Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data

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Main Goals

- Present a new framework for labeling sequence data: Conditional Random Fields (CRFs)
- Describe the label bias problem
- Motivate the use of CRFs to solve the label bias problem
- Define the structure and properties of CRFs
- [Describe two training procedures for learning CRF parameters]
- [Sketch a proof of the convergence of the two training procedures]
- Compare experimentally to hidden Markov models (HMMs) and maximum entropy Markov models (MEMMs)

Labeling Sequence Data

- Given observed data sequences $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$
- A corresponding label sequence $\mathbf{y}_k$ for each data sequence $\mathbf{x}_{k,}$, and $Y = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n\}$

Prediction Task

Given a sequence **x** and model θ predict **y**

Learning Task

Given training sets X and Y, learn the best model θ

Notation

set of sequences: X, uppercase

sequence of observations: **x,** lowercase boldface, also called a data sequence

sequence of labels: **y**, lowercase boldface, also called a sequence of states

single observation: x, lowercase, also called a data value

Example label and observation sequence

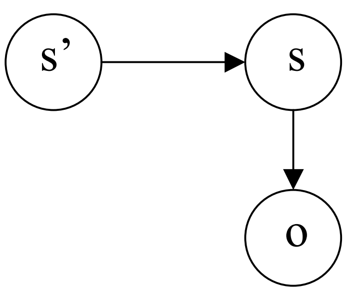
label y	observation x
<head>	X-NNTP-Poster: NewsHound v1.33
<head>	
<head>	Archive-name: acorn/faq/part2
<head>	Frequency: monthly
<head>	
<question>	2.6) What configuration of serial cable should
<question>	I use?
<answer>	Here follows a diagram of the necessary
<answer>	connections programs to work properly. They
<answer>	are as far as know agreed upon by commercial
<answer>	comms software developers fo
<answer>	
<answer>	Pins 1, 4, and 8 must be connected together
<answer>	is to avoid the well known serial port chip bugs.

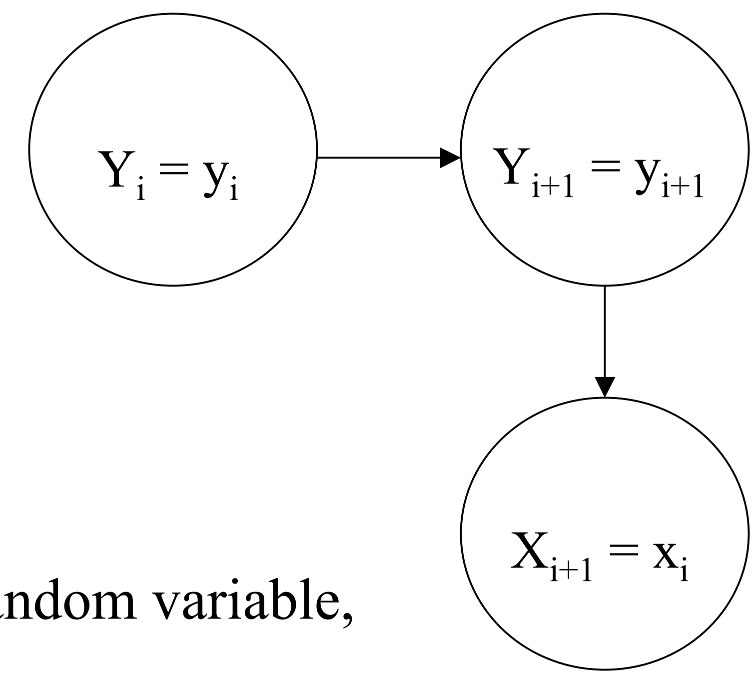
label sequence **y**　　　　observation sequence **x**

Generative Modeling (HMMs)

Given training set X with label sequences Y:

- Train a model θ that maximizes $P(X, Y \mid \theta)$
- For a new data sequence $\mathbf{x}$, the predicted label $\mathbf{y}$ maximizes $P(\mathbf{y} \mid \mathbf{x}) = P(\mathbf{y} \mid \mathbf{x}, \theta)P(\mathbf{x} \mid \theta)$



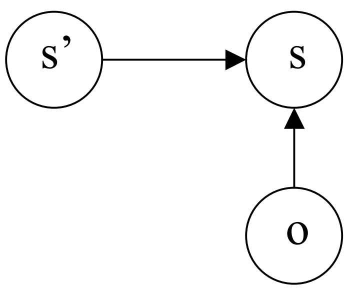


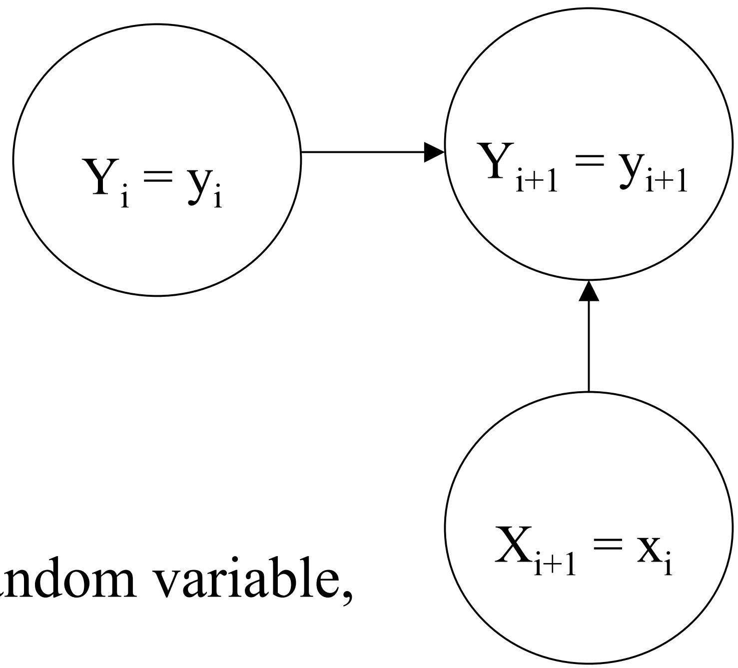
A = a, where A is a random variable, and a is an outcome

