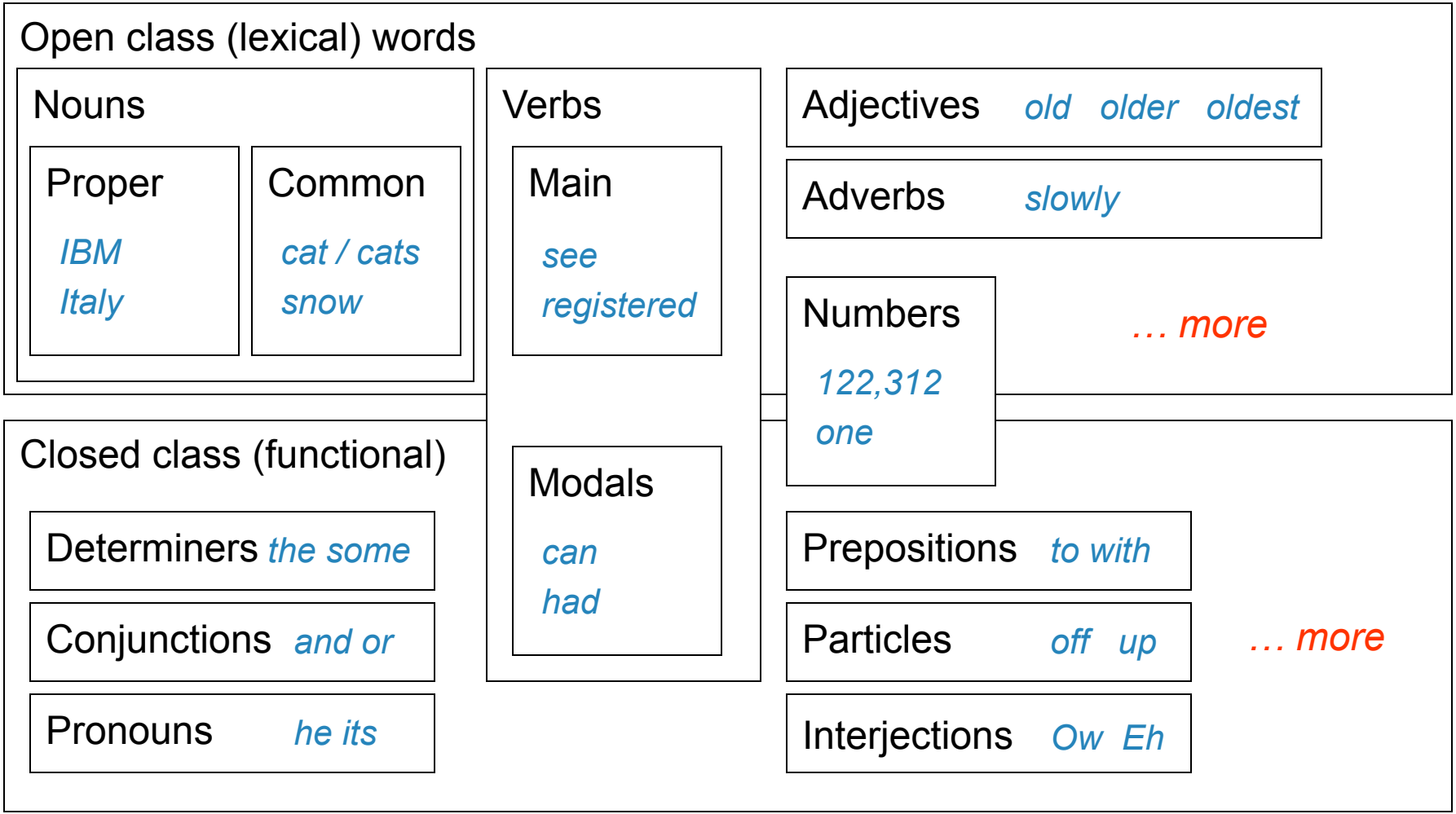

# Part-of-speech tagging

A simple but useful form of linguistic analysis

Christopher Manning


# Parts of Speech

- Perhaps starting with Aristotle in the West (384–322 BCE), there was the idea of having parts of speech
  - a.k.a lexical categories, word classes, “tags”, POS
- It comes from Dionysius Thrax of Alexandria (c. 100 BCE) the idea that is still with us that there are 8 parts of speech
  - But actually his 8 aren’t exactly the ones we are taught today
    - Thrax: noun, verb, article, adverb, preposition, conjunction, participle, pronoun
    - School grammar: noun, verb, adjective, adverb, preposition, conjunction, pronoun, interjection


