Natural Language Processing

Neural Sequence Labeling

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Includes slides/images from Graham Neubig, Emma Strubell, Wei Xu, Greg Durrett

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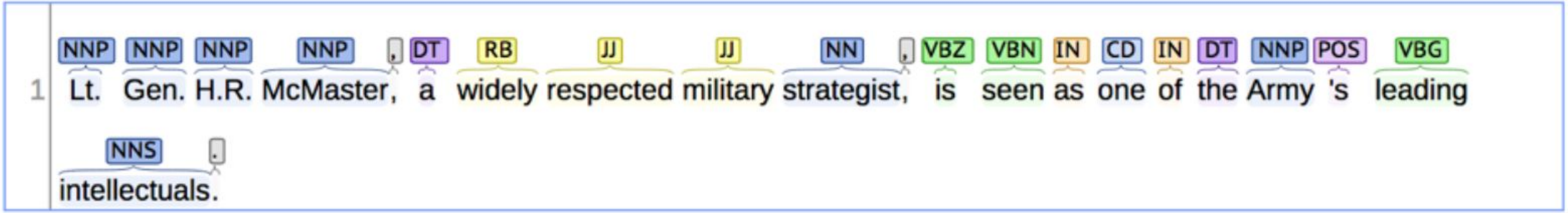
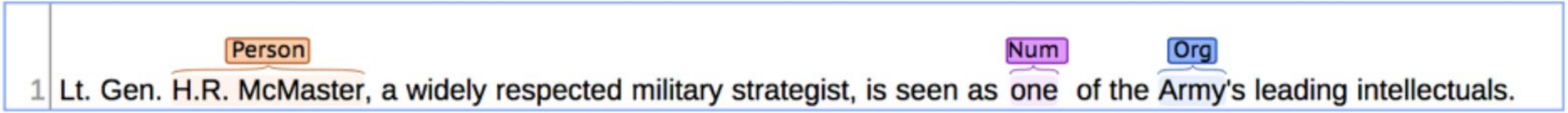
Recap: Sequence Labeling

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

Part-of-Speech:

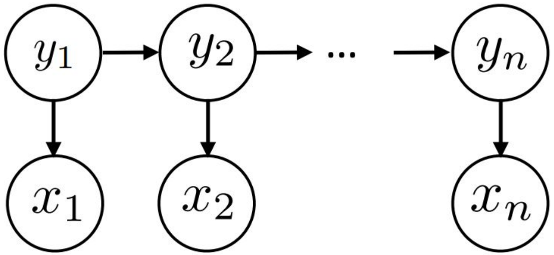


Named Entity Recognition:



O O B-PER I-PER O O O O . . . .

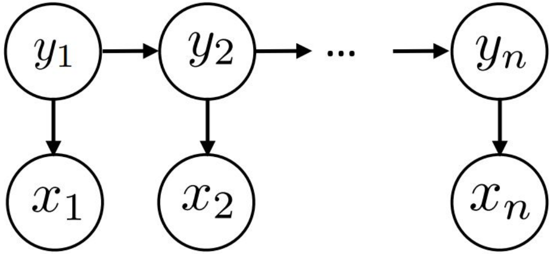
Recap: Generative Models of Sequence Labeling



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

- Training: Maximum Likelihood Estimation (Count and Divide)
- Inference (decoding): $\text{argmax}_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) = \text{argmax}_{\mathbf{y}} \frac{P(\mathbf{y}, \mathbf{x})}{\cancel{P(\mathbf{x})}}$
- Viterbi: $\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1}) P(x_i|s) \text{score}_{i-1}(y_{i-1})$

Limitations of HMMs



I will friend him on Facebook.

- Difficult to handle a word with an unseen tag or an unknown word
- HMMs don't allow adding additional features.
  - e.g. Facebook is capitalized (should be a NN), friend is followed by will, might be a VB.
- HMMs perform poorly on more complex tasks like Named Entity Recognition (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		

- Why might an HMM not do so well here?
  - Lots of O's, so tags are not as informative [about the context].
  - Lots of unknown entities at test time – smoothing will not work.

