CS388: Natural Language Processing

Lecture 5: Named Entity Recognition, CRFs

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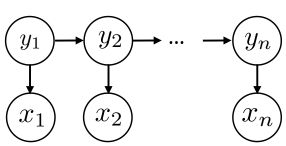
Administrivia

- Mini 1 grading underway
- Project 1 due next Thursday

Recall: HMMs

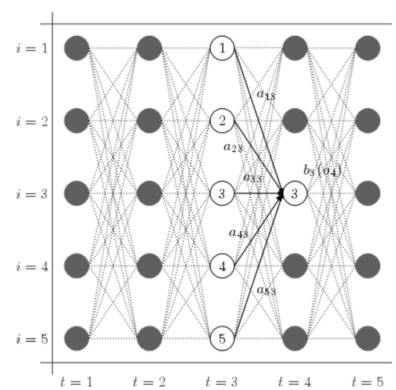
- Input $\mathbf{x} = (x_1, ..., x_n)$ Output $\mathbf{y} = (y_1, ..., y_n)$



$$P(\mathbf{y}, \mathbf{x}) = P(y_1) \prod_{i=2}^{n} P(y_i | y_{i-1}) \prod_{i=1}^{n} P(x_i | y_i)$$

- Training: maximum likelihood estimation (count + normalize)
- Inference problem: $\text{argmax}_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) = \text{argmax}_{\mathbf{y}} \frac{P(\mathbf{y}, \mathbf{x})}{\cancel{P(\mathbf{x})}}$
- Viterbi: $\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1}) P(x_i|s) \text{score}_{i-1}(y_{i-1})$

Recall: Viterbi Algorithm



- Compute scores for next timestep (score of optimal tag sequence ending with tag *i* at timestep *t*)

slide credit: Dan Klein

Viterbi/HMMs: Other Resources

- Lecture notes from my undergrad course (posted online)
  - We ignore the STOP token here. It's not in the tag set and just don't use these probabilities
- Eisenstein Chapter 7.3 **but** the notation covers a more general case than what's discussed for HMMs
- Jurafsky+Martin 8.4.5

This Lecture

- Conditional random fields
- Features for NER
- Inference and Learning in CRFs
- Next time: finish up NER systems

Named Entity Recognition

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

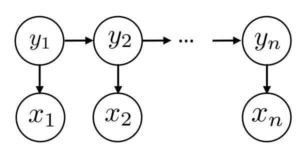
Barack Obama will travel to Hangzhou today for the G20 meeting .

PERSON LOC ORG

- BIO tagset: begin, inside, outside
- Sequence of tags — should we use an HMM?
- Why might an HMM not do so well here?
  - Lots of O's
  - Insufficient features/capacity with multinomials (especially for unks)

HMMs Pros and Cons

- 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

Conditional Random Fields

Conditional Random Fields

- Flexible discriminative model for tagging tasks that can use arbitrary features of the input. Similar to logistic regression, but *structured*

B-PER I-PER

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

Curr_word=Barack & **Label=B-PER**

Next_word=Obama & **Label=B-PER**

Curr_word_starts_with_capital=True & **Label=B-PER**

Posn_in_sentence=1st & **Label=B-PER**

Label=B-PER & Next-Label = I-PER

…

Tagging with Logistic Regression

- Logistic regression over each tag individually:

"different features" approach to features for a single tag

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

Probability of the *i*th word getting assigned tag *y* (B-PER, etc.)

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
- Conditional model: ***x*** is observed, ***y*** isn't

Example: "Emission Features" f_e

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, $\mathbf{x}$)

[CurrWord=*Obama* & label=I-PER, PrevWord=*Barack* & label=I-PER, CurrWordIsCapitalized & label=I-PER, …]

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, $\mathbf{x}$)

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*

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_e(\tilde{y}_i, i, \mathbf{x}) + \sum_{i=2}^{n} \mathbf{w}^\top \mathbf{f}_t(\tilde{y}_{i-1}, \tilde{y}_i, i, \mathbf{x})\right)$$

- 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

Example

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)