Discriminative Modeling (MEMMs)

Given training set X with label sequences Y:

- Train a model θ that maximizes P(Y | X, θ)
- For a new data sequence **x**, the predicted label **y** maximizes P(**y** | **x**, θ)



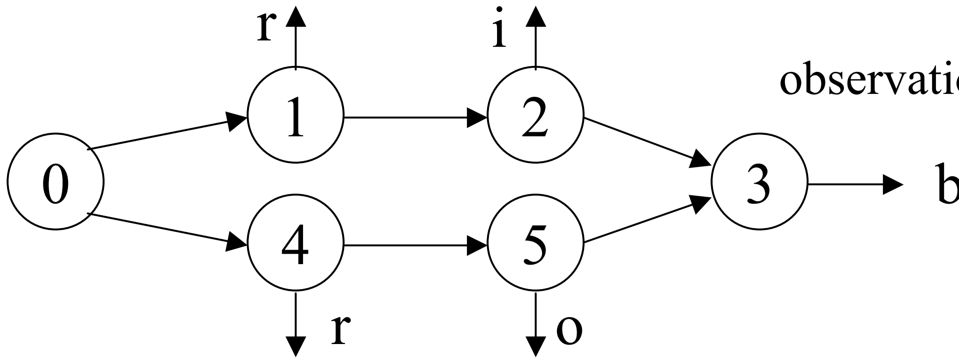


A = a, where A is a random variable, and a is an outcome

rib/rob models

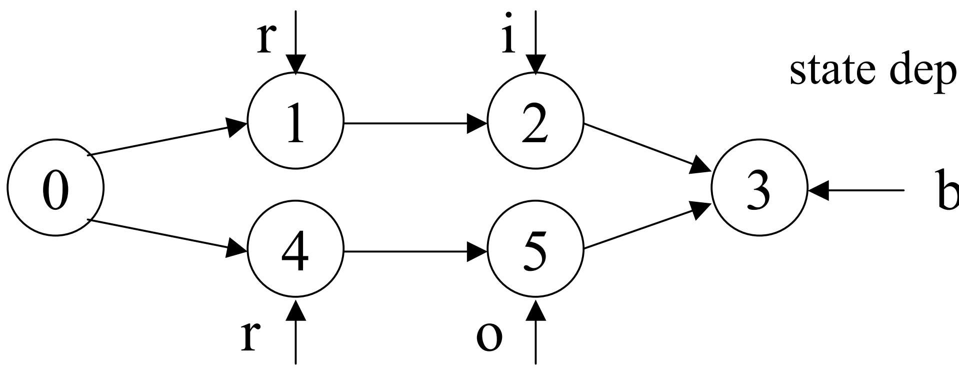
Training data: {<rib, 123>, <rob, 453>}

HMM



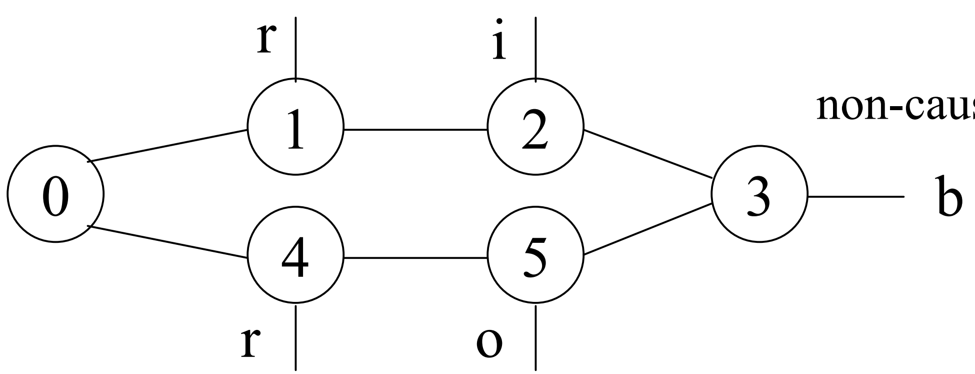
observation depends on the state

MEMM



state depends on the observation

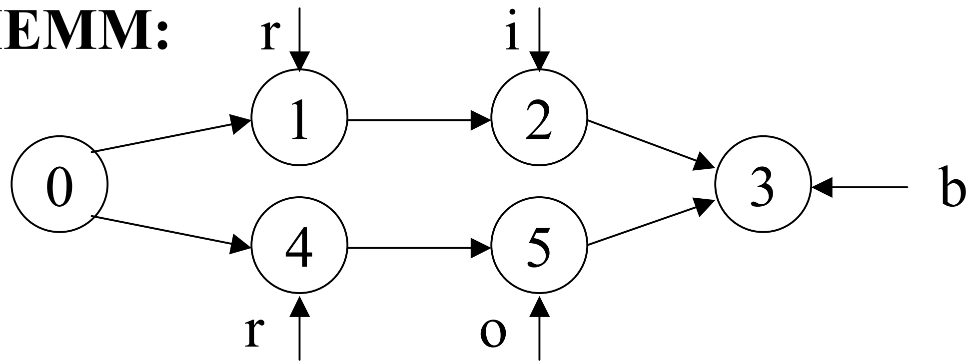
CRF



non-causal model

Label Bias Problem

Consider this MEMM:



The label sequence 1,2 should score higher when ri is observed compared to ro.
Or, we expect P(1 and 2 | ri) to be greater than P(1 and 2 | ro).

