Conditional Random Fields and Structured Perceptron

Instructor: Wei Xu
Ohio State University
CSE 5525

Some slides from Eric Xing and Michael Collins

Previously, we saw MEMMs…

$$P(t_1 \dots t_n | w_1 \dots w_n) = \prod_{i=1}^{n} q(t_i | t_{i-1}, w_1 \dots w_n, i)$$

$$= \prod_{i=1}^{n} \frac{e^{v \cdot f(t_i, t_{i-1}, w_1 \dots w_n, i)}}{\sum_{t'} e^{v \cdot f(t', t_{i-1}, w_1 \dots w_n, i)}}$$

MEMMs: The Label Bias Problem

$$P(t_1, \ldots, t_n | w_1 \ldots w_n) = \prod_{i=1}^{n} \frac{e^{v \cdot f(t_i, t_{i-1}, w_1 \ldots w_n, i)}}{\sum_{t'} e^{v \cdot f(t', t_{i-1}, w_1 \ldots w_n, i)}}$$

These are forced to sum to 1 Locally

Q: Is that really necessary?

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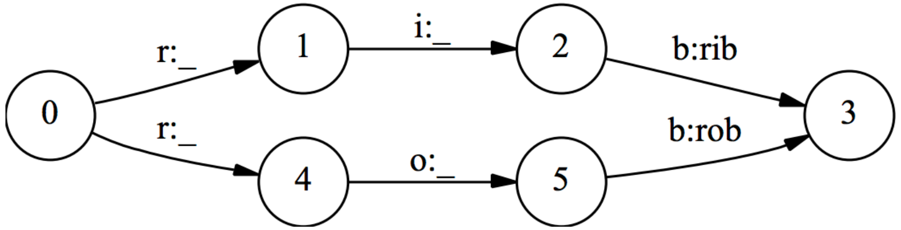
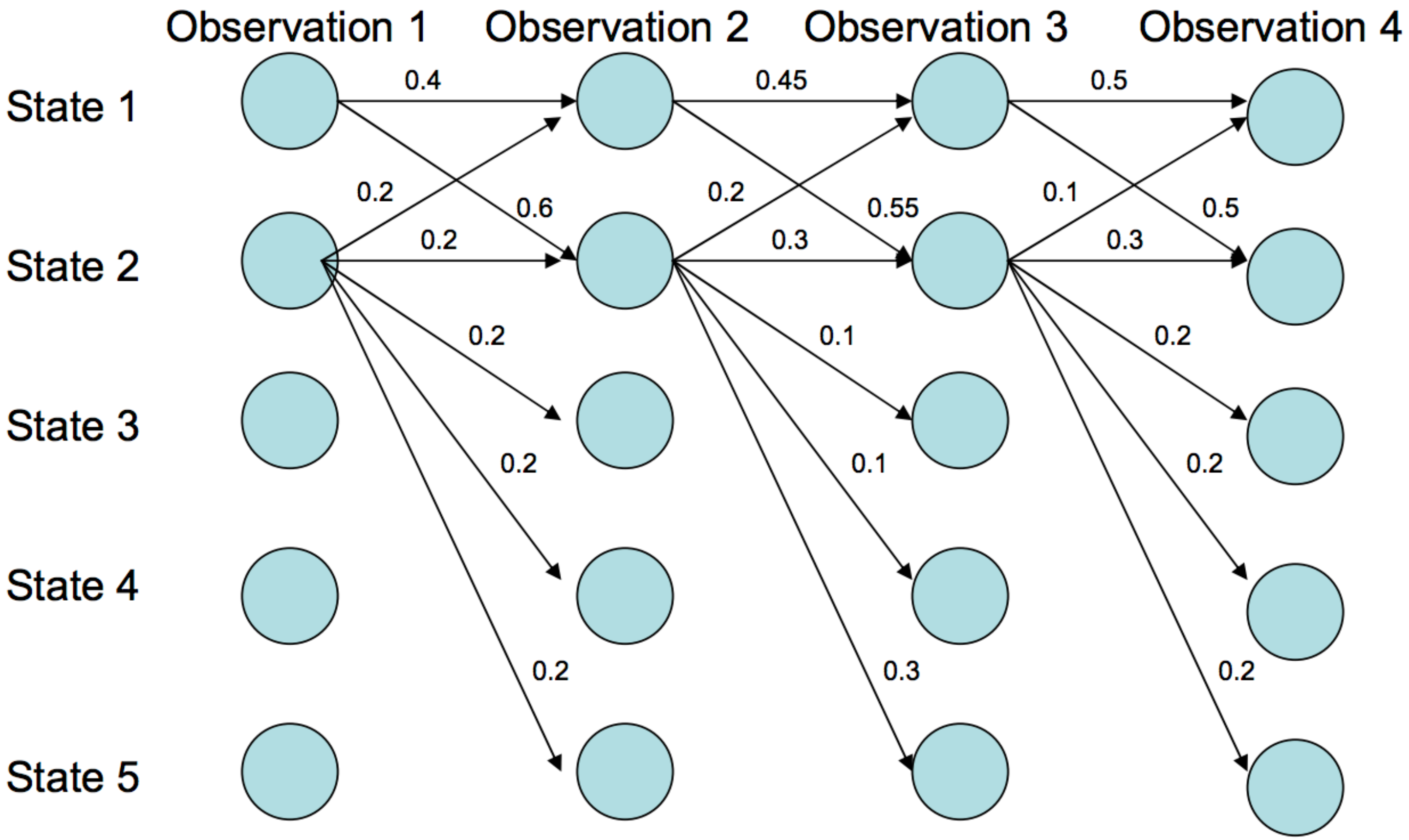