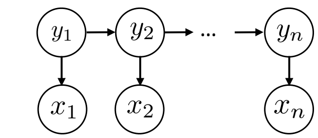
Sequential CRFs

$$P(\mathbf{y} = \tilde{\mathbf{y}}|\mathbf{x}) = \frac{1}{Z} \exp\left(\sum_{i=1}^{n} \mathbf{w}^\top \mathbf{f}_e(\tilde{y}_i, i, \mathbf{x}) + \sum_{i=2}^{n} \mathbf{w}^\top \mathbf{f}_t(\tilde{y}_{i-1}, \tilde{y}_i, i, \mathbf{x})\right)$$

- Critical property: this structure is going to allow us to use dynamic programming (Viterbi) to sum or max over all sequences
- How does this compare to HMMs?

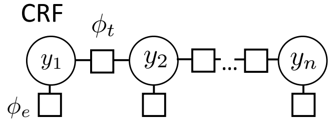
HMMs vs. CRFs

HMM



$$P(\mathbf{y},\mathbf{x}) = P(y_1)P(x_1|y_1)P(y_2|y_1)P(x_2|y_2)\dots$$
$$= P(y_1)\prod_{i=2}^{n} P(y_i|y_{i-1})\prod_{i=1}^{n} P(x_i|y_i)$$

CRF



$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1},y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i,i,\mathbf{x}))$$

- Both models are expressible in different factor graph notation
- Phis are “potentials”, used in the general CRF formulation

HMMs vs. CRFs

- HMMs: in the standard HMM, emissions consider one word at a time
- CRFs support features over many words simultaneously, non-independent features (e.g., suffixes and prefixes), not generative models
- Naive Bayes : logistic regression :: HMMs : CRFs
  local vs. global normalization <-> generative vs. discriminative
  (locally normalized discriminative models do exist (MEMMs))

CRFs in General

- CRFs: discriminative model with the following form:

$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_k \exp(\phi_k(\mathbf{x},\mathbf{y}))$$

normalizer

any real-valued scoring function of its arguments

- Our special case: linear feature-based potentials $\phi_k(\mathbf{x},\mathbf{y}) = w^\top f_k(\mathbf{x},\mathbf{y})$

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

- Problem: intractable inference in the general case! Computing *Z* requires an exponent sum

Features for NER

Basic Features for NER

$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

O B-LOC

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

Transitions: $f_t(y_{i-1}, y_i) =$ Ind[y_{i-1} — y_i] = Ind[O — B-LOC]

Emissions: $f_e(y_6, 6, \mathbf{x}) =$ Ind[B-LOC & Current word = *Hangzhou*]
Ind[B-LOC & Prev word = *to*]

Emission Features for NER

$\phi_e(y_i, i, \mathbf{x})$

LOC
Leicestershire is a nice place to visit…

PER
Leonardo DiCaprio won an award…

LOC
I took a vacation to Boston

ORG
Apple released a new version…

LOC PER
Texas governor Greg Abbott said

ORG
According to the New York Times…

Emission Features for NER

- 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
- Gazetteers

Leicestershire

Boston

Apple released a new version…

According to the New York Times…

CRFs Outline

- Model: $P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_{i=2}^{n} \exp(\phi_t(y_{i-1}, y_i)) \prod_{i=1}^{n} \exp(\phi_e(y_i, i, \mathbf{x}))$

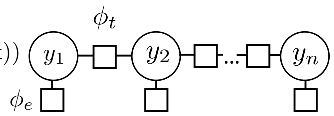
$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

- Inference
- Learning

Inference and Learning in CRFs

Computing (arg)maxes

$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1}, y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i, i, \mathbf{x}))$$



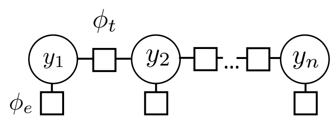
- $\mathrm{argmax}_{\mathbf{y}} P(\mathbf{y}|\mathbf{x})$: can use Viterbi exactly as in HMM case

$$\max_{y_1,\ldots,y_n} e^{\phi_t(y_{n-1},y_n)} e^{\phi_e(y_n,n,\mathbf{x})} \ldots e^{\phi_e(y_2,2,\mathbf{x})} e^{\phi_t(y_1,y_2)} e^{\phi_e(y_1,1,\mathbf{x})}$$