Mathematically,

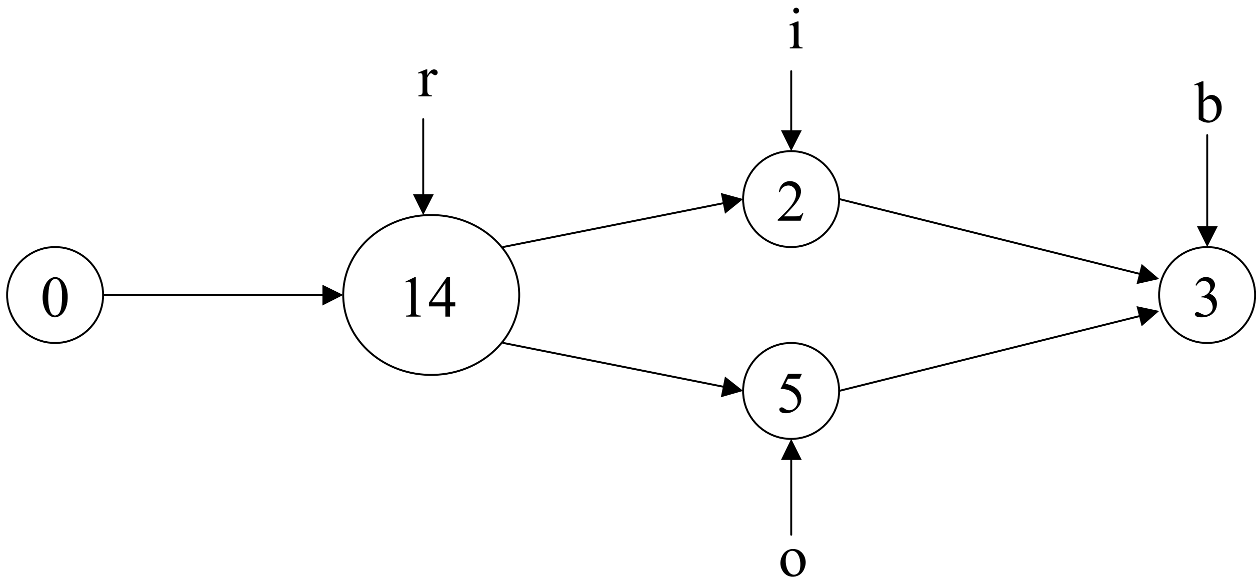
P(1 and 2 | ro) = P(2 | 1 and ro)P(1 | ro) = P(2 | 1 and o)P(1 | r)

P(1 and 2 | ri) = P(2 | 1 and ri)P(1 | ri) = P(2 | 1 and i)P(1 | r)

Since P(2 | 1 and x) = 1 for all x, P(1 and 2 | ro) = P(1 and 2 | ri)
In the training data, label value 2 is the only label value observed after label value 1
Therefore P(2 | 1) = 1, so P(2 | 1 and x) = 1 for all x

Changing the Set of States

Example:



P(14 and 2 | ri) = P(2 | 14and ri)P(14 | ri) = P(2 | 14 and i)P(14 | r) = (1)(1) = 1

P(14 and 2 | ro) = P(2 | 14 and ro)P(14 | ro) = P(2 | 14 and o)P(14 | r) = (0)(1) = 0

This is a solution to the label bias problem.

But, changing the set of states would be impractical.

Conditional Random Fields (CRFs)

Disadvantages of MEMMs

$P(\mathbf{y} \mid \mathbf{x})$ = product of factors, one for each label

Each factor can depend only on previous label, and not future labels

So, let

$$P(\mathbf{y} \mid \mathbf{x}) = \exp\left(\sum_k f_k(\mathbf{y}, \mathbf{x})\right)$$

where each f_k is a property of part of **y** and **x**

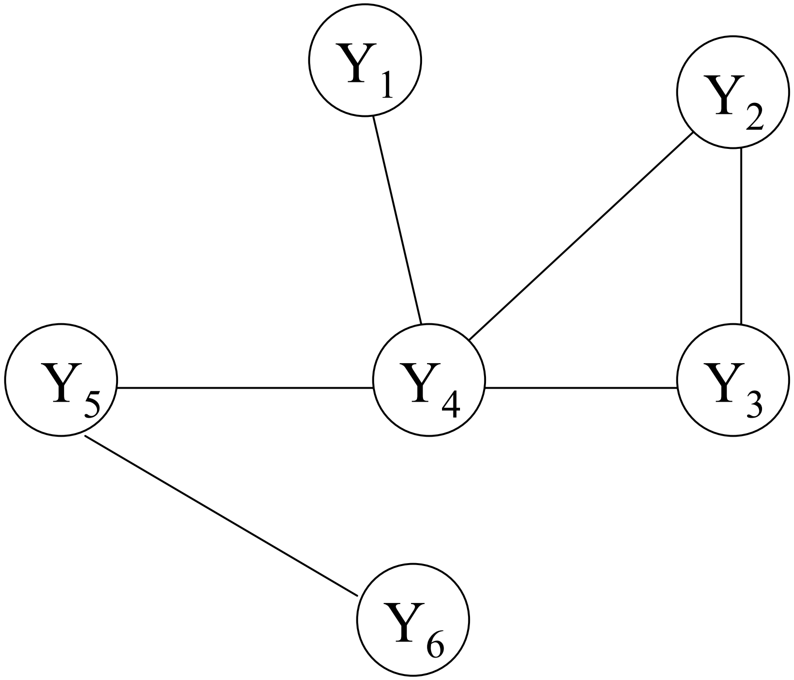
Example: $f_k(\mathbf{x}, \mathbf{y}) = 1$ is X_i is uppercase and label Y_i is a proper noun.