Open class (lexical) words
Nouns
Proper
IBM
Italy
Common
cat / cats
snow
Verbs
Main
see
registered
Adjectives old older oldest
Adverbs slowly
Numbers
122,312
one
… more
Closed class (functional)
Modals
can
had
Determiners the some
Conjunctions and or
Pronouns he its
Prepositions to with
Particles off up
Interjections Ow Eh
… more


# Open vs. Closed classes

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


# 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.


# POS Tagging

- Input: Plays well with others
- Ambiguity: NNS/VBZ UH/JJ/NN/RB IN NNS
- Output: Plays/VBZ well/RB with/IN others/NNS
- Uses:
  - Text-to-speech (how do we pronounce "lead"?)
  - Can write regexps like (Det) Adj* N+ over the output for phrases, etc.
  - As input to or to speed up a full parser
  - If you know the tag, you can back off to it in other tasks

Penn Treebank POS tags


# POS tagging performance

- How many tags are correct? (Tag accuracy)
  - About 97% currently
  - But baseline is already 90%
    - Baseline is performance of stupidest possible method
      - Tag every word with its most frequent tag
      - Tag unknown words as nouns
  - Partly easy because
    - Many words are unambiguous
    - You get points for them (*the*, *a*, etc.) and for punctuation marks!


# 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


# 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. E.g., *that*
  - I know *that* he is honest = IN
  - Yes, *that* play was nice = DT
  - You can't go *that* far = RB
- 40% of the word tokens are ambiguous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# Part-of-speech tagging revisited

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# Sources of information

- What are the main sources of information for POS tagging?
  - Knowledge of neighboring words
    - Bill saw that man yesterday
    - NNP NN DT NN NN
    - VB VB(D) IN VB NN
  - Knowledge of word probabilities
    - *man* is rarely used as a verb….
- The latter proves the most useful, but the former also helps


# More and Better Features ➔ Feature-based tagger

- 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: Importantly: -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% overall / 82.6% unknown


# Overview: POS Tagging Accuracies

- Rough accuracies:
  - Most freq tag: ~90% / ~50%
  - Trigram HMM: ~95% / ~55%
  - Maxent P(t|w): 93.7% / 82.6%
  - TnT (HMM++): 96.2% / 86.0%
  - MEMM tagger: 96.9% / 86.9%
  - Bidirectional dependencies: 97.2% / 90.0%
  - Upper bound: ~98% (human agreement)

Most errors on unknown words


# How to improve supervised results?

- Build better features!

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | RB | | | | |
| PRP | VBD | IN | RB | IN | PRP | VBD | . |
| They | left | as | soon | as | he | arrived | . |

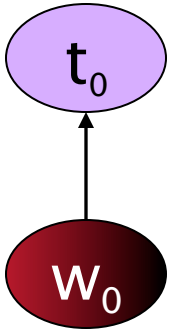
- We could fix this with a feature that looked at the next word

| | | | | | |
|---|---|---|---|---|---|
| | JJ | | | | |
| NNP | NNS | VBD | | VBN | . |
| Intrinsic | flaws | remained | | undetected | . |

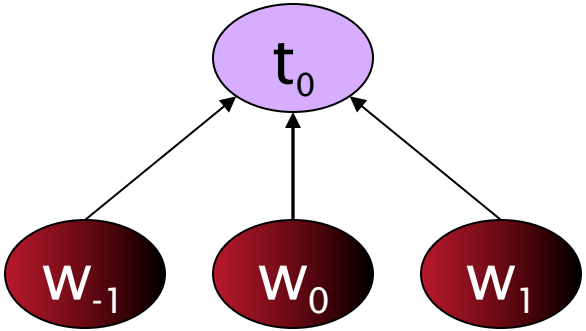
- We could fix this by linking capitalized words to their lowercase versions


# Tagging Without Sequence Information

## Baseline




## Three Words




| Model | Features | Token | Unknown | Sentence |
|---|---|---|---|---|
| Baseline | 56,805 | **93.69%** | 82.61% | 26.74% |
| 3Words | 239,767 | **96.57%** | 86.78% | 48.27% |

Using words only in a straight classifier works as well as a basic (HMM or discriminative) sequence model!!


# Summary of POS Tagging

For tagging, the change from generative to discriminative model **does not by itself** result in great improvement

One profits from models for specifying dependence on **overlapping features of the observation** such as spelling, suffix analysis, etc.

An MEMM allows integration of rich features of the observations, but can suffer strongly from assuming independence from following observations; this effect can be relieved by adding dependence on following words

This additional power (of the MEMM ,CRF, Perceptron models) has been shown to result in improvements in accuracy

The **higher accuracy** of discriminative models comes at the price of **much slower training**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