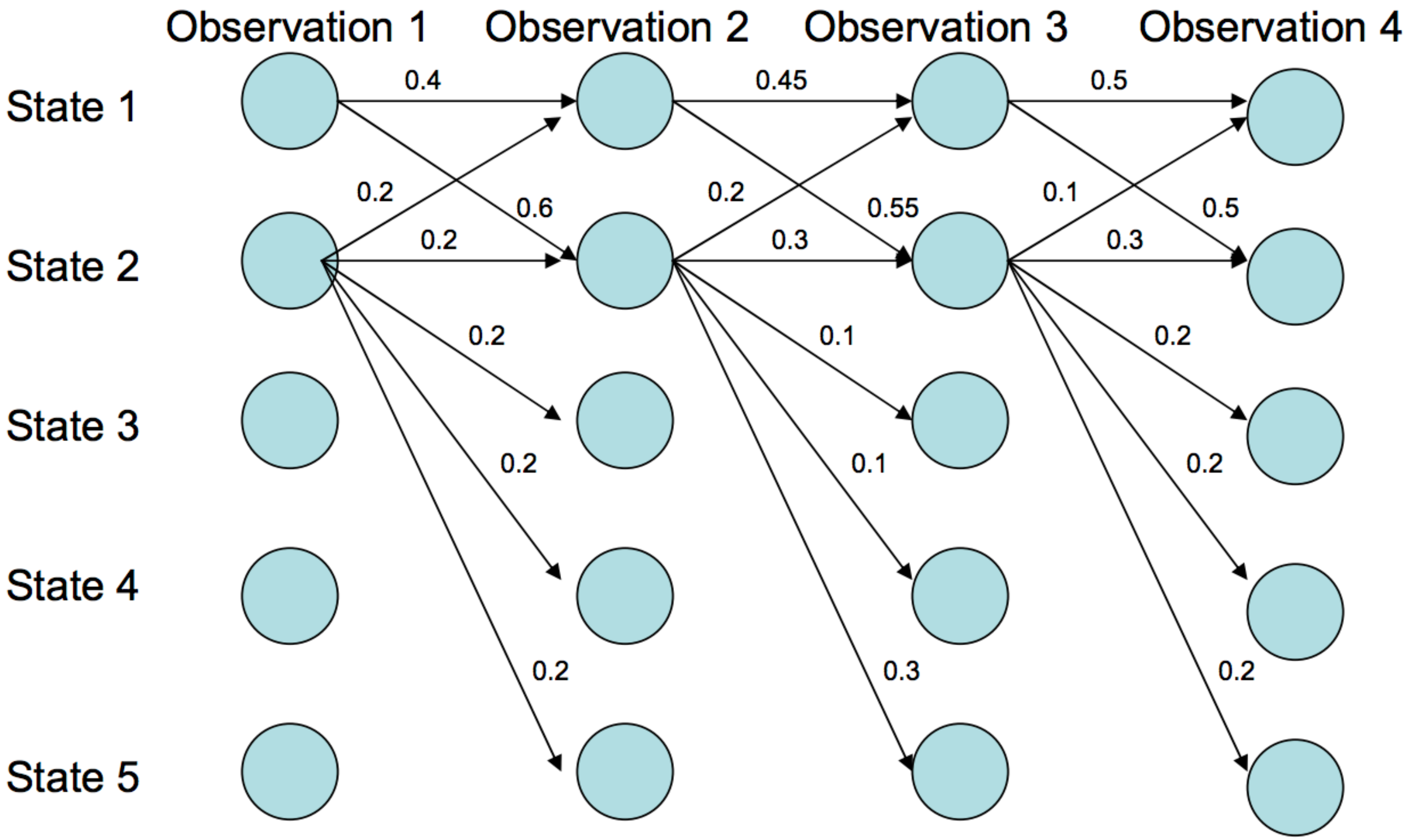
Figure 1. Label bias example, after (Bottou, 1991). For conciseness, we place observation-label pairs $o : l$ on transitions rather than states; the symbol '_' represents the null output label.

Lafferty et al. 2001. Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data.