Random Field Example

Let G = (Y, E) be a graph where each vertex Y_v is a random variable

Suppose $P(Y_v \mid \text{all other } Y) = P(Y_v \mid \text{neighbors}(Y_v))$ then Y is a random field

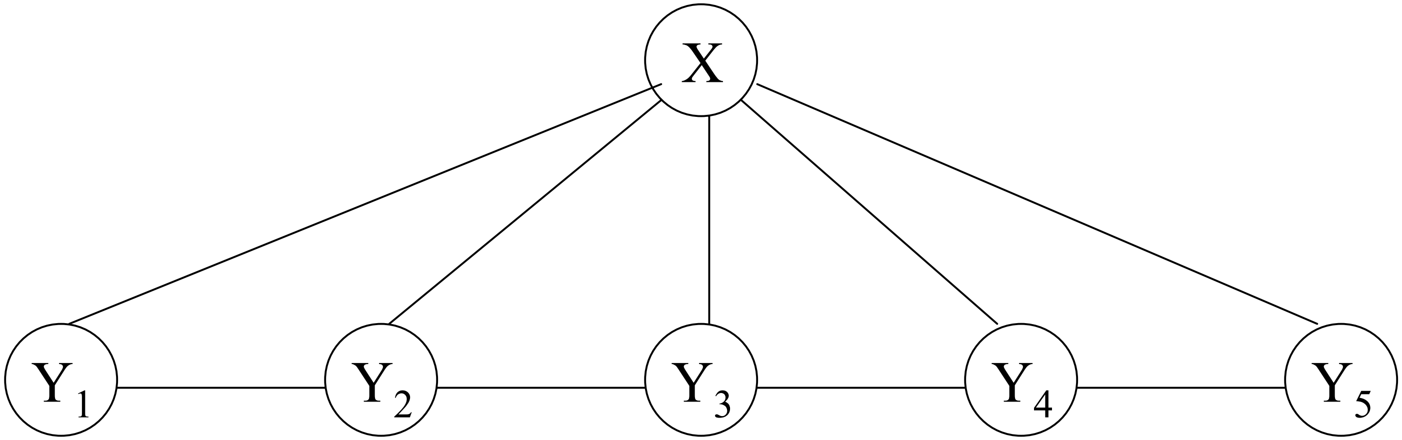
Example:



- $P(Y_5 \mid \text{all other } Y) = P(Y_5 \mid Y_4, Y_6)$

Conditional Random Field Example

Suppose $P(Y_v \mid X, \text{all other } Y) = P(Y_v \mid X, \text{neighbors}(Y_v))$
then X with Y is a **conditional** random field



- $P(Y_3 \mid X, \text{all other } Y) = P(Y_3 \mid X, Y_2, Y_4)$
- Think of X as observations and Y as labels

Conditional Distribution

If Y is a tree, the distribution over the label sequence Y = y, given X = x, is:

$$p_\Theta(\mathbf{y} \mid \mathbf{x}) \propto$$

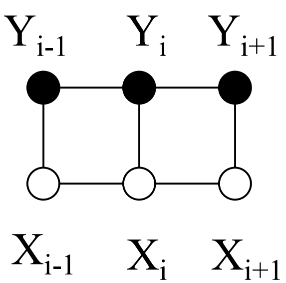
$$\exp\left(\sum_{e \in E, k} \lambda_k f_k(e, \mathbf{y}|_e, \mathbf{x}) + \sum_{v \in V, k} \mu_k g_k(v, \mathbf{y}|_v, \mathbf{x}) \right) \quad (1)$$

- **x** is a data sequence outcome
- **y** is a label sequence outcome
- *v* is a vertex from vertex set V = set of label random variables
- *e* is an edge from edge set E over V
- f_k and g_k are given and fixed features; each g_k is a property of x and a vertex v for the label random variable associated with v.
- *k* is the number of features
- $\Theta = (\lambda_1, \lambda_2, \ldots; \mu_1, \mu_2, \ldots)$; λ_k and μ_k are parameters to be estimated
- $y|_e$ is the components of y defined by edge e
- $y|_v$ is one component of y defined by vertex v

Matrix Random Variable

- Add special start and stop states $\mathbf{y}_0$ = start and $\mathbf{y}_{n+1}$ = start
- e_i is the edge with labels $(\mathbf{Y}_{i-1}, \mathbf{Y}_i)$
- v_i is the vertex with label $\mathbf{Y}_i$
- curly Y = set of possible label values
- The matrix random variable has the range |curly Y| ×|curly Y|
- If $Y_i = y_i$ then $y_i \in$ curly Y

