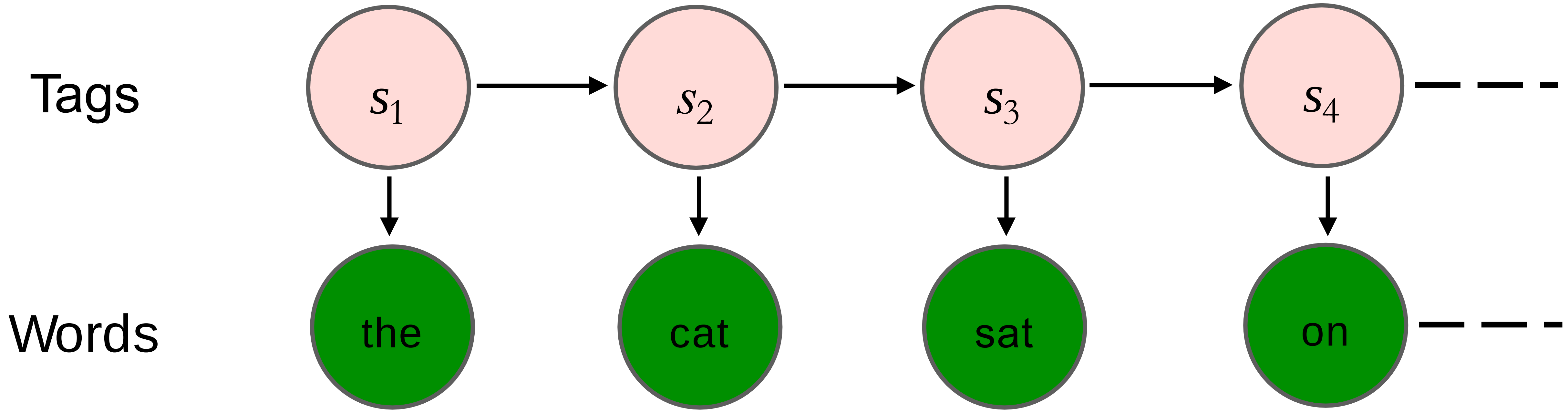
AIE1007: Natural Language Processing

L7: Sequence Models - 2

Autumn 2024

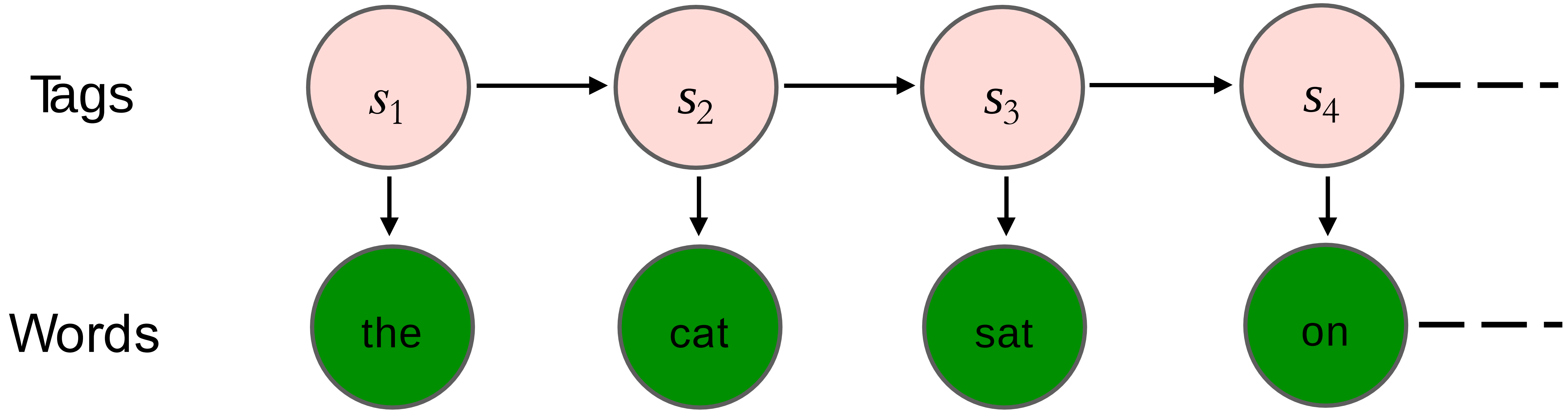
Recap: Hidden Markov models



1. Set of states S = {1, 2, ..., K} and set of observations $O = \{o_1, \ldots, o_n\}$
2. **Initial state probability distribution** $\pi(s_1)$
3. **Transition probabilities** $P(s_{t+1} \mid s_t)$
4. **Emission probabilities** $P(o_t \mid s_t)$