MEMMs: The Label Bias Problem



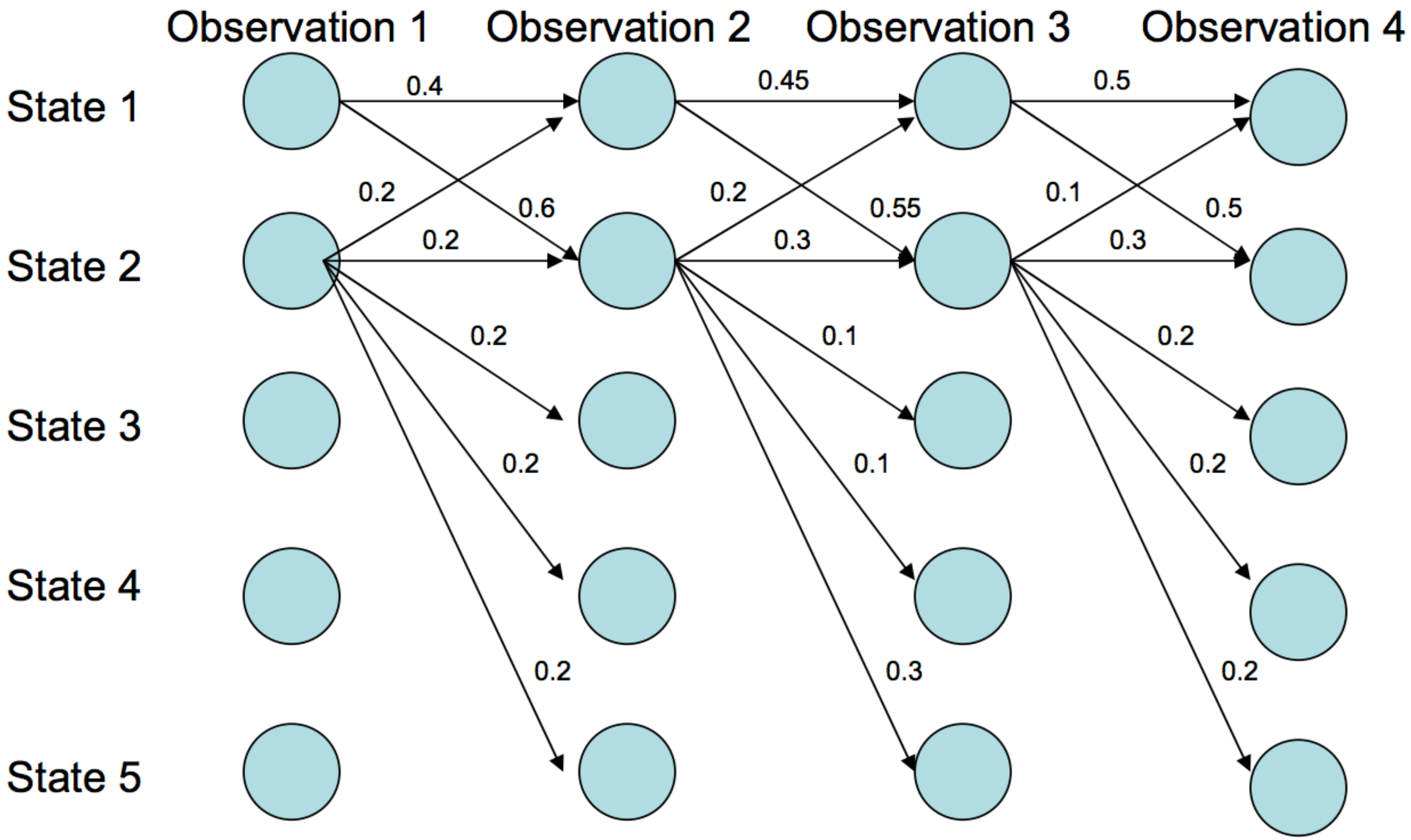
MEMMs: The Label Bias Problem



What the local transition probabilities say:

- State 1 almost always prefers to go to state 2
- State 2 almost always prefer to stay in state 2