Today: Discriminative Models

Goal: To tag a sequence

- Directly model p(y|x)
  - Simply using logistic regression, Maximum Entropy Markov Models (or MEMMs)
  - Conditional Random Fields (or CRFs).

Generative vs Discriminative Models

- Generative Models specify a *joint* distribution over the labels and the data. e.g. HMMs

$$p(\mathbf{y}, \mathbf{x}) = p(\mathbf{y})p(\mathbf{x}|\mathbf{y})$$

- Discriminative models compute the *conditional* distribution of the labels given the input. You want to **discriminate** between different labels.

$$p(\mathbf{y}|\mathbf{x})$$

Discriminative Model

- General form:

$$p(\mathbf{y}|\mathbf{x})$$

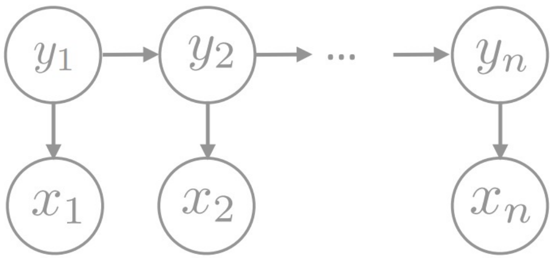
- Zero-th order Markov assumption

$$\prod_{i=1}^{n} p(y_i|\mathbf{x})$$

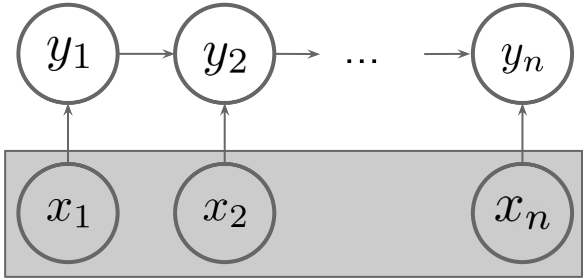
- First order Markov assumption

$$\prod_{i=1}^{n} p(y_i|y_{i-1}, \mathbf{x})$$

HMM



MEMM



Maximum Entropy Markov Models

$$\boxed{t_1, t_2, \ldots, t_C}$$

$$\prod_{i=1}^{n} p(y_i | y_{i-1}, \mathbf{x})$$

A text classification problem (with more than 2 classes)

multiclass logistic regression

Define a score function $s(y_i, y_{i-1}, \mathbf{x})$

$$p(y_i = t_j | y_{i-1}, \mathbf{x}) \propto e^{s(y_i = t_j, y_{i-1}, \mathbf{x})}$$

$$p(y_i = t_j | y_{i-1}, \mathbf{x}) = \frac{e^{s(y_i = t_j, y_{i-1}, \mathbf{x})}}{\sum_{k=1}^{C} e^{s(y_i = t_k, y_{i-1}, \mathbf{x})}}$$

Normalization

Scoring Function

$$s(y_i, y_{i-1}, \mathbf{x}) = \underbrace{\mathbf{w}}_{\text{weights (vector)}} \cdot \underbrace{\phi(y_i, y_{i-1}, \mathbf{x})}_{\text{Feature function (vector)}}$$

Three Questions

1. How to define features?
2. How to learn the weights for features?
3. How to perform inference (decoding)?

How to define features

$$\phi(y_i, y_{i-1}, \mathbf{x}) = \begin{array}{|c|c|c|c|c|c|c|c|c|c|c|c|c|c|c|} \hline \overset{\text{xi=run}}{1} & 0 & \dots & \underset{\text{yi=VB}}{1} & \dots & 0 & \dots & \underset{\text{yi-1=MD}}{1} & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \hline \end{array}$$

Example: I will run.

- What is the current word, xi?
  - Number of features: size of vocabulary
- What is the previous label y_{i-1}
  - Number of features: total number of tags
- What is the previous word x_{i-1} … ?
  - Number of features: size of vocabulary

More interesting features

I will absolutely friend you on Facebook.

- Is the current word capitalized?
- Does the current (or previous) word end in -ly, -ed, …
- Does the current word contain digits, or a period?