Strong assumptions

Recap: Hidden Markov models



1. **Markov assumption**:

$$P(s_{t+1} \mid s_1, \ldots, s_t) \approx P(s_{t+1} \mid s_t)$$

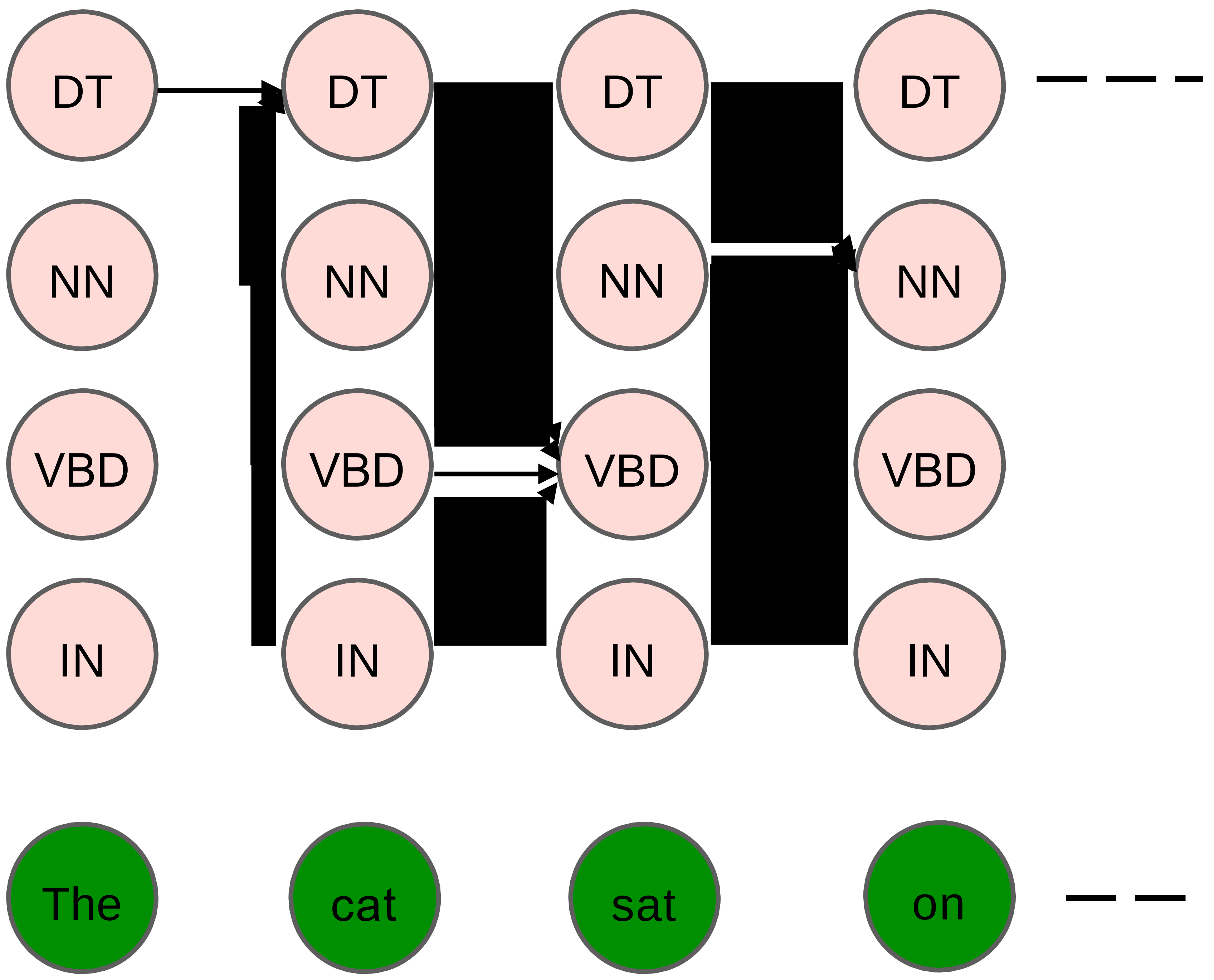
2. **Output independence**:

$$P(o_t \mid s_1, \ldots, s_t) \approx P(o_t \mid s_t)$$

1) assumes (**s**)tate sequences do not have very strong priors/long-range dependencies