Suppose that $p_\Theta(Y \mid X)$ is a CRF given by (1). Assume Y is a chain. For each position i in the observation sequence $\mathbf{x}$, we define a matrix random variable $M_i(\mathbf{x}) = [M_i(y', y \mid \mathbf{x})]$ as:



$$M_i(y', y \mid \mathbf{x}) = \exp(\Lambda_i(y', y \mid \mathbf{x}))$$

$$\Lambda_i(y', y \mid \mathbf{x}) = \sum_k \lambda_k f_k(e_i, \mathbf{Y}|_{e_i}, Y|_{e_i} = (y', y), \mathbf{x}) + \sum_k \mu_k g_k(v_i, \mathbf{Y}|_{v_i} = y, \mathbf{x})$$

Conditional Probability for CRFs

The conditional probability of a label sequence **y** is

$$p_\Theta(\mathbf{y} \mid \mathbf{x}) = \frac{\prod_{i=1}^{n+1} M_i(\mathbf{y}_{i-1}, \mathbf{y}_i \mid \mathbf{x})}{\left(\prod_{i=1}^{n+1} M_i(\mathbf{x})\right)_{\text{start, stop}}}$$

- n is length of sequence $y = y_1 \ldots y_n$
- y_0 = start and y_{n+1} = stop

Parameter Estimation

Input: training data D = $\{(x^{(i)}, y^{(i)})\}$, where i = 1…N with empirical distribution $\widetilde{p}(x, y)$

Output: parameters $\Theta = (\lambda_1, \lambda_2, \ldots; \mu_1, \mu_2, \ldots)$

Maximize: the log-likelihood objective function:

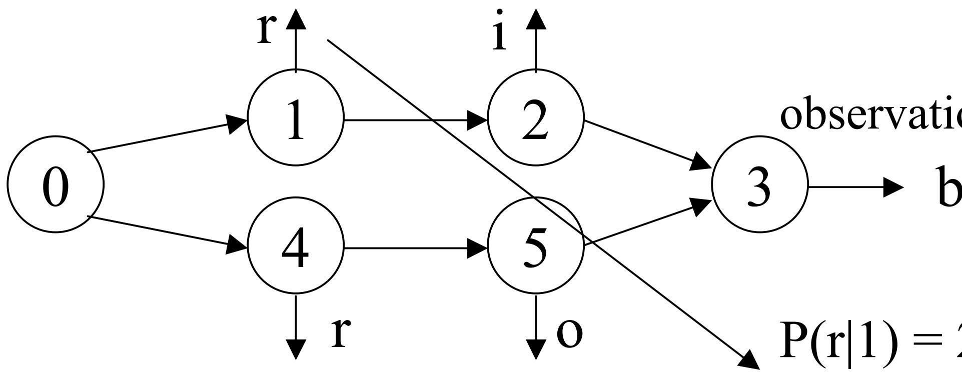
$$
\begin{aligned}
O(\Theta) &= \sum_{i=1}^{N} \log p_{\Theta}(\mathbf{y}^{(i)} \mid \mathbf{x}^{(i)}) \\
&\propto \sum_{\mathbf{x},\mathbf{y}} \widetilde{p}(\mathbf{x},\mathbf{y}) \log p_{\Theta}(\mathbf{y} \mid \mathbf{x})
\end{aligned}
$$

- This is an expectation.

rib/rob models

Training data {<rib, 123>, <rob, 453>}

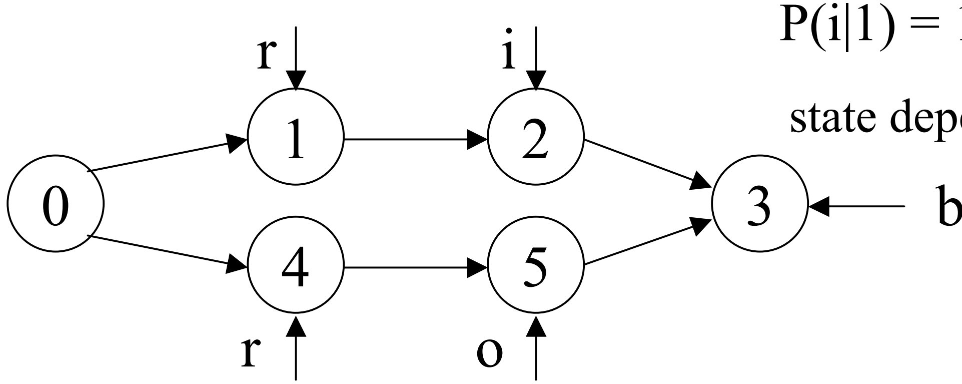
HMM



observation depends on the state

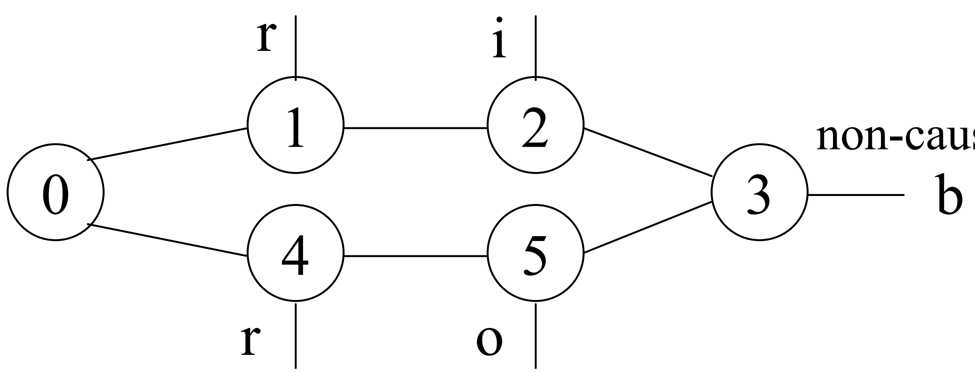
P(r|1) = 29/32,
P(i|1) = 1/32 = P(o|1) = P(b|1)