Features can also be learned

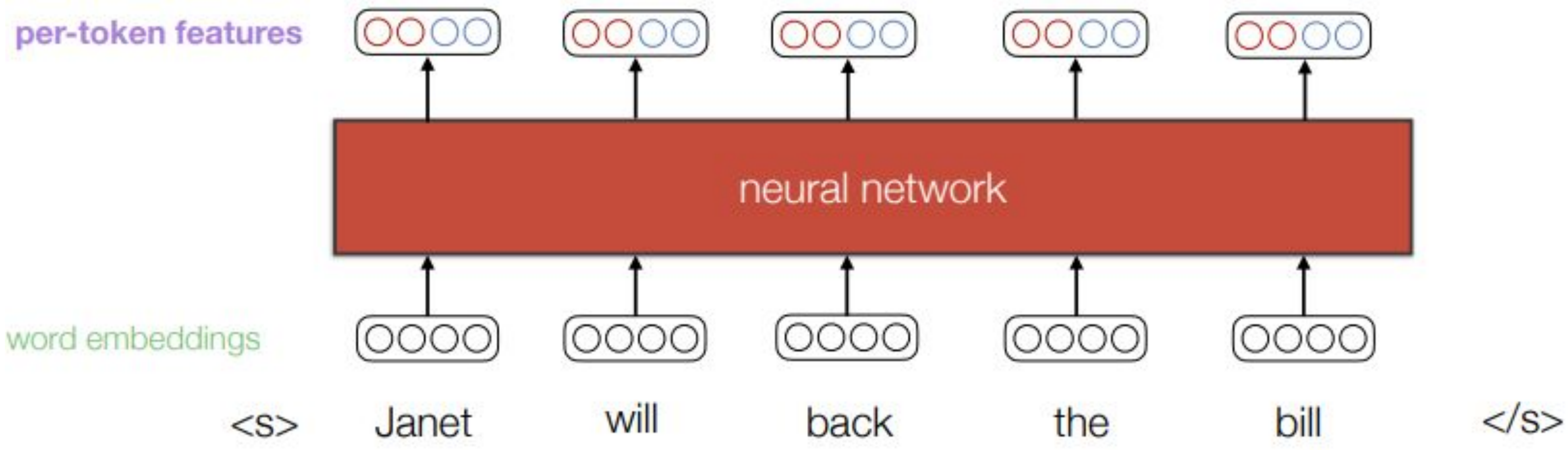
Using neural networks.

Basic Idea: encode the sequence of words into a sequence of vectors

Features can also be learned

Using neural networks.

Basic Idea: encode the sequence of words into a sequence of vectors



Features can also be learned

How to encode: Recurrent Neural Networks

$$h_i = F_\theta(h_{i-1}, x_i) \qquad h_0 = \mathbf{0}$$

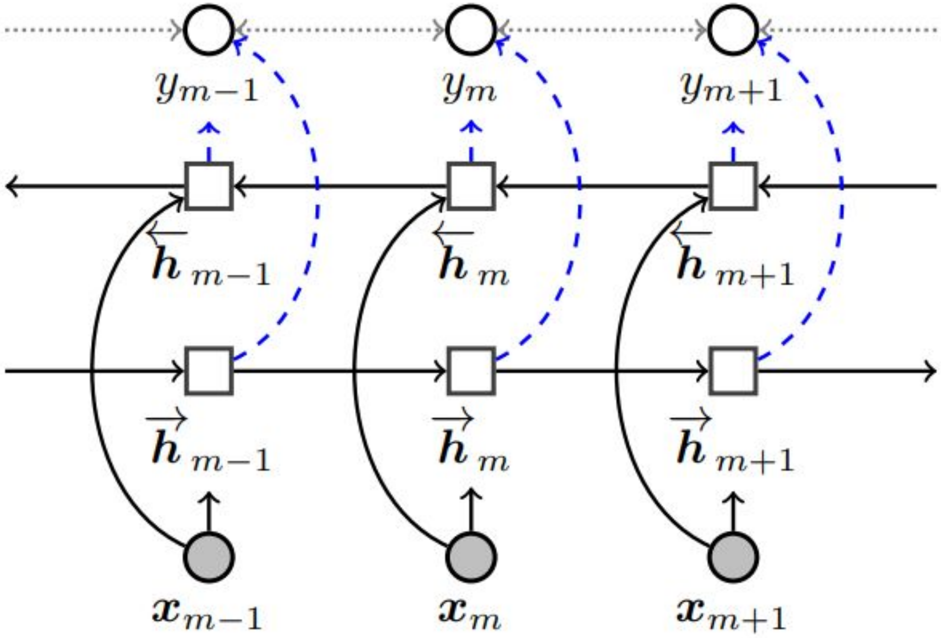
Token Feature at i — Token Feature at i-1 — Input at i