2) assumes neighboring (**s**)tates don't affect current (**o**)bservation

Recap: Viterbi decoding



$M[i,j]$ stores joint probability of most probable sequence of states ending with state *j* at time *i*

$$M[i,j] = \max_k M[i-1,k]\ P(s_j \mid s_k)\ P(o_i \mid s_j) \quad 1 \leq k \leq K \quad 1 \leq i \leq n$$

Backward: Pick $\max_k M[n,k]$ and backtrack using B

Trigram hidden Markov models

What we have seen so far is also called bigram HMM

Can be extended to trigram, 4-gram etc.

MLE estimate: $P(s_i \mid s_{i-1}, s_{i-2}) = \frac{Count(s_i, s_{i-1}, s_{i-2})}{Count(s_{i-1}, s_{i-2})}$

Can add smoothing techniques to avoid zero probabilities!

Viterbi: $M[i, j, k] = \max_r M[i-1, k, r] \; P(s_j \mid s_k, s_r) \; P(o_i \mid s_j) \quad 1 \leq j, k, r \leq K \quad 1 \leq i \leq n$

most probable sequence of states ending with state *j* at time *i*, and state *k* at *i-1*

Time complexity: $O(nK^3)$

Maximum Entropy Markov Models (MEMMs)

ICML 2000

Maximum Entropy Markov Models
for Information Extraction and Segmentation

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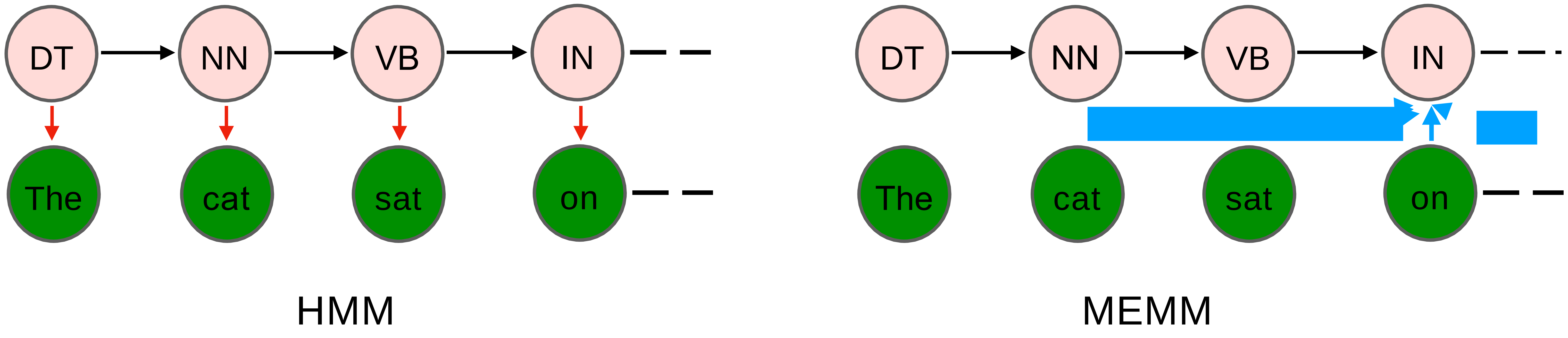
Generative vs discriminative models

- HMM is a *generative* model
- Can we model $P(s_1, \ldots, s_n \mid o_1, \ldots, o_n)$ directly?

