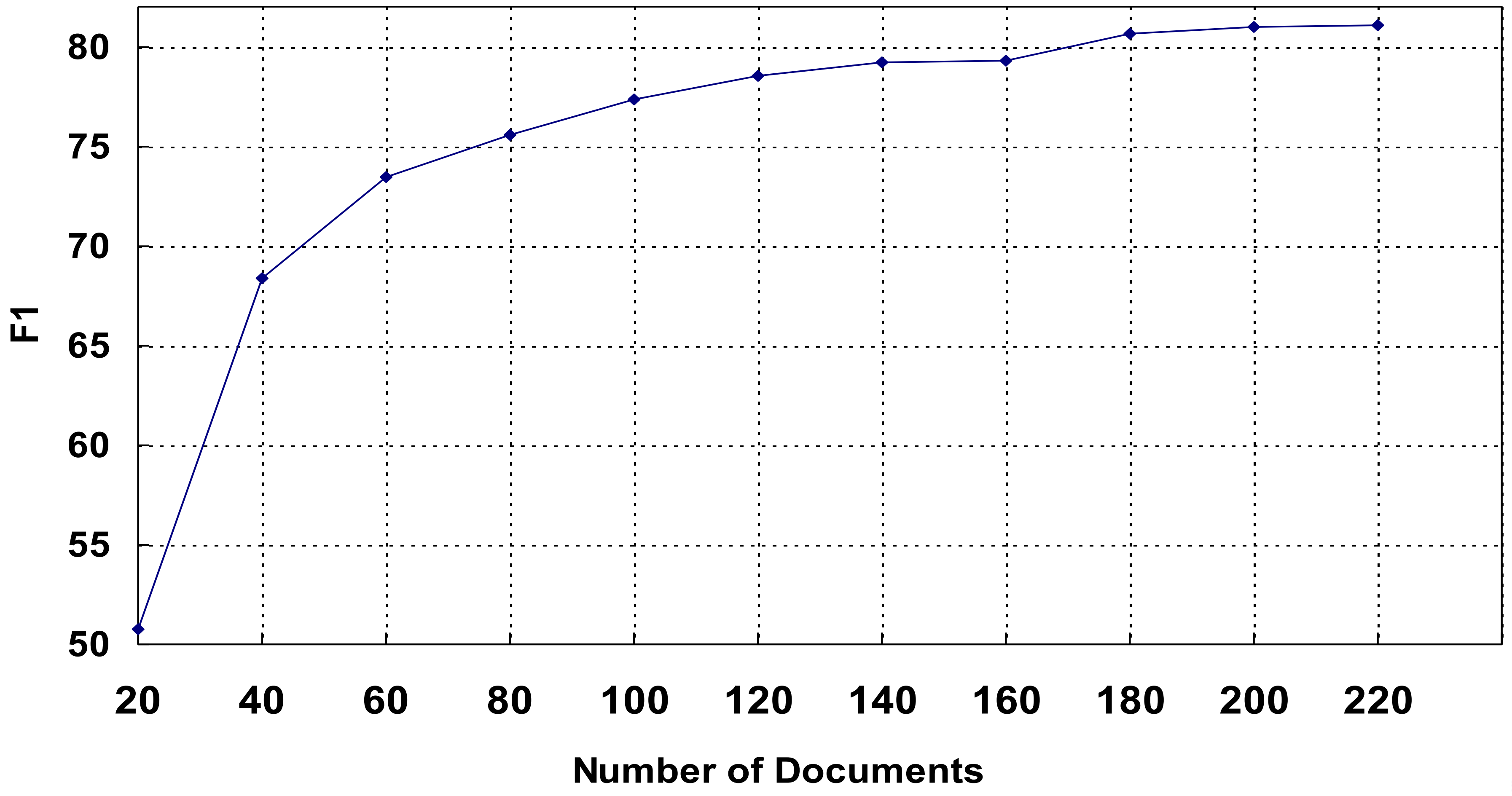
| Class | Subtype | N° | Total |
|---|---|---|---|
| ENAMEX | Person | 333 | 537 |
| | Organization | 129 | |
| | Location | 75 | |
| TIMEX | Date | 45 | 48 |
| | Time | 3 | |
| NUMEX | Money | 5 | 13 |
| | Percent | 8 | |

## Results of the Italian NER

- 11-fold cross validation (confidence at 99%)

| | Basic Model | +Modified Features | +Accent treatment |
|---|---|---|---|
| **Average F1** | **77.98±2.5** | **79.08±2.5** | **79.75±2.5** |