$$\phi(y_i, y_{i-1}, \mathbf{x}) = G(h_i, y_i, y_{i-1})$$

What is F:

- LSTM
- Transformers
- …

Bi-RNN-CRF



y_{m-1}
y_m
y_{m+1}
$\overleftarrow{\boldsymbol{h}}_{m-1}$
$\overleftarrow{\boldsymbol{h}}_m$
$\overleftarrow{\boldsymbol{h}}_{m+1}$
$\overrightarrow{\boldsymbol{h}}_{m-1}$
$\overrightarrow{\boldsymbol{h}}_m$
$\overrightarrow{\boldsymbol{h}}_{m+1}$
$\boldsymbol{x}_{m-1}$
$\boldsymbol{x}_m$
$\boldsymbol{x}_{m+1}$

How to estimate the weights?

$$p(y_i|y_{i-1}, \mathbf{x}) = \frac{e^{s(y_i, y_{i-1}, \mathbf{x})}}{\sum_{i=1}^{C} e^{s(y_i, y_{i-1}, \mathbf{x})}}$$

$$s(y_i, y_{i-1}, \mathbf{x}) = \mathbf{w} \cdot \phi(y_i, y_{i-1}, \mathbf{x})$$

- Supervised Classification (text and labels are provided as training data)

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

- Minimize cross entropy (aka Negative Log Likelihood) to find weights w and (also neural network parameters).

$$\sum -\log p(y_i|y_{i-1}, \mathbf{x})$$

How to decode? Viterbi again!

$$\arg\max_{\mathbf{y}} \prod_{i=1}^{n} p(y_i|y_{i-1})p(y_i|x_i) \longrightarrow \arg\max_{\mathbf{y}} \prod_{i=1}^{n} p(y_i|y_{i-1}, \mathbf{x})$$

HMM

MEMM

$$\text{score}_i(s) = \max_{y_{i-1}} \boxed{P(s|y_{i-1})P(x_i|s)}\text{score}_{i-1}(y_{i-1}) \longrightarrow \text{score}_i(s) = \max_{y_{i-1}} \boxed{p(s|y_{i-1}, \mathbf{x})}\text{score}_{i-1}(y_{i-1})$$

Viterbi decoding with HMMs

Viterbi decoding with MEMMs

How to decode?

$$\arg\max_{\mathbf{y}} \prod_{i=1}^{n} p(y_i | y_{i-1}, \mathbf{x})$$

$$\max_{y_1,\ldots,y_n} p(y_1|y_0,\mathbf{x})p(y_2|y_1,\mathbf{x})\ldots p(y_n|y_{n-1},\mathbf{x})$$

Say I knew the value of y_{n-1}= u

$$\text{score}_n(y_{n-1}=s) = \max_{(y_1,\ldots,y_{n-2})} p(y_1|y_0,\mathbf{x})\ldots p(y_{n-1}=s|y_{n-2},\mathbf{x})$$

$$\text{score}_n(y_n=s') = \max_{y_{n-1}} p(y_n=s'|y_{n-1},\mathbf{x})score_{n-1}(y_{n-1})$$

This recurrence relation can be solved by dynamic programming. AKA Viterbi algorithm

MEMMs - Summary

$$\prod_{i=1}^{n} p(y_i | y_{i-1}, \mathbf{x})$$

$$p(y_i | y_{i-1}, \mathbf{x}) = \frac{e^{s(y_i, y_{i-1}, \mathbf{x})}}{\sum_{i=1}^{C} e^{s(y_i, y_{i-1}, \mathbf{x})}}$$

$$s(y_i, y_{i-1}, \mathbf{x}) = \mathbf{w} \cdot \phi(y_i, y_{i-1}, \mathbf{x})$$

- Training – Cross Entropy Loss and Gradient Descent
- Decoding: Viterbi Algorithm $\arg\max_{\mathbf{y}} \prod_{i=1}^{n} p(y_i | y_{i-1}, \mathbf{x})$

Local Normalization

- MEMMs are locally normalized.