	Generative	**Discriminative**
Text classification	Naive Bayes: $P(c)P(d \mid c)$	Logistic Regression: $P(c \mid d)$
Sequence prediction	HMM: $P(s_1, \ldots, s_n)P(o_1, \ldots, o_n \mid s_1, \ldots, s_n)$	MEMM: $P(s_1, \ldots, s_n \mid o_1, \ldots, o_n)$

Maximum entropy Markov model (MEMM)



$$P(S \mid O) = \prod_{i=1}^{n} P(s_i \mid s_{i-1}, s_{i-2}, \ldots, s_1, O)$$

$$= \prod_{i=1}^{n} P(s_i \mid s_{i-1}, O)$$

$$O = \langle o_1, o_2, \ldots, o_n \rangle$$

Markov assumption:
Bigram MEMM

$$P(s_i = s \mid s_{i-1}, O) \propto \exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, O, i))$$

weights

features

Important: you can define features over entire word sequence O!

Use features and weights:

$$P(s_i = s \mid s_{i-1}, O) \propto \exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, O, i))$$

- *Which of the following is the correct way to calculate this probability?*

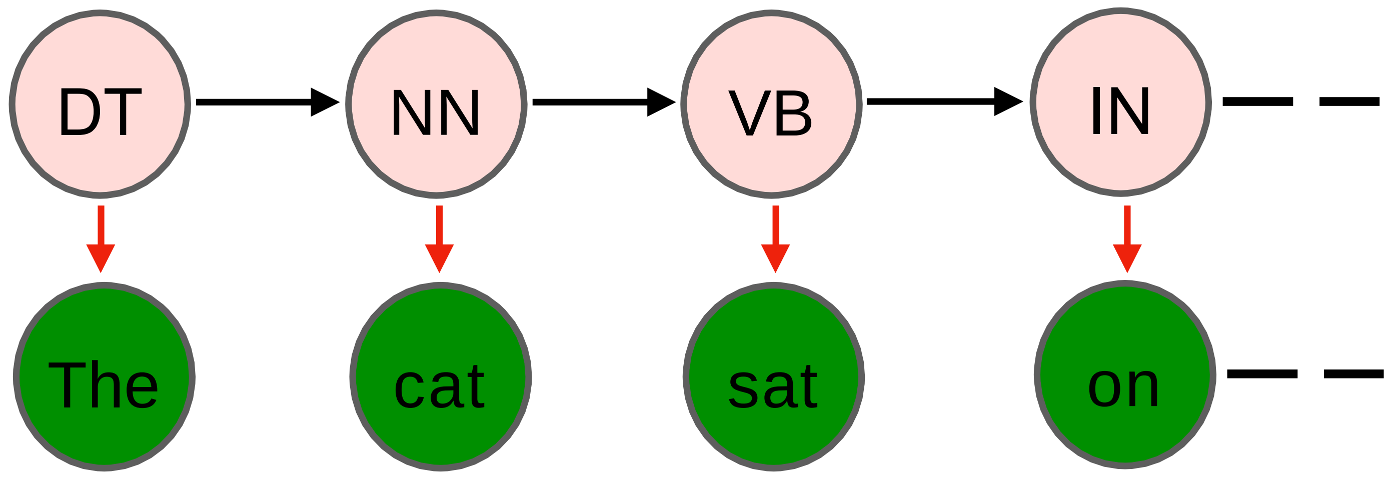
A) $P(s_i = s \mid s_{i-1}, O) = \dfrac{\exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, O, i))}{\sum_{s'=1}^{K} \exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1} = s', O, i))}$

B) $P(s_i = s \mid s_{i-1}, O) = \dfrac{\exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, O, i))}{\sum_{s'=1}^{K} \exp(\mathbf{w} \cdot \mathbf{f}(s_i = s', s_{i-1}, O, i))}$