MEMMs: The Label Bias Problem

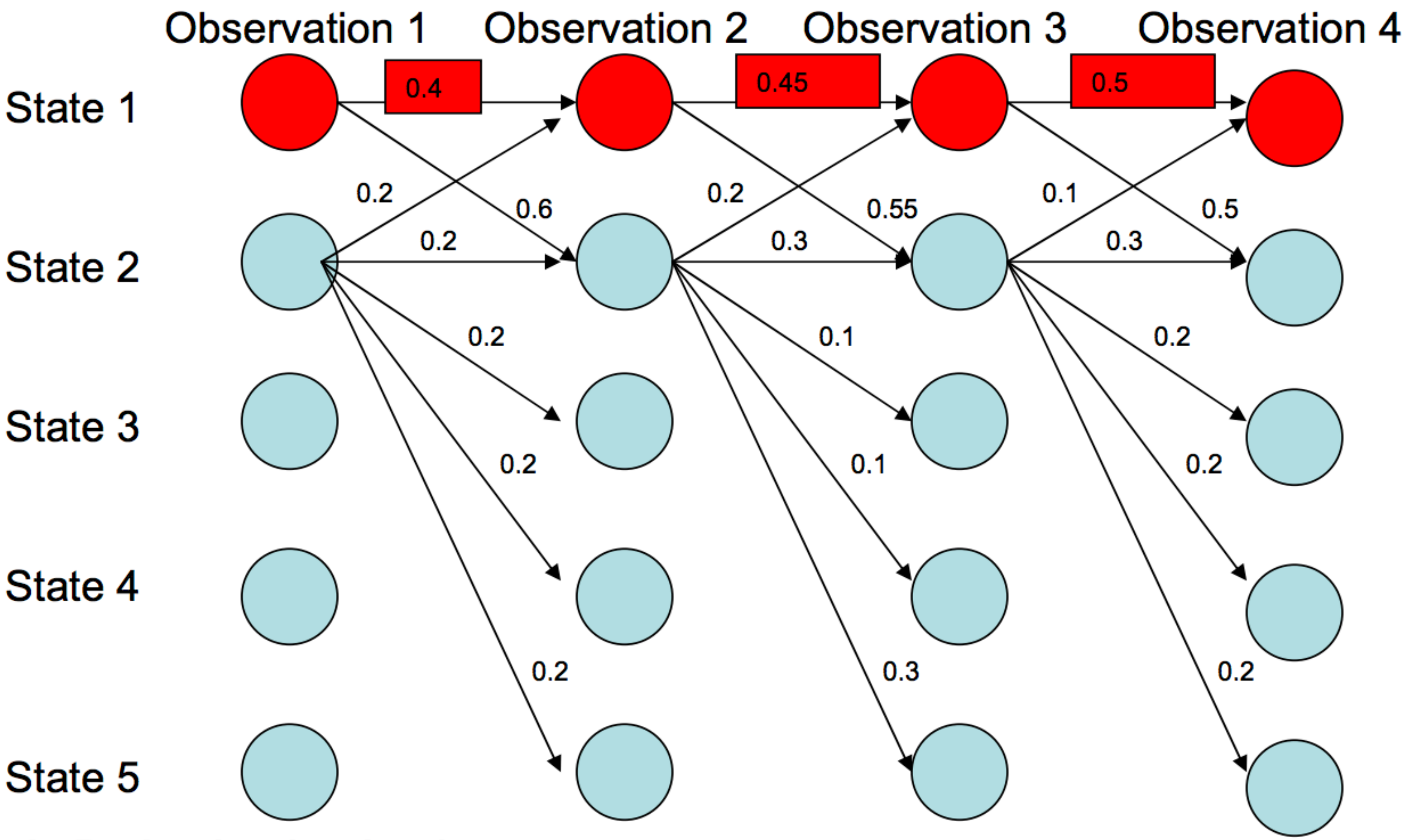


Probability of path 1->1->2->2:

- 0.4 X 0.55 X 0.3 = 0.066

Other paths:
1->1->1->1: 0.09
2->2->2->2: 0.018
1->2->1->2: 0.06

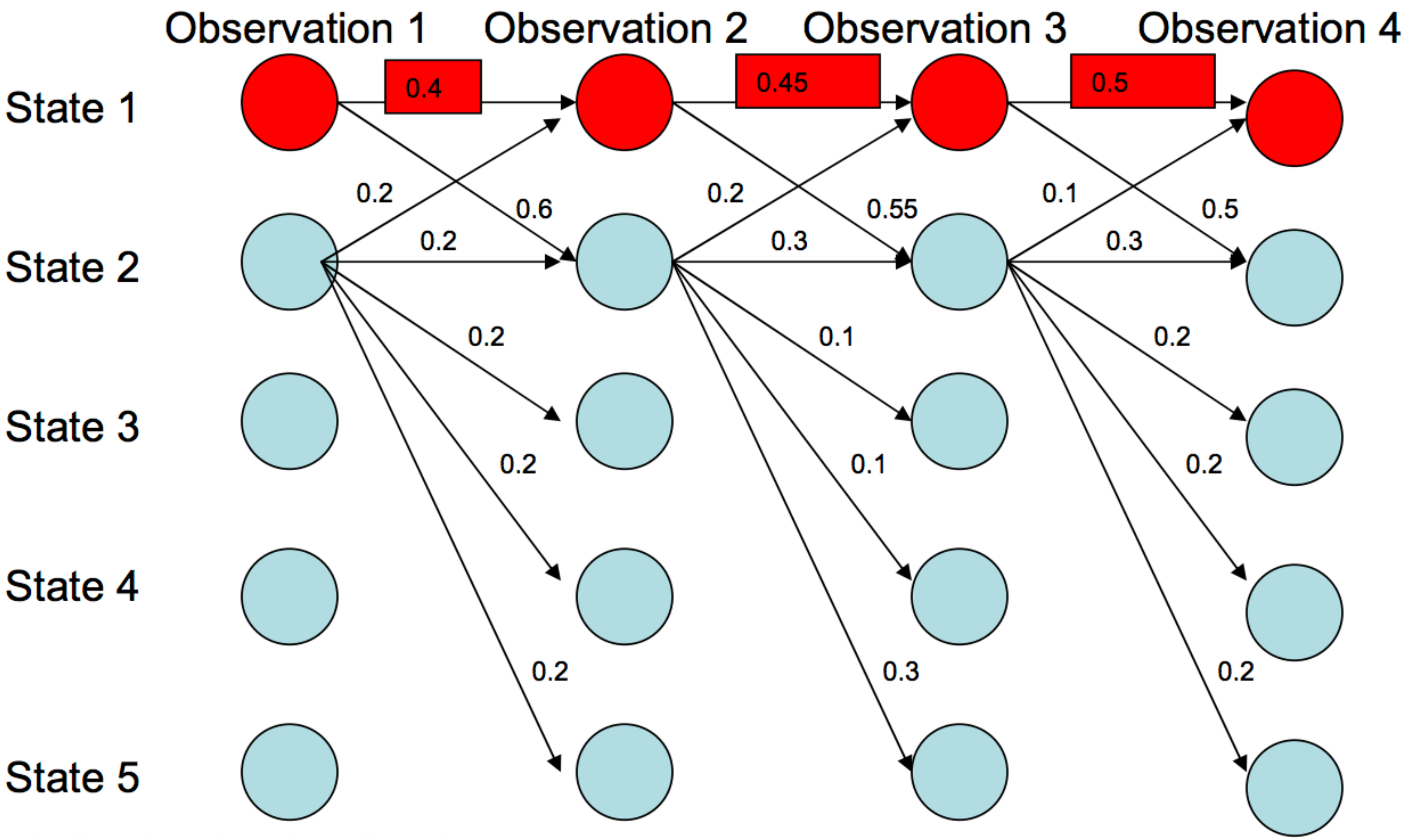
MEMMs: The Label Bias Problem



Most Likely Path: 1-> 1-> 1-> 1

- Although **locally** it seems state 1 wants to go to state 2 and state 2 wants to remain in state 2.
- **why?**

