# Statistical NLP

## Spring 2008

University of California Berkeley

Lecture 7: POS Tagging

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# Parts-of-Speech (English)

- One basic kind of linguistic structure: syntactic word classes

Open class (lexical) words
- Nouns
  - Proper: *IBM*, *Italy*
  - Common: *cat / cats*, *snow*
- Verbs
  - Main: *see*, *registered*
- Adjectives *yellow*
- Adverbs *slowly*
- Numbers *122,312*, *one*
- *… more*

Closed class (functional)
- Determiners *the some*
- Conjunctions *and or*
- Pronouns *he its*
- Modals *can*, *had*
- Prepositions *to with*
- Particles *off up*
- *… more*

| | | |
|---|---|---|
| CC | conjunction, coordinating | and both but either or |
| CD | numeral, cardinal | mid-1890 nine-thirty 0.5 one |
| DT | determiner | a all an every no that the |
| EX | existential there | there |
| FW | foreign word | gemeinschaft hund ich jeux |
| IN | preposition or conjunction, subordinating | among whether out on by if |
| JJ | adjective or numeral, ordinal | third ill-mannered regrettable |
| JJR | adjective, comparative | braver cheaper taller |
| JJS | adjective, superlative | bravest cheapest tallest |
| MD | modal auxiliary | can may might will would |
| NN | noun, common, singular or mass | cabbage thermostat investment subhumanity |
| NNP | noun, proper, singular | Motown Cougar Yvette Liverpool |
| NNPS | noun, proper, plural | Americans Materials States |
| NNS | noun, common, plural | undergraduates bric-a-brac averages |
| POS | genitive marker | ' 's |
| PRP | pronoun, personal | hers himself it we them |
| PRP$ | pronoun, possessive | her his mine my our ours their thy your |
| RB | adverb | occasionally maddeningly adventurously |
| RBR | adverb, comparative | further gloomier heavier less-perfectly |
| RBS | adverb, superlative | best biggest nearest worst |
| RP | particle | aboard away back by on open through |
| TO | "to" as preposition or infinitive marker | to |
| UH | interjection | huh howdy uh whammo shucks heck |
| VB | verb, base form | ask bring fire see take |
| VBD | verb, past tense | pleaded swiped registered saw |
| VBG | verb, present participle or gerund | stirring focusing approaching erasing |
| VBN | verb, past participle | dilapidated imitated reunifed unsettled |
| VBP | verb, present tense, not 3rd person singular | twist appear comprise mold postpone |
| VBZ | verb, present tense, 3rd person singular | bases reconstructs marks uses |
| WDT | WH-determiner | that what whatever which whichever |
| WP | WH-pronoun | that what whatever which who whom |
| WP$ | WH-pronoun, possessive | whose |
| WRB | Wh-adverb | however whenever where why |

# Part-of-Speech Ambiguity

- Example

| | | | | | |
|---|---|---|---|---|---|
| VBD | | VB | | | |
| VBN | VBZ | VBP | VBZ | | |
| NNP | NNS | NN | NNS | CD | NN |
| Fed | raises | interest | rates | 0.5 | percent |

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

- Two basic sources of constraint:
  - Grammatical environment
  - Identity of the current word
- Many more possible features:
  - … but we won't be able to use them for a while

# Why POS Tagging?

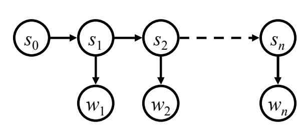
- Useful in and of itself
  - Text-to-speech: record, lead
  - Lemmatization: saw[v] → see, saw[n] → saw
  - Quick-and-dirty NP-chunk detection: grep {JJ | NN}* {NN | NNS}
- Useful as a pre-processing step for parsing
  - Less tag ambiguity means fewer parses
  - However, some tag choices are better decided by parsers

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | IN | | | |
| DT | NNP | NN | VBD | VBN | RP | NN | NNS | |
| The | Georgia | branch | had | taken | on | loan | commitments | … |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | VDN | | | |
| DT | NN | IN | NN | VBD | NNS | VBD | |
| The | average | of | interbank | offered | rates | plummeted | … |