MEMM



state depends on the observation

CRF



non-causal model

Modeling the label bias problem

- Each state emits its designated symbol with probability 29/32 and the other symbols with probability 1/32 (on picture)
- They train MEMM and CRF with the same topologies
- A run consists of 2,000 training examples and 500 test examples, trained to convergence
- CRF error is 4.6%, and MEMM error is 42%
- MEMM fails to discriminate between the two branches

Mixed-order HMM

State transition probabilities are given by

$$p_\alpha(\mathbf{y}_i \mid \mathbf{y}_{i-1}, \mathbf{y}_{i-2}) = \alpha p_2(\mathbf{y}_i \mid \mathbf{y}_{i-1}, \mathbf{y}_{i-2}) + (1-\alpha)\, p_1(\mathbf{y}_i \mid \mathbf{y}_{i-1})$$

Emission probabilities are given by

$$p_\alpha(\mathbf{x}_i \mid \mathbf{y}_i, \mathbf{x}_{i-1}) = \alpha p_2(\mathbf{x}_i \mid \mathbf{y}_i, \mathbf{x}_{i-1}) + (1-\alpha)\, p_1(\mathbf{x}_i \mid \mathbf{y}_i)$$

$\alpha = 0$ is a standard first-order HMM.

A first –order HMM has transition probabilities given by

$$p_\alpha(\mathrm{y}_i \mid \mathrm{y}_{i-1}, \mathrm{y}_{i-2}) = (1-\alpha) p_1(\mathrm{y}_i \mid \mathrm{y}_{i-1})$$

And emission probabilities given by

$$p_\alpha(\mathrm{x}_i \mid \mathrm{y}_i, \mathrm{x}_{i-1}) = (1-\alpha) p_1(\mathrm{x}_i \mid \mathrm{y}_i)$$

