POS Tagging

Trigram Taggers

NNP VBZ NN NNS CD NN
Fed raises interest rates 0.5 percent

- Normal HMM "bigram" model: y_1 = NNP, y_2 = VBZ, …
- Trigram model: y_1 = (<S>, NNP), y_2 = (NNP, VBZ), …
- Probabilities now look like P((NNP, VBZ) | (<S>, NNP)) — more context! We know the verb is occurring two words after <S>
- Tradeoff between model capacity and data size — trigrams are a "sweet spot" for POS tagging

HMM POS Tagging

- Penn Treebank English POS tagging (see homework): 44 tags
- Baseline: assign each word its most frequent tag: ~90% accuracy
- Trigram HMM: ~95% accuracy / 55% on words not seen in train
- TnT tagger (Brants 1998, tuned HMM): 96.2% acc / 86.0% on unks
- MaxEnt tagger (Toutanova + Manning 2000): 96.9% / 87.0%
- State-of-the-art (BiLSTM-CRFs): 97.5% / 89%+

Slide credit: Dan Klein

Errors

	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

JJ/NN NN
official knowledge

VBD RP/IN DT NN
made up the story

RB VBD/VBN NNS
recently sold shares

(NN NN: tax cut, art gallery, …)

Slide credit: Dan Klein / Toutanova + Manning (2000)

Remaining Errors

- Lexicon gap (word not seen with that tag in training): 4.5% of errors
- Unknown word: 4.5%
- Could get right: 16% (many of these involve parsing!)
- Difficult linguistics: 20%

VBD / VBP? (past or present?)

They set up absurd situations, detached from reality

- Underspecified / unclear, gold standard inconsistent / wrong: **58%**

adjective or verbal participle? JJ / VBN?

a $ 10 million fourth-quarter charge against discontinued operations

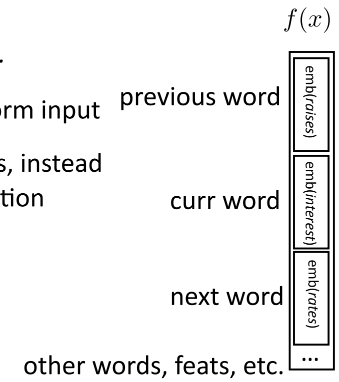
Manning 2011 "Part-of-Speech Tagging from 97% to 100%: Is It Time for Some Linguistics?"

POS with Feedforward Networks

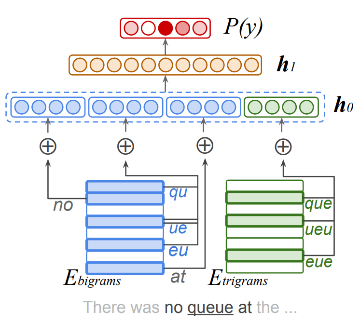
??

*Fed raises **interest** rates in order to …*

- Word embeddings for each word form input
- $f(x)$ doesn't look like a bag-of-words, instead captures position-sensitive information



POS with Feedforward Networks



- Botha et al. (2017): small FFNNs for NLP tasks
- Use bag-of-character bigram + trigram embeddings for each word
- Hidden layer mixes these different signals and learns feature conjunctions

Botha et al. (2017)

POS with Feedforward Networks

- Works well on a range of languages
- Better than a RNN-based approach (Gillick et al., 2016)

Lang.	*L.R.*	*Mom.*	γ	*Steps*	*Acc.*
Small FF ($\frac{1}{2}$ Dim.) + Clusters					
bg	0.1	0.8	128k	210k	97.76
cs	0.05	0.9	32k	420k	98.06
da	0.05	0.9	16k	240k	95.33
en	0.05	0.8	8k	300k	93.06
fi	0.05	0.9	16k	390k	94.66
fr	0.08	0.9	128k	120k	95.28
de	0.08	0.9	16k	90k	92.13
el	0.08	0.9	16k	60k	97.42
id	0.08	0.9	8k	690k	92.15
it	0.05	0.9	64k	210k	97.42
fa	0.1	0.8	8k	510k	96.19
es	0.08	0.9	8k	60k	94.79
sv	0.1	0.8	16k	300k	95.76

Botha et al. (2017)

CRFs and NER

Named Entity Recognition

B-PER I-PER O O O B-LOC O O O B-ORG O O

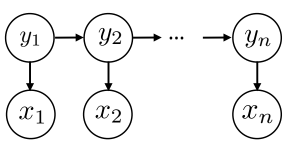
Barack Obama will travel to Hangzhou today for the G20 meeting .

PERSON LOC ORG

- Frame as a sequence problem with a BIO tagset: begin, inside, outside
- Why might an HMM not do so well here?
  - Lots of O's, so tags aren't as informative about context
  - Want to use context features (*to Hangzhou* => *Hangzhou* is a LOC)
- Conditional random fields (CRFs) can help solve these problems

HMMs

- Big advantage: transitions, scoring pairs of adjacent y's



- Big downside: not able to incorporate useful word context information
- Solution: switch from generative to discriminative model (conditional random fields) so we can condition on the *entire input*.
- Conditional random fields: logistic regression + features on pairs of y's

Tagging with Logistic Regression

- Logistic regression over each tag individually:

"different features" approach to features for a single tag

$$P(y_i = y|\mathbf{x}, i) = \frac{\exp(\mathbf{w}^\top \mathbf{f}(y, i, \mathbf{x}))}{\sum_{y' \in \mathcal{Y}} \exp(\mathbf{w}^\top \mathbf{f}(y', i, \mathbf{x}))}$$