# HMMs

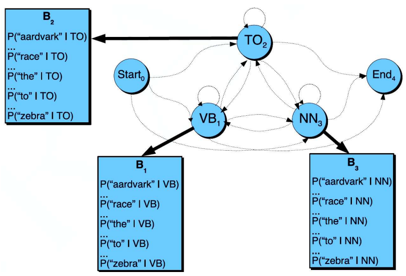
- We want a model of sequences s and observations w




$$P(\mathbf{s}, \mathbf{w}) = \prod_i P(s_i|s_{i-1})P(w_i|s_i)$$

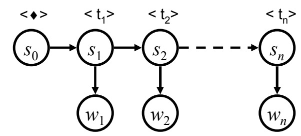
- Assumptions:
  - States are tag n-grams
  - Usually a dedicated start and end state / word
  - Tag/state sequence is generated by a markov model
  - Words are chosen independently, conditioned only on the tag/state
  - These are totally broken assumptions: why?

## Transitions and Emissions

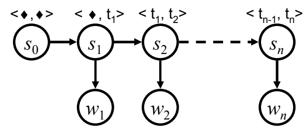



## Transitions

- Transitions P(s|s') encode well-formed tag sequences
  - In a bigram tagger, states = tags




  - In a trigram tagger, states = tag pairs




## Estimating Transitions

- Use standard smoothing methods to estimate transitions:

$$P(t_i \mid t_{i-1}, t_{i-2}) = \lambda_2 \hat{P}(t_i \mid t_{i-1}, t_{i-2}) + \lambda_1 \hat{P}(t_i \mid t_{i-1}) + (1 - \lambda_1 - \lambda_2)\hat{P}(t_i)$$

- Can get a lot fancier (e.g. KN smoothing), but in this case it doesn't buy much
- One option: encode more into the state, e.g. whether the previous word was capitalized (Brants 00)

## Estimating Emissions

$$P(\mathbf{s}, \mathbf{w}) = \prod_i P(s_i \mid s_{i-1}) P(w_i \mid s_i)$$

- Emissions are tricker:
  - Words we've never seen before
  - Words which occur with tags we've never seen
  - One option: break out the Good-Turning smoothing
  - Issue: words aren't black boxes:

    343,127.23 11-year Minteria reintroducibly

  - Unknown words usually broken into word classes

    $D^+$,$D^+$.$D^+$ $D^+$-$x^+$ $Xx^+$ $x^+$"ly"

  - Another option: decompose words into features and use a maxent model along with Bayes' rule

$$P(w \mid t) = P_{MAXENT}(t \mid w) P(w) / P(t)$$

## Better Features

- 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% / 82.6%

## Disambiguation

- Given these two multinomials, we can score any word / tag sequence pair

| <♦,♦> | <♦,NNP> | <NNP, VBZ> | <VBZ, NN> | <NN, NNS> | <NNS, CD> | <CD, NN> | <STOP> |
|---|---|---|---|---|---|---|---|
| | NNP | VBZ | NN | NNS | CD | NN | . |
| | Fed | raises | interest | rates | 0.5 | percent | . |

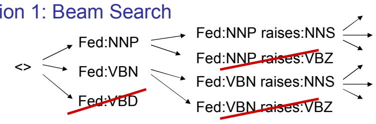
P(NNP|<♦,♦>) P(Fed|NNP) P(VBZ|<NNP,♦>) P(raises|VBZ) P(NN|VBZ,NNP).....