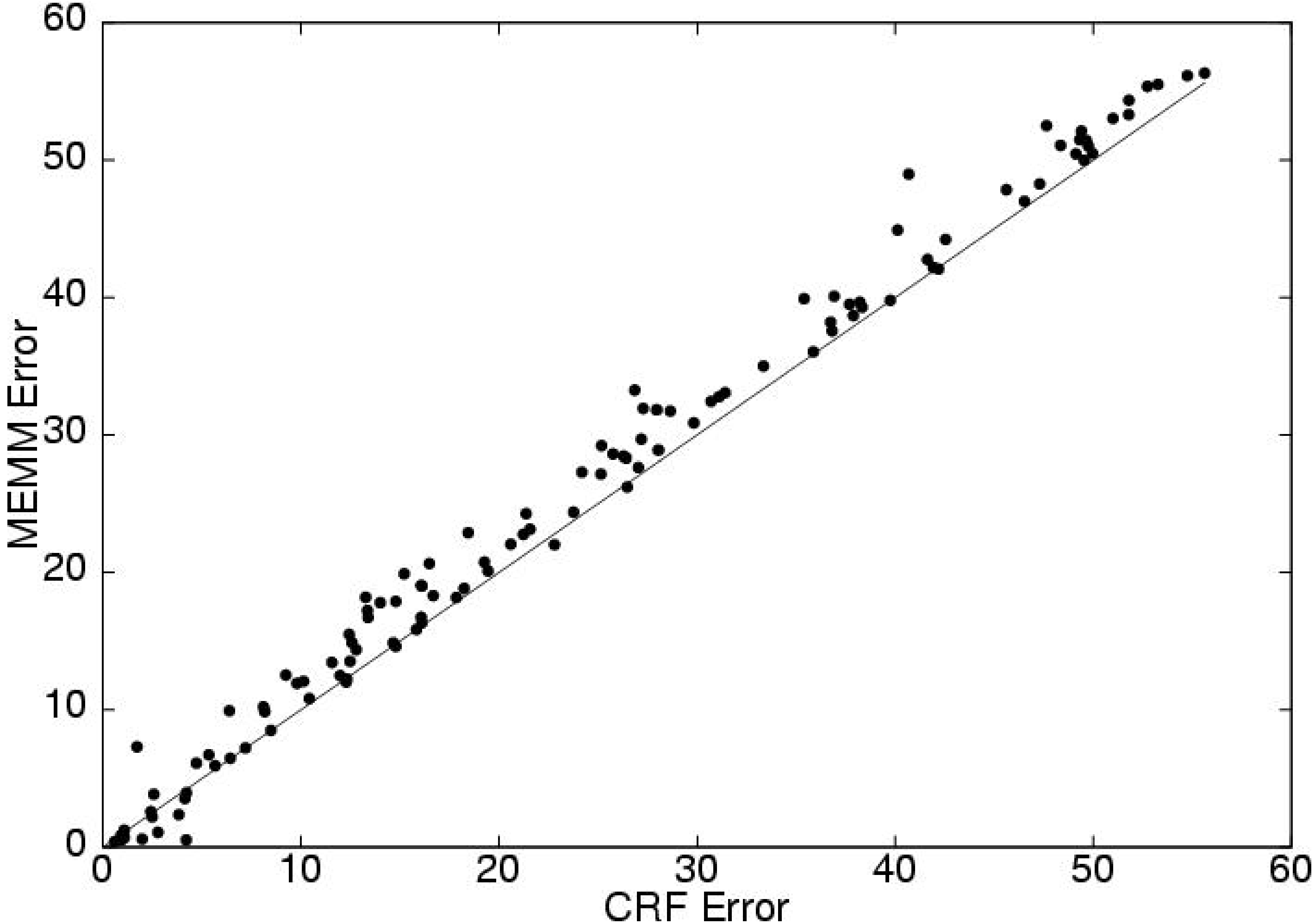
Modeling mixed-order sources

Experimental Setup

- For each randomly generated model, a sample of 1,000 sequences of length 25 is generated for training and testing
- On each randomly generated training set, a CRF is trained using Algorithm S, which is described in the paper
- On the same data an MEMM is trained using iterative scaling
- The Viterbi algorithm is used to label a test set
- *the advantages of the additional representational power of CRFs and MEMMs relative to HMMs.*