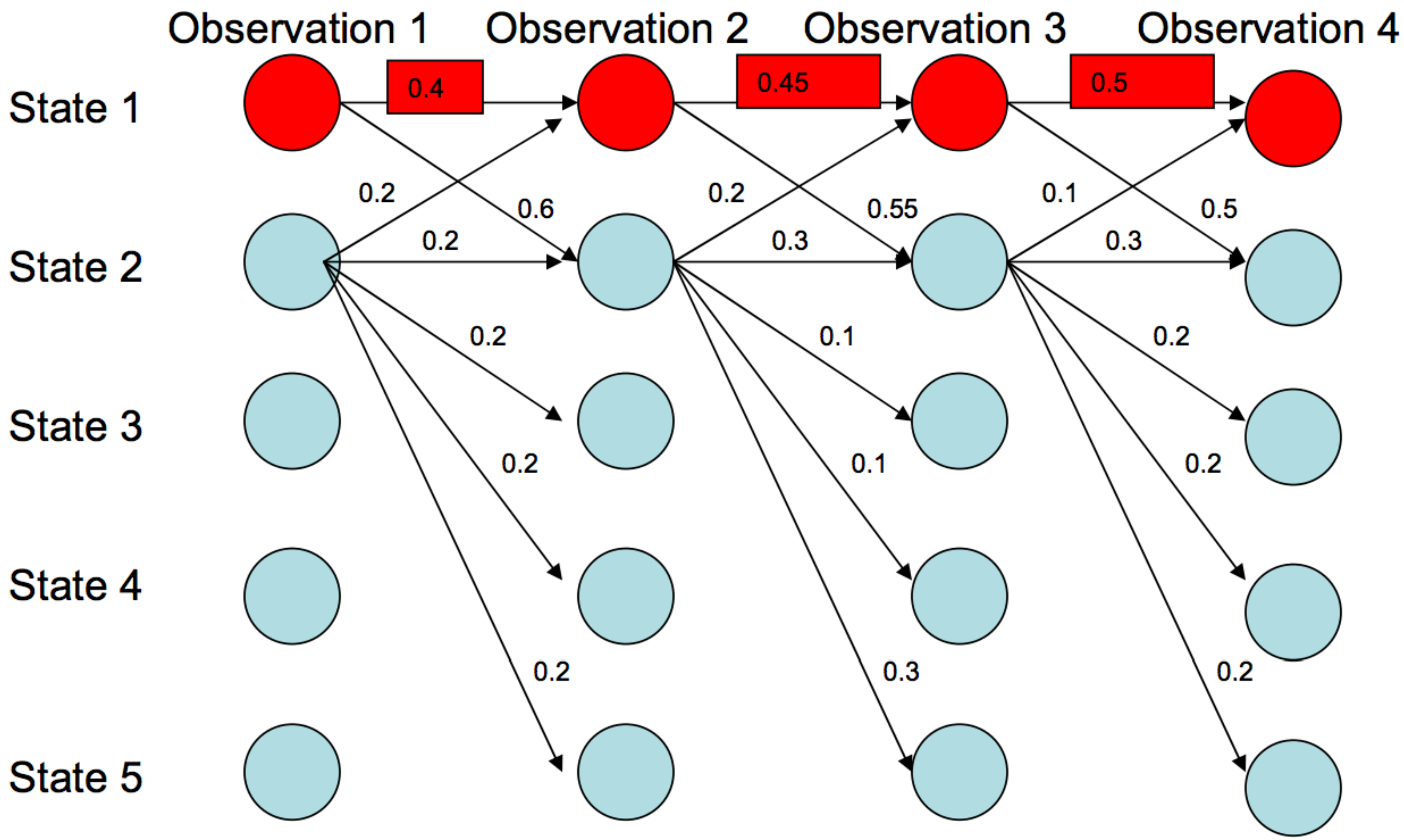
MEMMs: The Label Bias Problem



Most Likely Path: 1-> 1-> 1-> 1

- State 1 has only two transitions but state 2 has 5:
  - Average transition probability from state 2 is lower

