Natural Language Processing

Berkeley N L P

Part-of-Speech Tagging

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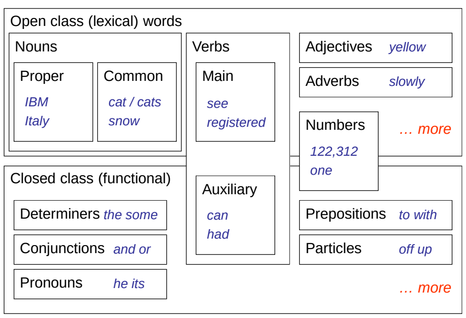
Parts of Speech

Parts-of-Speech (English)

- One basic kind of linguistic structure: syntactic word classes



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

- Words can have multiple parts of speech

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:
  - Suffixes, capitalization, name databases (gazetteers), etc…

Why POS Tagging?

- Useful in and of itself (more than you'd think)
  - 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

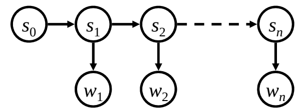
IN
DT NNP NN VBD VBN RP NN NNS
The Georgia branch had taken on loan commitments …

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

Part-of-Speech Tagging

Classic Solution: HMMs

- We want a model of sequences s and observations w

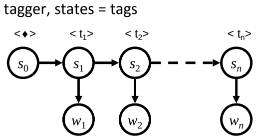


$$P(\mathbf{s}, \mathbf{w}) = \prod_i P(s_i | s_{i-1}) P(w_i | s_i)$$

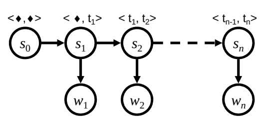
- Assumptions:
  - States are tag n-grams
  - Usually a dedicated start and end state / word
  - Tag/state sequence is generated by a markov model
  - Words are chosen independently, conditioned only on the tag/state
  - These are totally broken assumptions: why?

States

- States encode what is relevant about the past
- 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:

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

- Can get a lot fancier (e.g. KN smoothing) or use higher orders, 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)
- BIG IDEA: The basic approach of state-splitting / refinement turns out to be very important in a range of tasks

Estimating Emissions

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

- Emissions are trickier:
  - Words we've never seen before
  - Words which occur with tags we've never seen them with
  - One option: break out the fancy smoothing (e.g. KN, Good-Turing)
  - Issue: unknown words aren't black boxes:

    343,127.23 11-year Minteria reintroducibly

  - Basic solution: unknown words classes (affixes or shapes)

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

  - Common approach: Estimate P(t|w) and invert
  - [Brants 00] used a suffix trie as its (inverted) emission model

Disambiguation (Inference)

- Problem: find the most likely (Viterbi) sequence under the model

$$\mathbf{t}^* = \arg\max_{\mathbf{t}} P(\mathbf{t}|\mathbf{w})$$

- Given model parameters, we can score any tag sequence

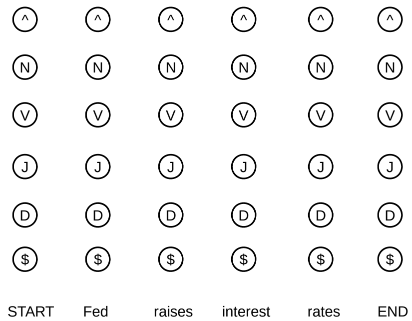
<♦,♦>	<♦,NNP>	<NNP, VBZ>	<VBZ, NN>	<NN, NNS>	<NNS, CD>	<CD, NN>	<STOP>
	NNP	VBZ	NN	NNS	CD	NN	.
	Fed	raises	interest	rates	0.5	percent	.

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

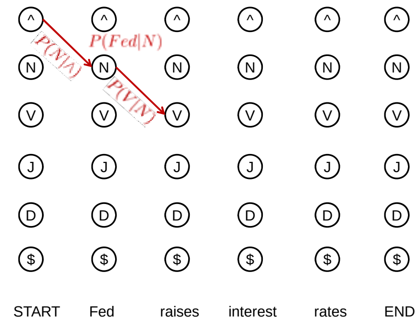
- In principle, we're done – list all possible tag sequences, score each one, pick the best one (the Viterbi state sequence)

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

The State Lattice / Trellis



The State Lattice / Trellis



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 ~97.5%)
- 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%
  - TnT (HMM++): 96.2% / 86.0%
  - Maxent P(t|w): 93.7% / 82.6%
  - MEMM tagger: 96.9% / 86.9%
  - State-of-the-art: 97+% / 89+%
  - Upper bound: ~98%

Most errors on unknown words

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

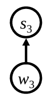
VBD RP/IN DT NN
made up the story

RB VBD/VBN NNS
recently sold shares

Richer Features

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 — 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%



Why Linear Context is Useful

- Lots of rich local information!

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

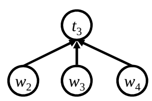
  - We could fix this with a feature that looked at the next word

JJ
NNP NNS VBD VBN .
Intrinsic flaws remained undetected .