- In principle, we're done – list all possible tag sequences, score each one, pick the best one (the Viterbi state sequence)

NNP VBZ NN NNS CD NN ⇨ logP = -23
NNP NNS NN NNS CD NN ⇨ logP = -29
NNP VBZ VB NNS CD NN ⇨ logP = -27

## Finding the Best Trajectory

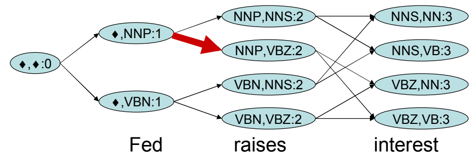
- Too many trajectories (state sequences) to list
- Option 1: Beam Search




  - A beam is a set of partial hypotheses
  - Start with just the single empty trajectory
  - At each derivation step:
    - Consider all continuations of previous hypotheses
    - Discard most, keep top k, or those within a factor of the best, (or some combination)
- Beam search works relatively well in practice
  - … but sometimes you want the optimal answer
  - … and you need optimal answers to validate your beam search

## The Path Trellis

- Represent paths as a trellis over states

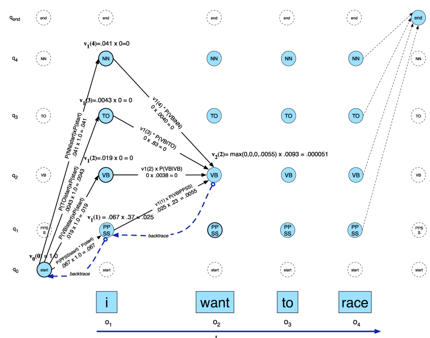



- Each arc ($s_1$:i $\rightarrow$ $s_2$:i+1) is weighted with the combined cost of:
  - Transitioning from $s_1$ to $s_2$ (which involves some unique tag t)
  - Emitting word i given t

P(VBZ | NNP, ♦) P(Fed | NNP)

- Each state path (trajectory):
  - Corresponds to a derivation of the word and tag sequence pair
  - Corresponds to a unique sequence of part-of-speech tags
  - Has a probability given by multiplying the arc weights in the path

## HMM Trellis




## The Viterbi Algorithm

- Dynamic program for computing

$$\delta_i(s) = \max_{s_0 \ldots s_{i-1} s} P(s_0 \ldots s_{i-1} s, w_1 \ldots w_{i-1})$$

  - The score of a best path up to position i ending in state s

$$\delta_0(s) = \begin{cases} 1 & if\ s = <\bullet,\bullet> \\ 0 & otherwise \end{cases}$$

$$\delta_i(s) = \max_{s'} P(s \mid s') P(w \mid s') \delta_{i-1}(s')$$

  - Also store a backtrace

$$\psi_i(s) = \arg\max_{s'} P(s \mid s') P(w \mid s') \delta_{i-1}(s')$$

- Memoized solution
- Iterative solution

## So How Well Does It Work?

- Choose the most common tag
  - 90.3% with a bad unknown word model
  - 93.7% with a good one
- TnT (Brants, 2000):
  - A carefully smoothed trigram tagger
  - Suffix trees for emissions
  - 96.7% on WSJ text (SOA is ~97.2%)
- Noise in the data
  - Many errors in the training and test corpora

DT NN IN NN VBD NNS VBD
The average of interbank offered rates plummeted …

  - Probably about 2% guaranteed error from noise (on this data)

JJ JJ NN
chief executive officer

NN JJ NN
chief executive officer

JJ NN NN
chief executive officer

NN NN NN
chief executive officer

## Overview: Accuracies

- Roadmap of (known / unknown) 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%
  - Cyclic tagger: 97.2% / 89.0%
  - Upper bound: ~98%

Most errors on unknown words

# What's Next for POS Tagging

- 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
- Solution: maximum entropy sequence models (next class)
- Reality check:
  - Taggers are already pretty good on WSJ journal text…
  - What the world needs is taggers that work on other text!