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

Conditional distribution sums to one for each step i.

$$p(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{n} \frac{e^{\mathbf{w}\cdot\phi(y_i, y_{i-1}, \mathbf{x})}}{\sum_{i=1}^{C} e^{\mathbf{w}\cdot\phi(y_i, y_{i-1}, \mathbf{x})}}$$

Local Normalization to Global Normalization

Conditional Random Fields

- If we do global normalization, we get “conditional random fields” or CRFs.

$$\prod_{i=1}^{n} \frac{e^{\mathbf{w}\cdot\phi(y_i,y_{i-1},\mathbf{x})}}{\sum_{i=1}^{C} e^{\mathbf{w}\cdot\phi(y_i,y_{i-1},\mathbf{x})}} \longrightarrow p(\mathbf{y}|\mathbf{x}) = \frac{e^{\mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})}}{\sum_{\mathbf{y}'} e^{\mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})}}$$

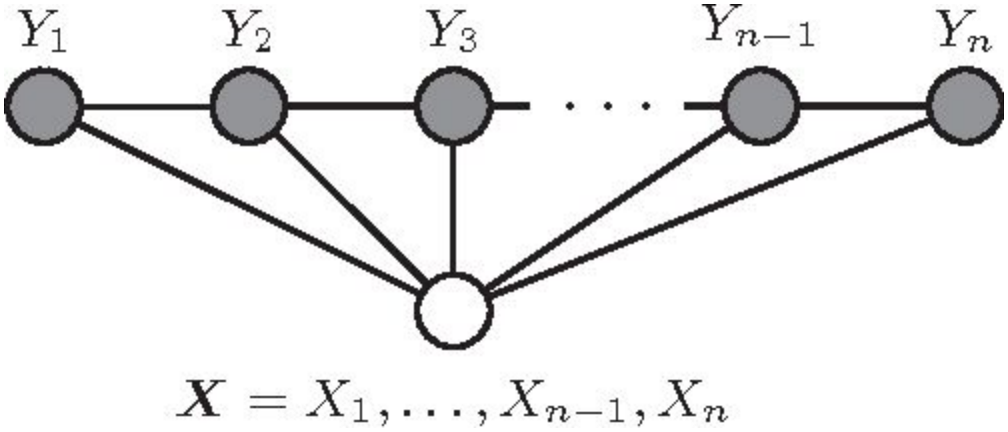
$$\Phi(\mathbf{y},\mathbf{x}) = \sum_{i=1}^{n} \phi(y_i, y_{i-1}, \mathbf{x})$$

Global Feature vector

Old feature vector

CRF - Undirected Graphical Model

$$\Phi(\mathbf{y}, \mathbf{x}) = \sum_{i=1}^{n} \phi(y_i, y_{i-1}, \mathbf{x})$$



CRFs

- How to find the weights – training?
  - Same as MEMM, minimize cross entropy
  - We have the same set of weights we had with MEMM. How they are learned is different (and better).

- How to find tags at test time – decoding?
  - Viterbi

Decoding with CRFs - Viterbi Algorithm

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} \frac{e^{\mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})}}{\sum_{\mathbf{y}'} e^{\mathbf{w}\cdot\Phi(\mathbf{y}',\mathbf{x})}}$$

Independent of **y**

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} e^{\mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})}$$

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} \mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})$$

Decoding with CRFs - Viterbi Algorithm

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} \mathbf{w} \cdot \Phi(\mathbf{y}, \mathbf{x})$$

$$\boxed{\Phi(\mathbf{y}, \mathbf{x}) = \sum_{i=1}^{n} \phi(y_i, y_{i-1}, \mathbf{x})}$$

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} \mathbf{w} \cdot \sum_{i=1}^{n} \phi(y_i, y_{i-1}, \mathbf{x})$$