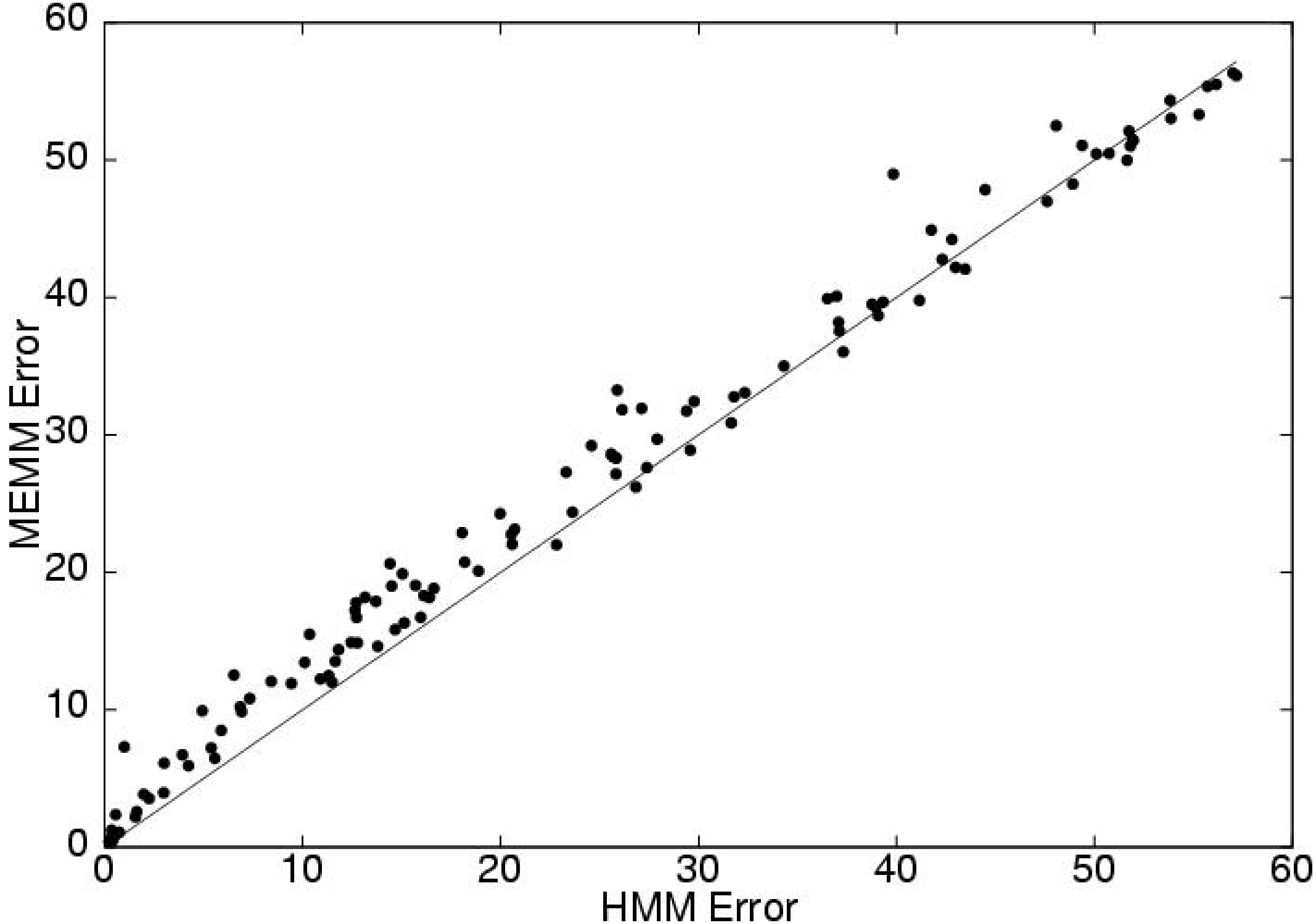
MEMM versus CRF

- CRF usually outperforms the MEMM



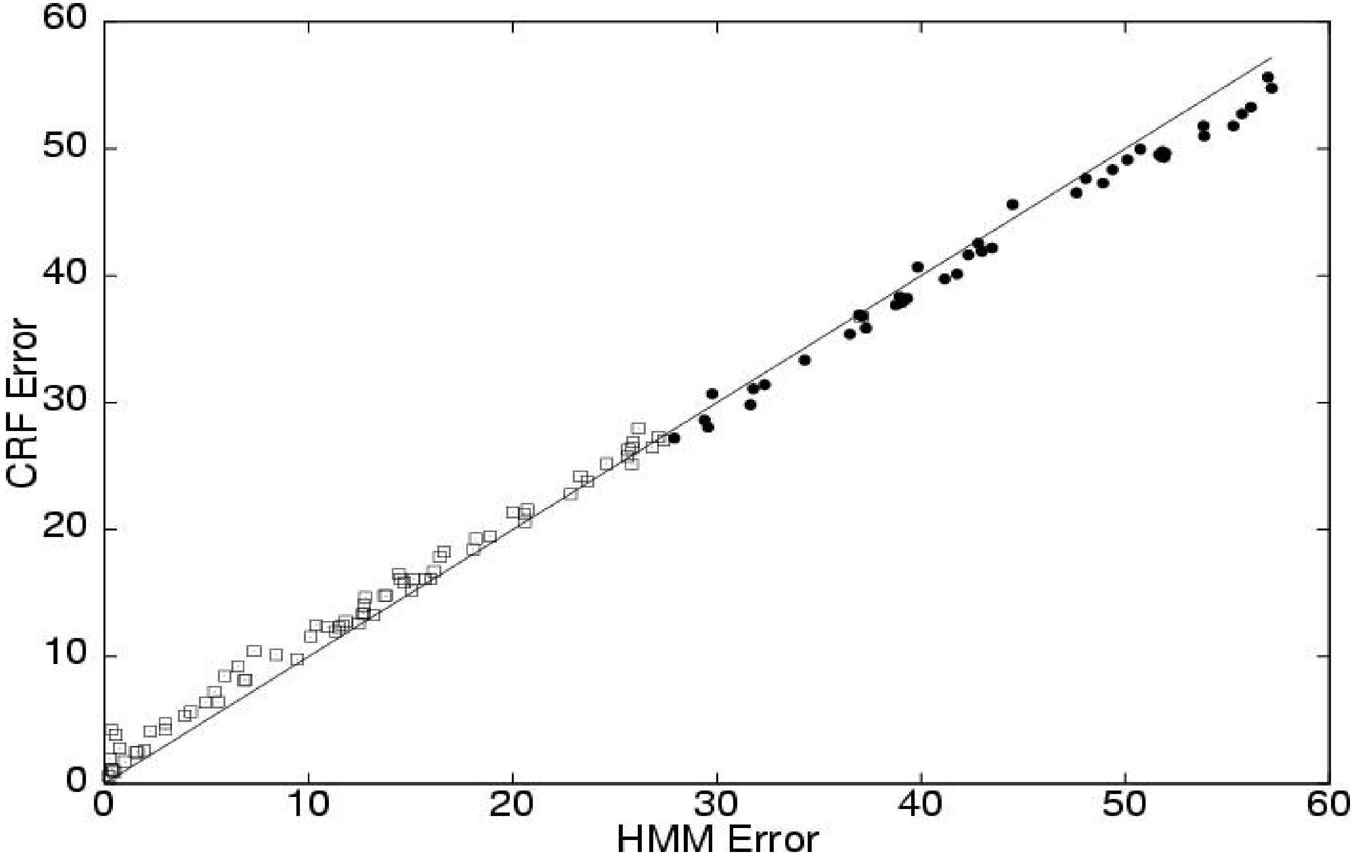
MEMM versus HMM

- The HMM outperforms the MEMM



CRF versus HMM

Each open square represents a data set with α < 1/2, and a solid circle indicates a data set with α ≥ 1/2; When the data is mostly second order (α ≥ 1/2), the discriminatively trained CRF usually outperforms the HMM



UPenn Tagging Task

- 45 tags (syntactic), 1M words training

DT	NN	NN		NN		VBZ	RB	JJ
The	**asbestos**	**fiber**	**;**	**crocidolite**	**;**	**is**	**unusually**	**resilient**

IN	PRP	VBZ	DT	NNS		IN		RB	JJ	NNS
once	**it**	**enters**	**the**	**lungs**	**;**	**with**	**;**	**even**	**brief**	**exposures**

TO	PRP	VBG	NNS	WDT	VBP	RP	NNS	JJ	
to	**it**	**causing**	**symptoms**	**that**	**show**	**up**	**decades**	**later**	**;**

NNS	VBD
researchers	**said**

POS tagging experiment 1

- Compared HMMs, MEMMs, and CRFs on Penn treebank POS tagging
- Trained first-order HMM, MEMM, and CRF models as in the synthetic data experiments
- Introduced parameters $\mu_{y,x}$ for each tag-word pari and $\lambda_{y'y}$ for each tag-tag pari in the training set
- oov = out-of-vocabulary, and are not observed in the training set

model	error	oov error
HMM	5.69%	45.99%
MEMM	6.37%	54.61%
CRF	5.55%	48.05%

POS tagging experiment 2

- Compared HMMs, MEMMs, and CRFs on Penn treebank POS tagging
- Each word in a given input sentence must be labeled with one of 45 syntactic tags
- Add a small set of orthographic features: whether a spelling begins with a number or upper case letter, whether it contains a hyphen, and if it contains one of the following suffixes: -ing, -ogy, -ed, -s, -ly, -ion, -tion, -ity, -ies

				using spelling features		
model	error	oov error	error	delta	oov error	delta
HMM	5.69%	45.99%				
MEMM	6.37%	54.61%	4.81%	-25%	26.99%	-50%
CRF	5.55%	48.05%	4.27%	-24%	23.76%	-50%

Presentation Message

- Discriminative models are prone to the label bias problem
- CRFs provide the benefits of discriminative models
- CRFs solve the label bias problem well, and demonstrate good performance