  - We could fix this by linking capitalized words to their lowercase versions
- Solution: discriminative sequence models (MEMMs, CRFs)
- Reality check:
  - Taggers are already pretty good on WSJ journal text…
  - What the world needs is taggers that work on other text!
  - Though: other tasks like IE have used the same methods to good effect

Sequence-Free Tagging?

- What about looking at a word and its 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?

Feature-Rich Sequence Models

- Problem: HMMs make it hard to work with arbitrary features of a sentence
- Example: name entity recognition (NER)

PER PER O O O O O O ORG O O O O O LOC LOC O
Tim Boon has signed a contract extension with Leicestershire which will keep him at Grace Road .

Local Context

	Prev	Cur	Next
State	Other	???	???
Word	at	Grace	Road
Tag	IN	NNP	NNP
Sig	x	Xx	Xx

MEMM Taggers

- Idea: left-to-right local decisions, condition on previous tags and also entire input

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

  - Train up $P(t_i|w,t_{i-1},t_{i-2})$ as a normal maxent model, then use to score sequences
  - This is referred to as an MEMM tagger [Ratnaparkhi 96]
  - Beam search effective! (Why?)
  - What about beam size 1?

NER Features

Because of regularization term, the more common prefixes have larger weights even though entire-word features are more specific.

Feature Weights

Feature Type	Feature	PERS	LOC
Previous word	at	-0.73	0.94
Current word	Grace	0.03	0.00
Beginning bigram	<G	0.45	-0.04
Current POS tag	NNP	0.47	0.45
Prev and cur tags	IN NNP	-0.10	0.14
Previous state	Other	-0.70	-0.92
Current signature	Xx	0.80	0.46
Prev state, cur sig	O-Xx	0.68	0.37
Prev-cur-next sig	x-Xx-Xx	-0.69	0.37
P. state - p-cur sig	O-x-Xx	-0.20	0.82
…			
Total:		**-0.58**	**2.68**

Local Context

	Prev	Cur	Next
State	Other	???	???
Word	at	Grace	Road
Tag	IN	NNP	NNP
Sig	x	Xx	Xx

Conditional Random Fields (and Friends)

Perceptron Taggers

[Collins 01]

- Linear models:

$$\text{score}(\mathbf{t}|\mathbf{w}) = \lambda^\top f(\mathbf{t}, \mathbf{w})$$

- … that decompose along the sequence

$$= \lambda^\top \sum_i f(t_i, t_{i-1}, \mathbf{w}, i)$$

- … allow us to predict with the Viterbi algorithm

$$\mathbf{t}^* = \arg\max_{\mathbf{t}} \text{score}(\mathbf{t}|\mathbf{w})$$

- … which means we can train with the perceptron algorithm (or related updates, like MIRA)

Conditional Random Fields

- Make a maxent model over entire taggings
  - MEMM

$$P(\mathbf{t}|\mathbf{w}) = \prod_i \frac{1}{Z(i)} \exp\left(\lambda^\top f(t_i, t_{i-1}, \mathbf{w}, i)\right)$$

  - CRF

$$P(\mathbf{t}|\mathbf{w}) = \frac{1}{Z(\mathbf{w})} \exp\left(\lambda^\top f(\mathbf{t}, \mathbf{w})\right)$$

$$= \frac{1}{Z(\mathbf{w})} \exp\left(\lambda^\top \sum_i f(t_i, t_{i-1}, \mathbf{w}, i)\right)$$

$$= \frac{1}{Z(\mathbf{w})} \prod_i \phi_i(t_i, t_{i-1})$$

CRFs

- Like any maxent model, derivative is:

$$\frac{\partial L(\lambda)}{\partial \lambda} = \sum_k \left(\mathbf{f}_k(\mathbf{t}^k) - \sum_{\mathbf{t}} P(\mathbf{t}|\mathbf{w}_k)\mathbf{f}_k(\mathbf{t}) \right)$$

- So all we need is to be able to compute the expectation of each feature (for example the number of times the label pair *DT-NN* occurs, or the number of times *NN-interest* occurs) **under the model distribution**

- Critical quantity: counts of posterior marginals:

$$\text{count}(w, s) = \sum_{i:w_i=w} P(t_i = s|\mathbf{w})$$

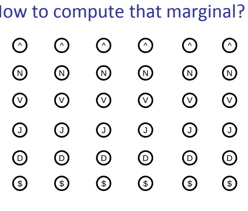
$$\text{count}(s \to s') = \sum_i P(t_{i-1} = s, t_i = s'|\mathbf{w})$$

Computing Posterior Marginals

- How many (expected) times is word w tagged with s?

$$\text{count}(w, s) = \sum_{i:w_i=w} P(t_i = s|\mathbf{w})$$

- How to compute that marginal?



$$\alpha_i(s) = \sum_{s'} \phi_i(s', s)\alpha_{i-1}(s')$$

$$\beta_i(s) = \sum_{s'} \phi_{i+1}(s, s')\beta_{i+1}(s')$$

$$P(t_i = s|\mathbf{w}) = \frac{\alpha_i(s)\beta_i(s)}{\alpha_N(\text{END})}$$

Transformation-Based Learning

- [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 definitely not the most accurate: 96.6% / 82.0 %

Learned Transformations

- 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**

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)

Unsupervised Tagging

Unsupervised Tagging?