# Learning Curve



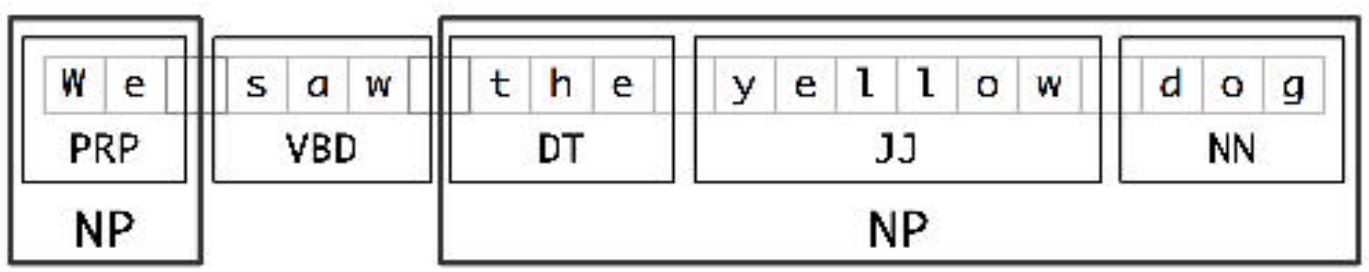
## Neural Networks for NER

In the last decade Neural Networks have obtained state of the art results for NER.

- **English** CoNLL 2003 dataset:
  Bi-LSTM: 90.94 F1 (Lample et al. 2016)
- **Italian** Evalita 2009 dataset (500+ documents):
  Recurrent Context Window Network: 82.81 F1 (Bonadiman et al. 2015)

## Chunking

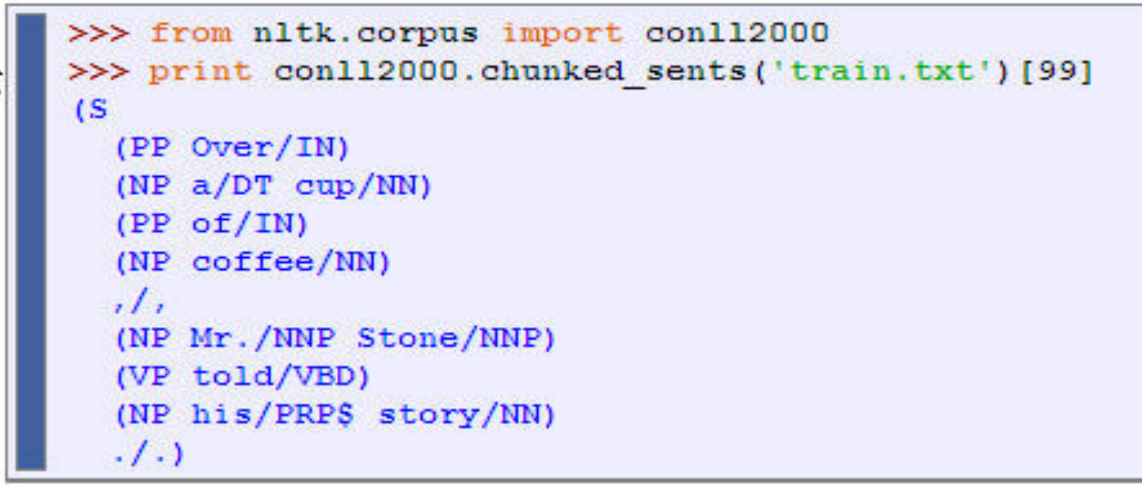
- Chunking useful for entity recognition
- Segment and label multi-token sequences



- Each of these larger boxes is called a chunk

## Chunking

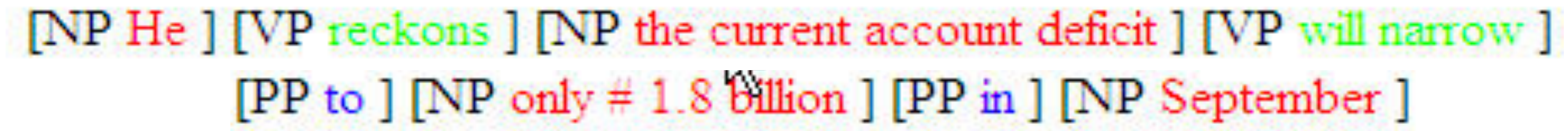
- The CoNLL 2000 corpus contains 270k words of Wall Street Journal text, annotated with part-of-speech tags and chunk tags.



```
>>> from nltk.corpus import conll2000
>>> print conll2000.chunked_sents('train.txt')[99]
(S
  (PP Over/IN)
  (NP a/DT cup/NN)
  (PP of/IN)
  (NP coffee/NN)
  ,/,
  (NP Mr./NNP Stone/NNP)
  (VP told/VBD)
  (NP his/PRP$ story/NN)
  ./.)
```

Three chunk types in CoNLL 2000:

- NP chunks
- VP chunks
- PP chunks



[NP He ] [VP reckons ] [NP the current account deficit ] [VP will narrow ] [PP to ] [NP only # 1.8 billion ] [PP in ] [NP September ]