Statistical NLP
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University of California
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Lecture 6: 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)
- Modals: *can*, *had*
- Determiners: *the some*
- Conjunctions: *and or*
- Pronouns: *he its*
- 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

Fed	raises	interest	rates	0.5	percent
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?

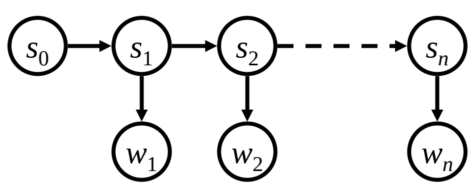
- Useful in and of itself
  - Text-to-speech: record, lead
  - Lemmatization: saw[v] → see, saw[n] → saw
  - Quick-and-dirty NP-chunk detection: grep {JJ | NN}* {NN | NNS}
- Useful as a pre-processing step for parsing
  - Less tag ambiguity means fewer parses
  - However, some tag choices are better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

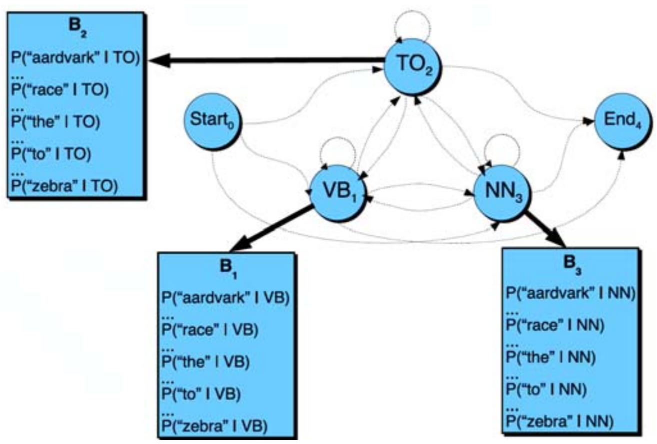
- We want a model of sequences s and observations w



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

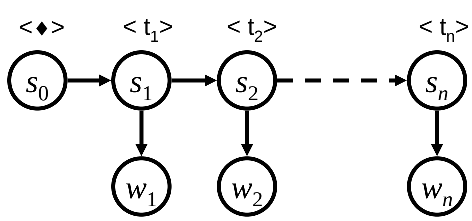
- Assumptions:
  - States are tag n-grams
  - Usually a dedicated start and end state / word
  - Tag/state sequence is generated by a markov model
  - Words are chosen independently, conditioned only on the tag/state
  - These are totally broken assumptions: why?

Transitions and Emissions

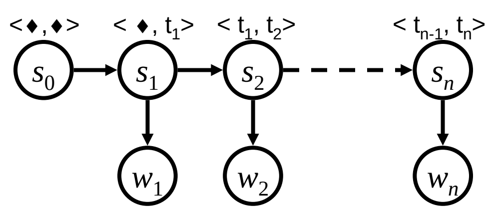


Transitions

- 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

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

- 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	.

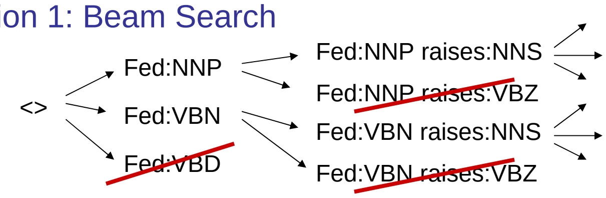
P(NNP|<♦,♦>) P(Fed|NNP) P(VBZ|<NNP,♦>) P(raises|VBZ) P(NN|VBZ,NNP)…..

- 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

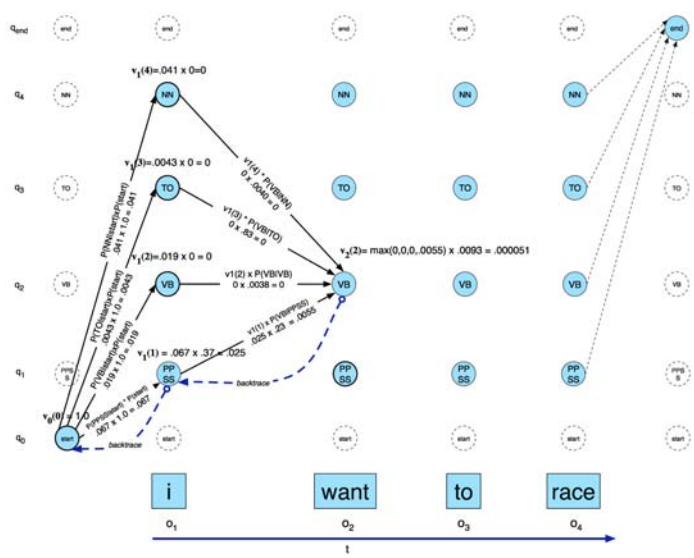
Finding the Best Trajectory

- 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

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(ti|w,ti-1,ti-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=future, t_0=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)