- $\exp(\phi_t(y_{i-1}, y_i))$ and $\exp(\phi_e(y_i, i, \mathbf{x}))$ play the role of the Ps now, use the exact same Viterbi dynamic program

Inference in General CRFs

- Can do efficient inference in any tree-structured CRF



- Max-product algorithm: generalization of Viterbi to arbitrary tree-structured graphs (sum-product is generalization of forward-backward)

CRFs Outline

- Model: $P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1}, y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i, i, \mathbf{x}))$

$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

- Inference: argmax P(**y**|**x**) from Viterbi
- Learning

Training CRFs

$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

- Logistic regression: $P(y|x) \propto \exp w^\top f(x,y)$
- For CRFs: maximize $\mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \log P(\mathbf{y}^*|\mathbf{x})$
- Gradient is analogous to logistic regression: gold feats — expected feats

$$\frac{\partial}{\partial w}\mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \sum_{i=2}^{n} f_t(y^*_{i-1}, y^*_i) + \sum_{i=1}^{n} f_e(y^*_i, i, \mathbf{x})$$

$$-\mathbb{E}_{\mathbf{y}}\left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

intractable!

Training CRFs

$$\frac{\partial}{\partial w}\mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \sum_{i=2}^{n} f_t(y^*_{i-1}, y^*_i) + \sum_{i=1}^{n} f_e(y^*_i, i, \mathbf{x})$$

$$-\mathbb{E}_{\mathbf{y}}\left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

- Let's focus on emission feature expectation

$$\mathbb{E}_{\mathbf{y}}\left[\sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right] = \sum_{\mathbf{y}\in\mathcal{Y}} P(\mathbf{y}|\mathbf{x})\left[\sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right] = \sum_{i=1}^{n}\sum_{\mathbf{y}\in\mathcal{Y}} P(\mathbf{y}|\mathbf{x}) f_e(y_i, i, \mathbf{x})$$

$$= \sum_{i=1}^{n}\sum_{s} P(y_i = s|\mathbf{x}) f_e(s, i, \mathbf{x})$$

Training CRFs

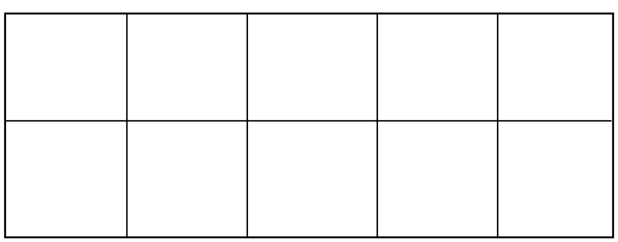
marginal probability

sum over timesteps

$$\sum_{i=1}^{n}\sum_{s} P(y_i = s|\mathbf{x}) f_e(s, i, \mathbf{x})$$

sum over tags

feats of that tag at that step



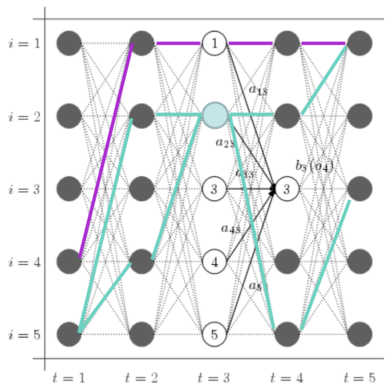
Forward-Backward Algorithm

- How do we compute these marginals $P(y_i = s|\mathbf{x})$?

$$P(y_i = s|\mathbf{x}) = \sum_{y_1,\ldots,y_{i-1},y_{i+1},\ldots,y_n} P(\mathbf{y}|\mathbf{x})$$

- What did Viterbi compute? $P(\mathbf{y}_{\max}|\mathbf{x}) = \max_{y_1,\ldots,y_n} P(\mathbf{y}|\mathbf{x})$
- Can compute marginals with dynamic programming as well using forward-backward