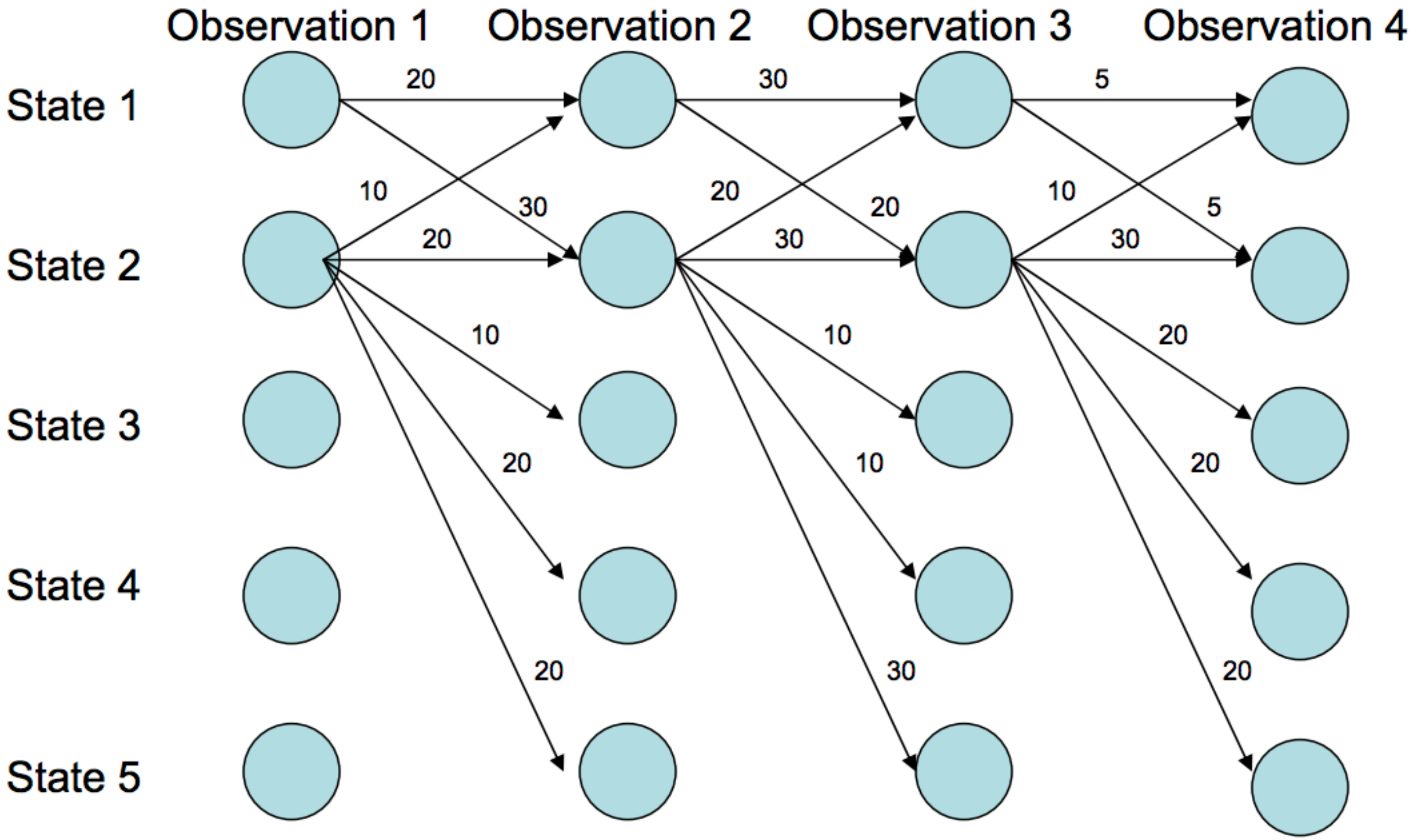
MEMMs: The Label Bias Problem



Label bias problem in MEMM:

• Preference of states with lower number of transitions over others

Solution: Do not normalize probabilities locally



From local probabilities to local potentials

- States with lower transitions do not have an unfair advantage!

MEMMs: The Label Bias Problem

- States with low entropy distributions effectively ignore observations

$$P(t_1, \ldots, t_n | w_1 \ldots w_n) = \prod_{i=1}^{n} \frac{e^{v \cdot f(t_i, t_{i-1}, w_1 \ldots w_n, i)}}{\sum_{t'} e^{v \cdot f(t', t_{i-1}, w_1 \ldots w_n, i)}}$$

These are forced to sum to 1 Locally

Q: is that really necessary?

From MEMMs to Conditional Random Fields

$$P(t_1, \ldots, t_n | w_1 \ldots w_n) \propto \prod_{i=1}^{n} e^{v \cdot f(t_i, t_{i-1}, w_1 \ldots w_n, i)}$$

Q: how can we make the distribution over tag sequences sum to 1?

From MEMMs to Conditional Random Fields

$$P(t_1, \ldots, t_n | w_1 \ldots w_n) = \frac{1}{Z(v, w_1, \ldots, w_n)} \prod_{i=1}^{n} e^{v \cdot f(t_i, t_{i-1}, w_1 \ldots w_n, i)}$$

$$Z(v, w_1, \ldots, w_n) = \sum_{t_1, \ldots, t_n} \prod_{i=1}^{n} e^{v \cdot f(t_i, t_{i-1}, w_1 \ldots w_n, i)}$$

CRF uses global normalizer to overcome the label bias problem of MEMM

- MEMMs use a per-state exponential model
- CRFs have a single exponential model for the joint probability of the entire label sequence

Conditional Random Fields

- Learning:
  - similar to MEMM (gradient descent or MAP perceptron)

- Inference:
  - similar to HMM (dynamic programming)

    1) given model parameters, find best tag sequence
    2) during learning, compute marginal probabilities and the Z

Gradient ascent

Loop While not converged:

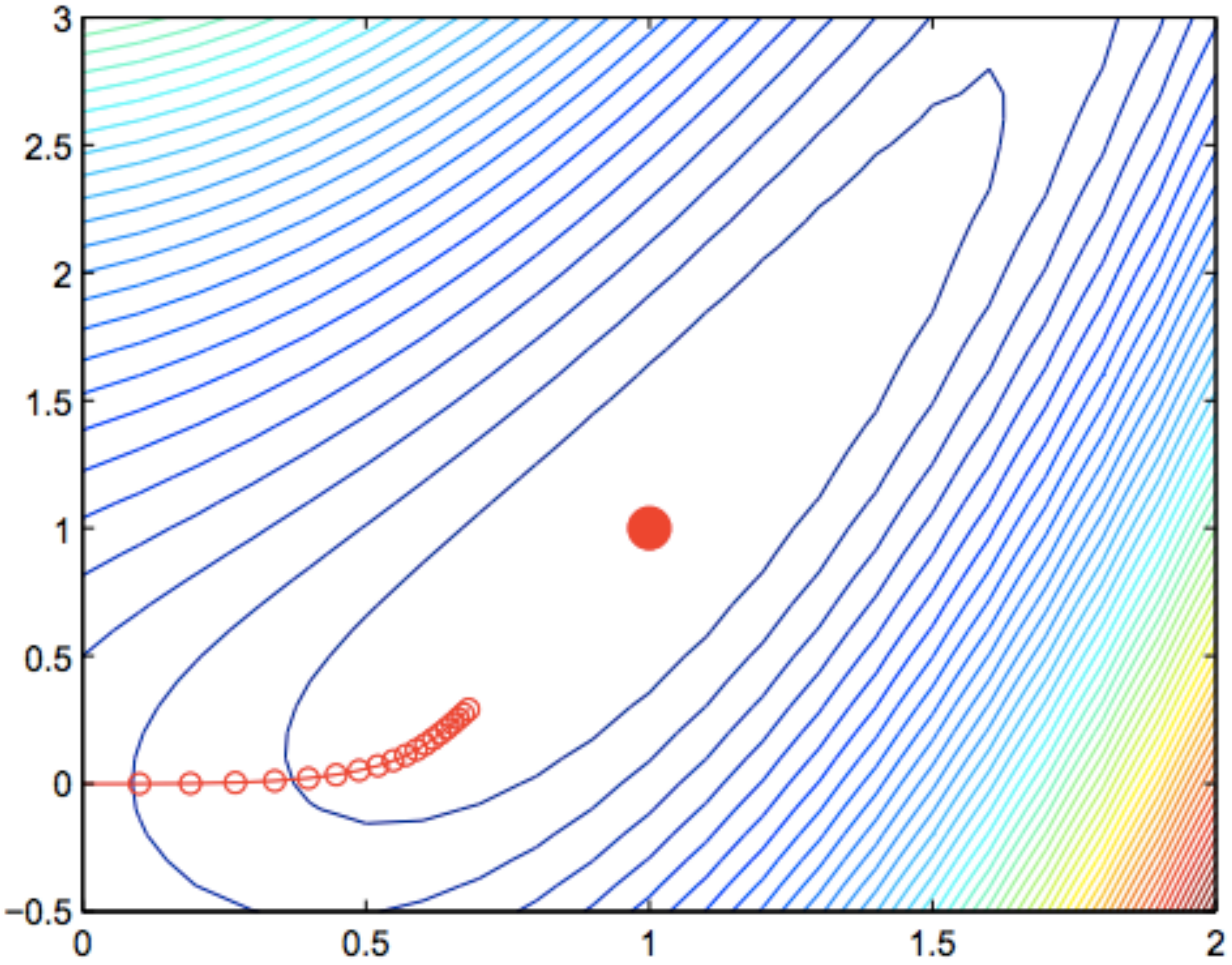
For all features **j**, compute and add derivatives

$$w_j^{\text{new}} = w_j^{\text{old}} + \eta \frac{\partial}{\partial w_j} \mathcal{L}(w)$$

$\mathcal{L}(w)$: Training set log-likelihood

$$\left(\frac{\partial \mathcal{L}}{\partial w_1}, \frac{\partial \mathcal{L}}{\partial w_2}, \ldots, \frac{\partial \mathcal{L}}{\partial w_n} \right)$$

Gradient ascent



Gradient of Log-Linear Models

$$\frac{\partial \mathcal{L}}{\partial w_j} = \sum_{i=1}^{D} f_j(y_i, d_i) - \sum_{i=1}^{D} \sum_{y \in Y} f_j(y, d_i) P(y|d_i)$$

MAP-based Learning (perceptron)

$$\frac{\partial \mathcal{L}}{\partial w_j} \approx \sum_{i=1}^{D} f_j(y_i, d_i) - \sum_{i=1}^{D} f_j(\arg\max_{y \in Y} P(y|d_i), d_i)$$

Conditional Random Field Gradient

$$\frac{\partial \mathcal{L}}{\partial w_j} = \sum_{i=1}^{D} \sum_{k} f_j(t_k, t_{k-1}, w_1, \ldots, w_n, k) -$$

$$\sum_{i=1}^{D} \sum_{t_1, \ldots, t_n} \sum_{k} f_j(t_k, t_{k-1}, w_1, \ldots, w_n, k) P(t_1, \ldots, t_n | w_1, \ldots, w_n)$$

Tractable! Can be computed with the dynamic programming (Forward-Backward) algorithm

MAP-based learning (perceptron)

$$\frac{\partial \mathcal{L}}{\partial w_j} \approx \sum_{i=1}^{D} \sum_{k} f_j(t_k, t_{k-1}, w_1, \ldots, w_n, k) -$$

$$\sum_{i=1}^{D} \sum_{k} f_j(\arg\max_{t_1,\ldots,t_n} P(t_1, \ldots, t_n | w_1, \ldots, w_n), w_1, \ldots, w_n, k)$$

Training a Tagger using the Perceptron Algorithm

can be computed with the dynamic programming (Viterbi) algorithm

Algorithm 40 STRUCTUREDPERCEPTRONTRAIN(**D**, *MaxIter*)