# Common Errors

- Common errors [from Toutanova & Manning 00]

| | JJ | NN | NNP | NNPS | RB | RP | IN | VB | VBD | VBN | VBP | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| JJ | 0 | **177** | **56** | 0 | **61** | 2 | 5 | 10 | 15 | **108** | 0 | 488 |
| NN | **244** | 0 | **103** | 0 | 12 | 1 | 1 | 29 | 5 | 6 | 19 | 525 |
| NNP | **107** | **106** | 0 | **132** | 5 | 0 | 7 | 5 | 1 | 2 | 0 | 427 |
| NNPS | 1 | 0 | **110** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 142 |
| RB | **72** | 21 | 7 | 0 | 0 | 16 | **138** | 1 | 0 | 0 | 0 | 295 |
| RP | 0 | 0 | 0 | 0 | **39** | 0 | **65** | 0 | 0 | 0 | 0 | 104 |
| IN | 11 | 0 | 1 | 0 | **169** | **103** | 0 | 1 | 0 | 0 | 0 | 323 |
| VB | 17 | **64** | 9 | 0 | 2 | 0 | 1 | 0 | 4 | 7 | **85** | 189 |
| VBD | 10 | 5 | 3 | 0 | 0 | 0 | 0 | 3 | 0 | **143** | 2 | 166 |
| VBN | **101** | 3 | 3 | 0 | 0 | 0 | 0 | 3 | **108** | 0 | 1 | 221 |
| VBP | 5 | 34 | 3 | 1 | 1 | 0 | 2 | **49** | 6 | 3 | 0 | 104 |
| Total | 626 | 536 | 348 | 144 | 317 | 122 | 279 | 102 | 140 | 269 | 108 | 3651 |

NN/JJ NN
official knowledge

VBD RP/IN DT NN
made up the story

RB VBD/VBN NNS
recently sold shares

# Sequence-Free Tagging?

- What about looking at a word and it's environment, but no sequence information?
  - Add in previous / next word — the __
  - Previous / next word shapes — X __ X
  - Occurrence pattern features — [X: x X occurs]
  - Crude entity detection — __ ….. (Inc.|Co.)
  - Phrasal verb in sentence? — put …… __
  - Conjunctions of these things
- All features except sequence: 96.6% / 86.8%
- Uses lots of features: > 200K
- Why isn't this the standard approach?

# Maxent Taggers

- One step up: also condition on previous tags

$$P(\mathbf{t}|\mathbf{w}) = \prod_i P_{\text{ME}}(t_i|\mathbf{w}, t_{i-1}, t_{i-2})$$

- Train up $P(t_i|w,t_{i-1},t_{i-2})$ as a normal maxent problem, then use to score sequences
- This is referred to as a *maxent tagger* [Ratnaparkhi 96]
- Beam search effective! (Why?)
- What's the advantage of beam size 1?

# Feature Templates

- We've been sloppy:
  - Features: $<w_0=\text{future}, t_0=\text{JJ}>$
  - Feature templates: $<w_0, t_0>$
- In maxent taggers:
  - Can now add *edge* feature templates:
    - $< t_{-1}, t_0>$
    - $< t_{-2}, t_{-1}, t_0>$
  - Also, mixed feature templates:
    - $< t_{-1}, w_0, t_0 >$

# Decoding

- Decoding maxent taggers:
  - Just like decoding HMMs
  - Viterbi, beam search, posterior decoding
- Viterbi algorithm (HMMs):

$$\delta_i(s) = \arg\max_{s'} P(s|s')P(w_{i-1}|s')\delta_{i-1}(s')$$

- Viterbi algorithm (Maxent):

$$\delta_i(s) = \arg\max_{s'} P(s|s', \mathbf{w})\delta_{i-1}(s')$$

# TBL Tagger

- [Brill 95] presents a *transformation-based* tagger
  - Label the training set with most frequent tags

    DT MD VBD VBD .
    The can was rusted .