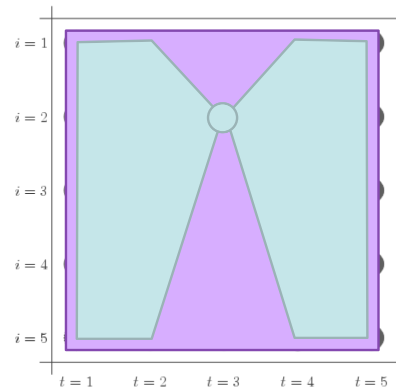
Forward-Backward Algorithm



$P(y_3 = 2|\mathbf{x}) =$

$$\frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

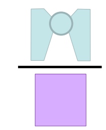
Forward-Backward Algorithm



$P(y_3 = 2|\mathbf{x}) =$

$$\frac{\text{sum of all paths through state 2 at time 3}}{\text{sum of all paths}}$$

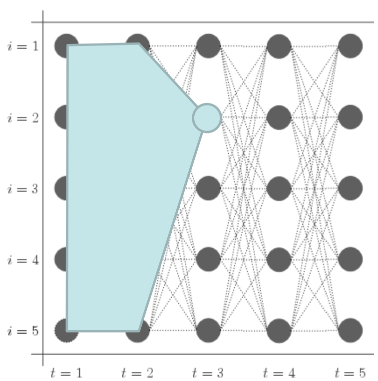
=



- Easiest and most flexible to do one pass to compute  and one to compute 

slide credit: Dan Klein

Forward-Backward Algorithm



- Initial:

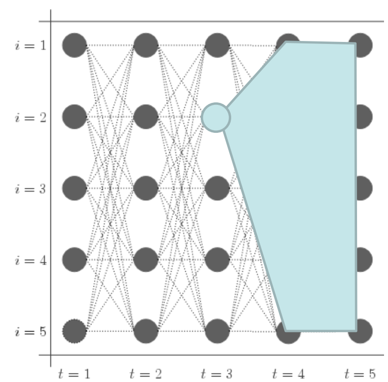
$\alpha_1(s) = \exp(\phi_e(s, 1, \mathbf{x}))$

- Recurrence:

$$\alpha_t(s_t) = \sum_{s_{t-1}} \alpha_{t-1}(s_{t-1}) \exp(\phi_e(s_t, t, \mathbf{x})) \exp(\phi_t(s_{t-1}, s_t))$$

- Same as Viterbi but summing instead of maxing!
- These quantities get very small! Store everything as log probabilities

Forward-Backward Algorithm



- Initial:

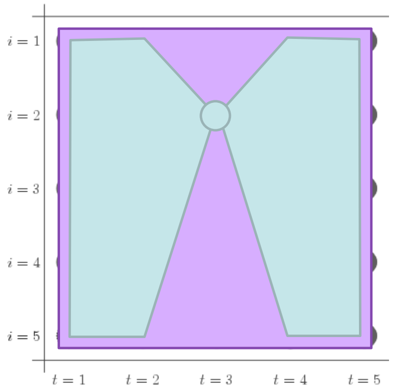
$\beta_n(s) = 1$

- Recurrence:

$$\beta_t(s_t) = \sum_{s_{t+1}} \beta_{t+1}(s_{t+1}) \exp(\phi_e(s_{t+1}, t+1, \mathbf{x})) \exp(\phi_t(s_t, s_{t+1}))$$

- Big differences: count emission for the *next* timestep (not current one)

Forward-Backward Algorithm



$$\alpha_1(s) = \exp(\phi_e(s, 1, \mathbf{x}))$$

$$\alpha_t(s_t) = \sum_{s_{t-1}} \alpha_{t-1}(s_{t-1}) \exp(\phi_e(s_t, t, \mathbf{x})) \exp(\phi_t(s_{t-1}, s_t))$$

$$\beta_n(s) = 1$$

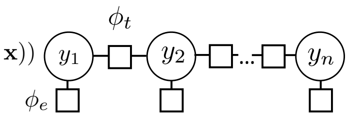
$$\beta_t(s_t) = \sum_{s_{t+1}} \beta_{t+1}(s_{t+1}) \exp(\phi_e(s_{t+1}, t+1, \mathbf{x})) \exp(\phi_t(s_t, s_{t+1}))$$

$$P(s_3 = 2|\mathbf{x}) = \frac{\alpha_3(2)\beta_3(2)}{\sum_i \alpha_3(i)\beta_3(i)}$$

- Does this explain why beta is what it is?
- What does the denominator here mean?