$w \leftarrow \mathbf{0}$ // initialize weights
for *iter* = 1 … *MaxIter* **do**
  for all $(x,y) \in \mathbf{D}$ **do**
    $\hat{y} \leftarrow \mathrm{argmax}_{\hat{y} \in \mathcal{Y}(x)}\, w \cdot \phi(x, \hat{y})$ // compute prediction
    if $\hat{y} \neq y$ **then**
      $w \leftarrow w + \phi(x, y) - \phi(x, \hat{y})$ // update weights
    end if
  end for
end for
return w // return learned weights

An Example

Say the correct tags for i'th sentence are

the/DT man/NN bit/VBD the/DT dog/NN

Under current parameters, output is

the/DT man/NN bit/NN the/DT dog/NN

Assume also that features track: (1) all bigrams; (2) word/tag pairs

Parameters incremented:

$$\langle \text{NN, VBD} \rangle, \langle \text{VBD, DT} \rangle, \langle \text{VBD} \rightarrow \text{bit} \rangle$$

Parameters decremented:

$$\langle \text{NN, NN} \rangle, \langle \text{NN, DT} \rangle, \langle \text{NN} \rightarrow \text{bit} \rangle$$

Experiments

- Wall Street Journal part-of-speech tagging data

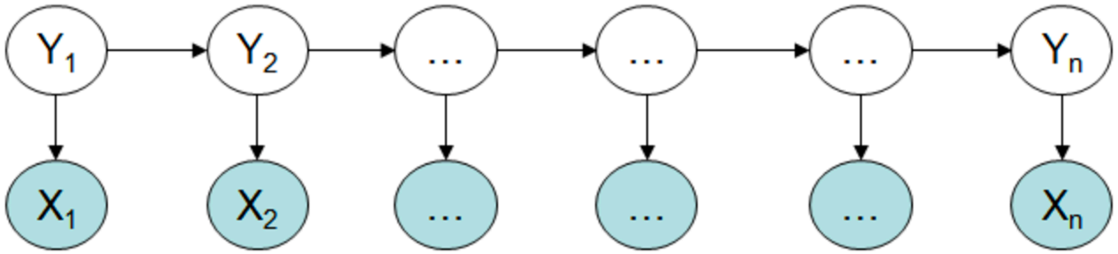
  Perceptron $=$ 2.89% error, Log-linear tagger $=$ 3.28% error

- [Ramshaw and Marcus, 1995] NP chunking data

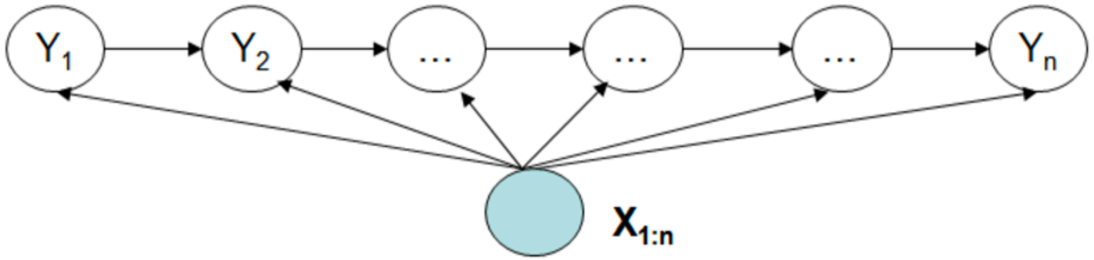
  Perceptron $=$ 93.63% accuracy, Log-linear tagger $=$ 93.29% accuracy

Collins 2002. Discriminative Training Methods for Hidden Markov Models: Theory and Experiments with Perceptron Algorithms

Summary

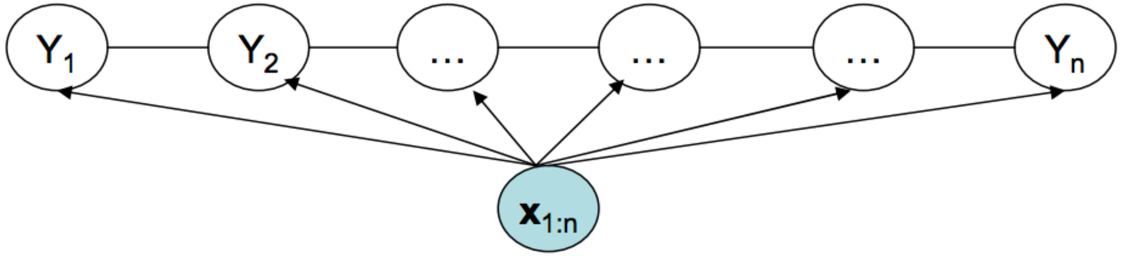


HMM



MEMM

$$P(\mathbf{y}_{1:n}|\mathbf{x}_{1:n}) = \prod_{i=1}^{n} P(y_i|y_{i-1}, \mathbf{x}_{1:n}) = \prod_{i=1}^{n} \frac{\exp(\mathbf{w}^T \mathbf{f}(y_i, y_{i-1}, \mathbf{x}_{1:n}))}{Z(y_{i-1}, \mathbf{x}_{1:n})}$$



CRF

$$P(\mathbf{y}_{1:n}|\mathbf{x}_{1:n}) = \frac{1}{Z(\mathbf{x}_{1:n})} \prod_{i=1}^{n} \phi(y_i, y_{i-1}, \mathbf{x}_{1:n}) = \frac{1}{Z(\mathbf{x}_{1:n}, \mathbf{w})} \prod_{i=1}^{n} \exp(\mathbf{w}^T \mathbf{f}(y_i, y_{i-1}, \mathbf{x}_{1:n}))$$