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} \sum_{i=1}^{n} \mathbf{w} \cdot \phi(y_i, y_{i-1}, \mathbf{x})$$

Decoding with CRFs - Viterbi Algorithm

$$\hat{\mathbf{y}} = \arg\max_{\mathbf{y}} \sum_{i=1}^{n} \mathbf{w} \cdot \phi(y_i, y_{i-1}, \mathbf{x})$$

This can be also solved with Viterbi!

$$\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1})P(x_i|s)\text{score}_{i-1}(y_{i-1})$$

Viterbi decoding with HMMs

$$\boxed{\text{score}_i(s) = \max_{y_{i-1}} \mathbf{w} \cdot \phi(s, y_i - 1, \mathbf{x}) + score_{i-1}(y_{i-1})}$$

Viterbi decoding with CRFs

Training CRF weights

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

- Supervised Classification (text and labels are provided as training data)

$$\mathcal{L}(\mathbf{w}) = -\log p(\mathbf{y}|\mathbf{x})$$

$$\mathcal{L}(\mathbf{w}) = -\log \frac{e^{\mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})}}{\sum_{\mathbf{y}'} e^{\mathbf{w}\cdot\Phi(\mathbf{y}',\mathbf{x})}}$$

Really expensive!

The normalization complexity is huge — every possible sequence of labels of length n

Can solve fast by dynamic programming!

$$\sum_{\mathbf{y}'} e^{\mathbf{w}\cdot\Phi(\mathbf{y}',\mathbf{x})}$$

$$\sum_{\mathbf{y}'} e^{\mathbf{w}\cdot\sum_{i=1}^{n}\phi(y_i,y_{i-1},\mathbf{x})}$$

$$\sum_{\mathbf{y}'} e^{\sum_{i=1}^{n}\mathbf{w}\cdot\phi(y_i,y_{i-1},\mathbf{x})}$$

Forward Algorithm

$$\sum_{\mathbf{y}'} e^{\sum_{i=1}^{n} \mathbf{w} \cdot \phi(y_i, y_{i-1}, \mathbf{x})}$$

$$\sum_{\mathbf{y}'} \prod_{i=1}^{n} e^{\mathbf{w} \cdot \phi(y_i, y_{i-1}, \mathbf{x})}$$

$$\boxed{\arg\max_{\mathbf{y}} \prod_{i=1}^{n} p(y_i | y_{i-1}, \mathbf{x})}$$

Both terms compute a product of some values dependent of yi, yi-1, and x

The max is replaced with sum

Dynamic Programming: Forward Algorithm

$$\sum_{\mathbf{y}'} \prod_{i=1}^{n} e^{\mathbf{w} \cdot \phi(y_i, y_{i-1}, \mathbf{x})}$$

$$\text{score}_i(s) = \max_{y_{i-1}} P(s|y_{i-1}) P(x_i|s) \text{score}_{i-1}(y_{i-1})$$

Viterbi decoding with HMMs

$$\text{score}_i(s) = \sum_{y_{i-1}} e^{\mathbf{w} \cdot \phi(s, y_i - 1, \mathbf{x})} \text{score}_{i-1}(y_{i-1})$$

Forward algorithm in CRFs

To summarize:

CRFs:

$$p(\mathbf{y}|\mathbf{x}) = \frac{e^{\mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})}}{\sum_{\mathbf{y}'} e^{\mathbf{w}\cdot\Phi(\mathbf{y},\mathbf{x})}}$$

$$\Phi(\mathbf{y},\mathbf{x}) = \sum_{i=1}^{n} \phi(y_i, y_{i-1}, \mathbf{x})$$

Features:

- Hand engineered or based on neural networks.

Training:

- Cross Entropy Loss (and Gradient Descent) + Forward Algorithm

Decoding

- Viterbi Algorithm

Readings

- Log Linear Models, MEMMs and CRFS (Michael Collins): crf.pdf (columbia.edu)
- BiLSTM-CRFs for sequence labeling: [1508.01991] Bidirectional LSTM-CRF Models for Sequence Tagging (arxiv.org)
- Natural Language Processing, Jacob Eisenstein (7.5.3): eisenstein-nov18.pdf (ucsd.edu)