  - Add transformation rules which reduce training mistakes
    - MD → NN : DT __
    - VBD → VBN : VBD __ .
  - Stop when no transformations do sufficient good
  - Does this remind anyone of anything?
- Probably the most widely used tagger (esp. outside NLP)
- … but not the most accurate: 96.6% / 82.0 %

# TBL Tagger II

- What gets learned? [from Brill 95]

| | Change Tag | | |
|---|---|---|---|
| # | From | To | Condition |
| 1 | NN | VB | Previous tag is *TO* |
| 2 | VBP | VB | One of the previous three tags is *MD* |
| 3 | NN | VB | One of the previous two tags is *MD* |
| 4 | VB | NN | One of the previous two tags is *DT* |
| 5 | VBD | VBN | One of the previous three tags is *VBZ* |
| 6 | VBN | VBD | Previous tag is *PRP* |
| 7 | VBN | VBD | Previous tag is *NNP* |
| 8 | VBD | VBN | Previous tag is *VBD* |
| 9 | VBP | VB | Previous tag is *TO* |
| 10 | POS | VBZ | Previous tag is *PRP* |
| 11 | VB | VBP | Previous tag is *NNS* |
| 12 | VBD | VBN | One of previous three tags is *VBP* |
| 13 | IN | WDT | One of next two tags is *VB* |
| 14 | VBD | VBN | One of previous two tags is *VB* |
| 15 | VB | VBP | Previous tag is *PRP* |
| 16 | IN | WDT | Next tag is *VBZ* |
| 17 | IN | DT | Next tag is *NN* |
| 18 | JJ | NNP | Next tag is *NNP* |
| 19 | IN | WDT | Next tag is *VBD* |
| 20 | JJR | RBR | Next tag is *JJ* |

| | Change Tag | | |
|---|---|---|---|
| # | From | To | Condition |
| 1 | NN | NNS | Has suffix **-s** |
| 2 | NN | CD | Has character **.** |
| 3 | NN | JJ | Has character **-** |
| 4 | NN | VBN | Has suffix **-ed** |
| 5 | NN | VBG | Has suffix **-ing** |
| 6 | ?? | RB | Has suffix **-ly** |
| 7 | ?? | JJ | Adding suffix **-ly** results in a word. |
| 8 | NN | CD | The word **$** can appear to the left. |
| 9 | NN | JJ | Has suffix **-al** |
| 10 | NN | VB | The word **would** can appear to the left. |
| 11 | NN | CD | Has character **0** |
| 12 | NN | JJ | The word **be** can appear to the left. |
| 13 | NNS | JJ | Has suffix **-us** |
| 14 | NNS | VBZ | The word **it** can appear to the left. |
| 15 | NN | JJ | Has suffix **-ble** |
| 16 | NN | JJ | Has suffix **-ic** |
| 17 | NN | CD | Has character **1** |
| 18 | NNS | NN | Has suffix **-ss** |
| 19 | ?? | JJ | Deleting the prefix **un-** results in a word |
| 20 | NN | JJ | Has suffix **-ive** |

# EngCG Tagger

- English constraint grammar tagger
  - [Tapanainen and Voutilainen 94]
  - Something else you should know about
  - Hand-written and knowledge driven
  - "Don't guess if you know" (general point about modeling more structure!)
  - Tag set doesn't make all of the hard distinctions as the standard tag set (e.g. JJ/NN)
  - They get stellar accuracies: 98.5% on *their* tag set
  - Linguistic representation matters…
  - … but it's easier to win when you make up the rules

# CRF Taggers

- Newer, higher-powered discriminative sequence models
  - CRFs (also voted perceptrons, M3Ns)
  - Do not decompose training into independent local regions
  - Can be deathly slow to train – require repeated inference on training set
- Differences tend not to be too important for POS tagging
- However: one issue worth knowing about in local models
  - "Label bias" and other explaining away effects
  - Maxent taggers' local scores can be near one without having both good "transitions" and "emissions"
  - This means that often evidence doesn't flow properly
  - Why isn't this a big deal for POS tagging?

# Domain Effects

- Accuracies degrade outside of domain
  - Up to triple error rate
  - Usually make the most errors on the things you care about in the domain (e.g. protein names)
- Open questions
  - How to effectively exploit unlabeled data from a new domain (what could we gain?)
  - How to best incorporate domain lexica in a principled way (e.g. UMLS specialist lexicon, ontologies)