Computing Marginals

$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z} \prod_{i=2}^{n} \exp(\phi_t(y_{i-1}, y_i)) \prod_{i=1}^{n} \exp(\phi_e(y_i, i, \mathbf{x}))$$



- Normalizing constant $Z = \sum_{\mathbf{y}} \prod_{i=2}^{n} \exp(\phi_t(y_{i-1}, y_i)) \prod_{i=1}^{n} \exp(\phi_e(y_i, i, \mathbf{x}))$
- Analogous to P(**x**) for HMMs
- For both HMMs and CRFs:

$$P(y_i = s|\mathbf{x}) = \frac{\text{forward}_i(s)\text{backward}_i(s)}{\sum_{s'} \text{forward}_i(s')\text{backward}_i(s')}$$

Z for CRFs, P(**x**) for HMMs

Posteriors vs. Probabilities

$$P(y_i = s|\mathbf{x}) = \frac{\text{forward}_i(s)\text{backward}_i(s)}{\sum_{s'} \text{forward}_i(s')\text{backward}_i(s')}$$

- Posterior is *derived* from the parameters and the data (conditioned on **x**!)

	$P(x_i|y_i), P(y_i|y_{i-1})$	$P(y_i|\mathbf{x}), P(y_{i-1}, y_i|\mathbf{x})$
HMM	Model parameter (usually multinomial distribution)	Inferred quantity from forward-backward
CRF	Undefined (model is by definition conditioned on **x**)	Inferred quantity from forward-backward

Training CRFs

- For emission features:

$$\frac{\partial}{\partial w}\mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \sum_{i=1}^{n} f_e(y_i^*, i, \mathbf{x}) - \sum_{i=1}^{n} \sum_{s} P(y_i = s|\mathbf{x}) f_e(s, i, \mathbf{x})$$

gold features — expected features under model

- Transition features: need to compute $P(y_i = s_1, y_{i+1} = s_2|\mathbf{x})$ using forward-backward as well
- …but you can build a pretty good system without learned transition features (use heuristic weights, or just enforce constraints like B-PER -> I-ORG is illegal)

CRFs Outline

- Model: $P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z}\prod_{i=2}^{n}\exp(\phi_t(y_{i-1}, y_i))\prod_{i=1}^{n}\exp(\phi_e(y_i, i, \mathbf{x}))$

$$P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x})\right]$$

- Inference: argmax P(**y**|**x**) from Viterbi

- Learning: run forward-backward to compute posterior probabilities; then

$$\frac{\partial}{\partial w}\mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \sum_{i=1}^{n} f_e(y_i^*, i, \mathbf{x}) - \sum_{i=1}^{n}\sum_{s} P(y_i = s|\mathbf{x}) f_e(s, i, \mathbf{x})$$

Pseudocode and Tips

Pseudocode

for each epoch

  for each example

    extract features on each emission and transition (look up in cache)

    compute potentials phi based on features + weights

    compute marginal probabilities with forward-backward

    accumulate gradient over all emissions and transitions

Implementation Tips for CRFs

- Caching is your friend! Cache feature vectors especially
- Try to reduce redundant computation, e.g. if you compute both the gradient and the objective value, don't rerun the dynamic program
- Exploit sparsity in feature vectors where possible, especially in feature vectors and gradients
- Do all dynamic program computation in log space to avoid underflow
- If things are too slow, run a profiler and see where time is being spent. Forward-backward should take most of the time

Debugging Tips for CRFs

- Hard to know whether inference, learning, or the model is broken!
- Compute the objective — is optimization working?
  - **Inference**: check gradient computation (most likely place for bugs)
    - Is $\sum_s \mathrm{forward}_i(s)\mathrm{backward}_i(s)$ the same for all *i*?
    - Do probabilities normalize correctly + look "reasonable"? (Nearly uniform when untrained, then slowly converging to the right thing)
  - **Learning**: is the objective going down? Try to fit 1 example / 10 examples. Are you applying the gradient correctly?
- If objective is going down but model performance is bad:
  - **Inference**: check performance if you decode the training set

Next Time

- Finish discussing NER
- Neural networks