- Over all tags:

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \prod_{i=1}^{n} P(y_i = \tilde{y}_i|\mathbf{x}, i) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}(\tilde{y}_i, i, \mathbf{x})\right)$$

- Score of a prediction: sum of weights dot features over each individual predicted tag (this is a simple CRF but not the general form)
- Set Z equal to the product of denominators; we'll discuss this in a few slides

Adding Structure

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}(\tilde{y}_i, i, \mathbf{x})\right)$$

- We want to be able to learn that some tags don't follow other tags — want to have features on tag *pairs*

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_e(\tilde{y}_i, i, \mathbf{x}) + \sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_t(\tilde{y}_i, \tilde{y}_{i+1}, i, \mathbf{x})\right)$$

- Score: sum of weights dot $\mathbf{f}_e$ features over each predicted tag ("emissions") plus sum of weights dot $\mathbf{f}_t$ features over tag pairs ("transitions")
- This is a sequential CRF

Features for NER

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_e(\tilde{y}_i, i, \mathbf{x}) + \sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_t(\tilde{y}_i, \tilde{y}_{i+1}, i, \mathbf{x})\right)$$

O B-LOC

Barack Obama will travel to Hangzhou today for the G20 meeting .

Transitions: $\mathbf{f}_t(\mathrm{O}, \text{B-LOC}, i = 5, \mathbf{x})$ = Indicator[O — B-LOC]

Emissions: $\mathbf{f}_e(\text{B-LOC}, i = 6, \mathbf{x})$ = Indicator[B-LOC & Curr word prefix = *H*]
Indicator[B-LOC & Prev word = *to*]

- We couldn't use a "previous word" feature in the HMM at all!

Features for NER

- Current word features (can use in HMM)
  - Capitalization
  - Word shape
  - Prefixes/suffixes
  - Lexical indicators
- Context features (can't use in HMM!)
  - Words before/after
  - Tags before/after
- Word clusters/embeddings
- Gazetteers

Leicestershire

Boston

Apple released a new version…

According to the New York Times…

Example

- CRFs assign a score to every possible tag sequence over a sentence

B-PER I-PER O O
Barack Obama will travel

feats = $\mathbf{f}_e$(B-PER, i=1, $\mathbf{x}$) + $\mathbf{f}_e$(I-PER, i=2, $\mathbf{x}$) + $\mathbf{f}_e$(O, i=3, $\mathbf{x}$) + $\mathbf{f}_e$(O, i=4, $\mathbf{x}$)
+ $\mathbf{f}_t$(B-PER, I-PER, i=1, $\mathbf{x}$) + $\mathbf{f}_t$(I-PER, O, i=2, $\mathbf{x}$) + $\mathbf{f}_t$(O, O, i=3, $\mathbf{x}$)

B-PER B-PER O O
Barack Obama will travel

feats = $\mathbf{f}_e$(B-PER, i=1, $\mathbf{x}$) + $\mathbf{f}_e$(B-PER, i=2, $\mathbf{x}$) + $\mathbf{f}_e$(O, i=3, $\mathbf{x}$) + $\mathbf{f}_e$(O, i=4, $\mathbf{x}$)
+ $\mathbf{f}_t$(B-PER, B-PER, i=1, $\mathbf{x}$) + $\mathbf{f}_t$(B-PER, O, i=2, $\mathbf{x}$) + $\mathbf{f}_t$(O, O, i=3, $\mathbf{x}$)

- *Obama* can start a new named entity (emission feats look okay), but we're not likely to have two PER entities in a row (transition feats)

Conditional Random Fields

- HMMs: $P(\mathbf{y}, \mathbf{x}) = P(y_1)P(x_1|y_1)P(y_2|y_1)P(x_2|y_2)\ldots$
- CRFs: discriminative models with the following globally-normalized form:

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_e(\tilde{y}_i, i, \mathbf{x}) + \sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_t(\tilde{y}_i, \tilde{y}_{i+1}, i, \mathbf{x})\right)$$

normalizer *Z*: must make this a probability distribution over all possible seqs

$$Z = \sum_{\mathbf{y}' \in \mathcal{Y}^n} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_e(y'_i, i, \mathbf{x}) + \sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_t(y'_i, y'_{i+1}, i, \mathbf{x})\right)$$

- CRFs in general: replace weights dot features with so-called "potential functions" over *y*'s

Inference and Learning

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_e(\tilde{y}_i, i, \mathbf{x}) + \sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_t(\tilde{y}_i, \tilde{y}_{i+1}, i, \mathbf{x})\right)$$

- Inference: Can use the Viterbi algorithm to find the highest scoring path if we replace HMM log probs with "scores" from weights dot features (initial distribution is removed)

$$\log P(x_i|y_i) \rightarrow \mathbf{w}^\top \mathbf{f}_e(y_i, i, \mathbf{x})$$

$$\log P(y_i|y_{i-1}) \rightarrow \mathbf{w}^\top \mathbf{f}_t(y_{i-1}, y_i, i, \mathbf{x})$$

- Learning: requires running *forward-backward* (like Viterbi but with summing instead of maxing over *y*'s) to compute *Z*, then doing some tricky math to compute gradients [outside scope of the course/not on midterm]

Takeaways

- CRFs provide a way to build structured feature-based models: logistic regression over structured objects like sequences
- Inference and learning can still be done efficiently but require dynamic programming
- CRFs don't have to be linear models; can use scores derived from neural networks ("neural CRFs")