- AKA part-of-speech induction
- Task:
  - Raw sentences in
  - Tagged sentences out
- Obvious thing to do:
  - Start with a (mostly) uniform HMM
  - Run EM
  - Inspect results

EM for HMMs: Process

- Alternate between recomputing distributions over hidden variables (the tags) and reestimating parameters
- Crucial step: we want to tally up how many (fractional) counts of each kind of transition and emission we have under current params:

$$\text{count}(w, s) = \sum_{i:w_i = w} P(t_i = s|\mathbf{w})$$

$$\text{count}(s \to s') = \sum_i P(t_{i-1} = s, t_i = s'|\mathbf{w})$$

- Same quantities we needed to train a CRF!

Merialdo: Setup

- Some (discouraging) experiments [Merialdo 94]
- Setup:
  - You know the set of allowable tags for each word
  - Fix k training examples to their true labels
    - Learn $P(w|t)$ on these examples
    - Learn $P(t|t_{-1},t_{-2})$ on these examples
  - On n examples, re-estimate with EM
- Note: we know allowed tags but not frequencies

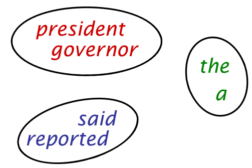
Merialdo: Results

	Number of tagged sentences used for the initial model						
	0	100	2000	5000	10000	20000	all
Iter	Correct tags (% words) after ML on 1M words						
0	77.0	90.0	95.4	96.2	96.6	96.9	97.0
1	80.5	92.6	95.8	96.3	96.6	96.7	96.8
2	81.8	93.0	95.7	96.1	96.3	96.4	96.4
3	83.0	93.1	95.4	95.8	96.1	96.2	96.2
4	84.0	93.0	95.2	95.5	95.8	96.0	96.0
5	84.8	92.9	95.1	95.4	95.6	95.8	95.8
6	85.3	92.8	94.9	95.2	95.5	95.6	95.7
7	85.8	92.8	94.7	95.1	95.3	95.5	95.5
8	86.1	92.7	94.6	95.0	95.2	95.4	95.4
9	86.3	92.6	94.5	94.9	95.1	95.3	95.3
10	86.6	92.6	94.4	94.8	95.0	95.2	95.2

Distributional Clustering

♦ *the president said that the downturn was over* ♦

president	the __ of
president	the __ said
governor	the __ of
governor	the __ appointed
said	sources __ ♦
said	president __ that
reported	sources __ ♦



[Finch and Chater 92, Shuetze 93, many others]

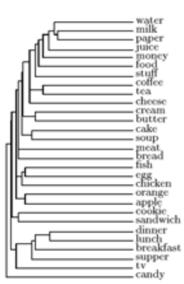
Distributional Clustering

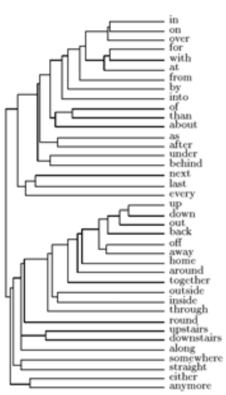
- Three main variants on the same idea:
  - Pairwise similarities and heuristic clustering
    - E.g. [Finch and Chater 92]
    - Produces dendrograms
  - Vector space methods
    - E.g. [Shuetze 93]
    - Models of ambiguity
  - Probabilistic methods
    - Various formulations, e.g. [Lee and Pereira 99]

Nearest Neighbors

word	nearest neighbors
accompanied	submitted banned financed developed authorized headed canceled awarded barred
almost	virtually merely formally fully quite officially just nearly only less
causing	reflecting forcing providing creating producing becoming carrying particularly
classes	elections courses payments losses computers performances violations levels pictures
directors	professionals investigations materials competitors agreements papers transactions
goal	mood roof eye image tool song pool scene gap voice
japanese	chinese iraqi american western arab foreign european federal soviet indian
represent	reveal attend deliver reflect choose contain impose manage establish retain
think	believe wish know realize wonder assume feel say mean bet
york	angeles francisco sox rouge kong diego zone vegas inning layer
on	through in at over into with from for by across
must	might would could cannot will should can may does helps
they	we you i he she nobody who it everybody there

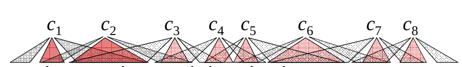
Dendrograms



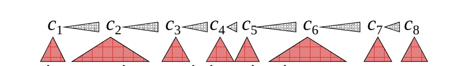


A Probabilistic Version?

$$P(S,C) = \prod_i P(c_i) P(w_i \mid c_i) P(w_{i-1}, w_{i+1} \mid c_i)$$



♦ *the president said that the downturn was over* ♦



♦ *the president said that the downturn was over* ♦