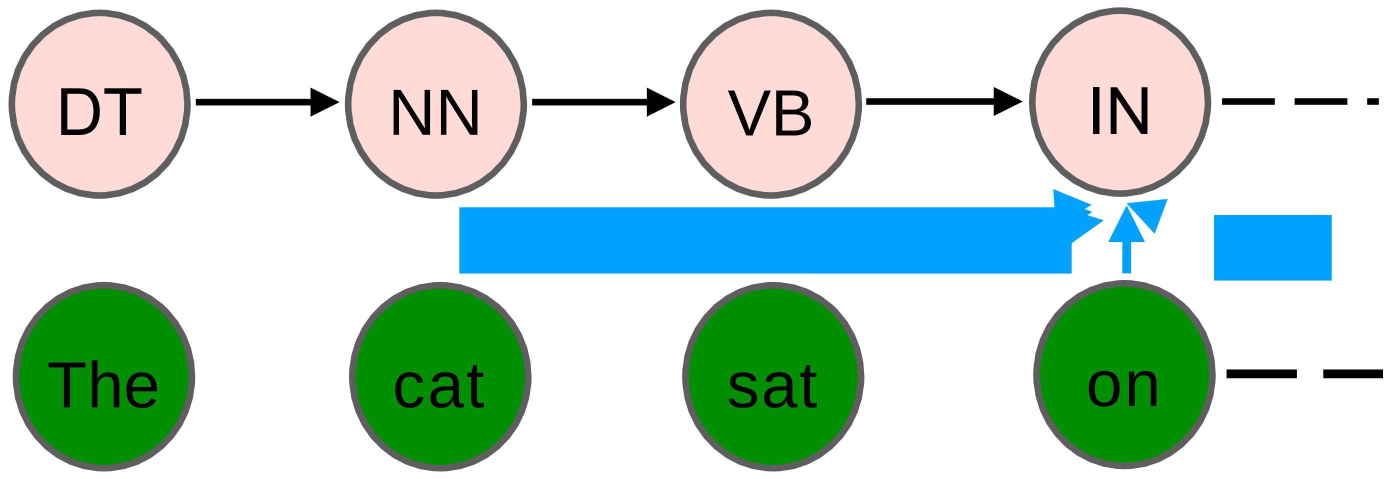
C) $P(s_i = s \mid s_{i-1}, O) = \dfrac{\exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, O, i))}{\sum_{O'} \exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, O', i))}$

The answer is (B)

Maximum entropy Markov model (MEMM)



HMM



MEMM

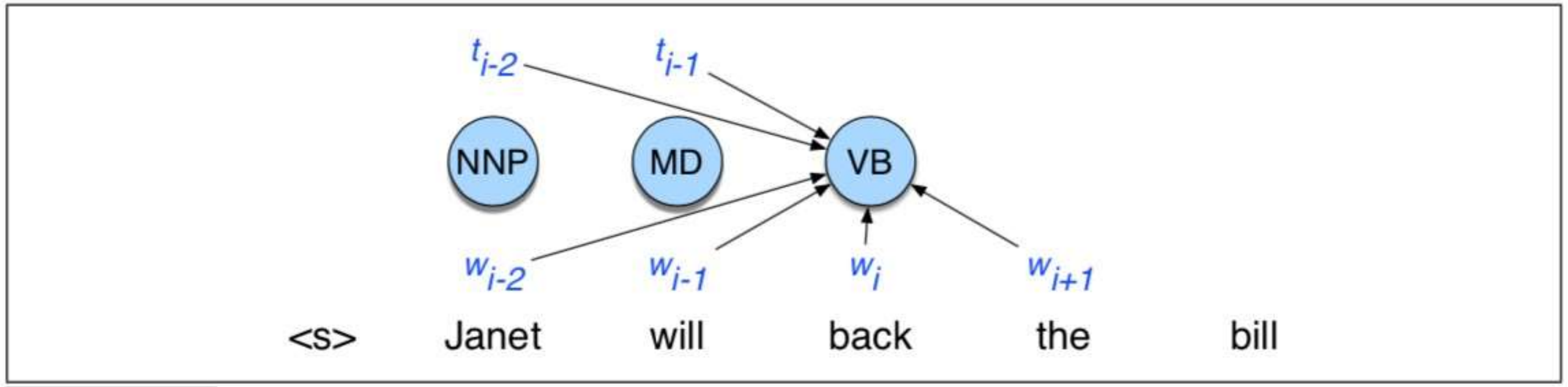
- Bigram MEMM: $O = \langle o_1, o_2, \ldots, o_n \rangle$

- Can be easily extended to trigram MEMM, 4-gram MEMM..

$$P(s_i = s \mid s_{i-1}, s_{i-2}, O) = \frac{\exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, s_{i-2}, O, i))}{\sum_{s'=1}^{K} \exp(\mathbf{w} \cdot \mathbf{f}(s_i = s', s_{i-1}, s_{i-2}, O, i))}$$

How to define features?

$$\mathbf{f}(s_i = s', s_{i-1}, s_{i-2}, O, i)$$



t_i = tags (states)

w_i = words (observations)

$$\langle t_i, w_{i-2}\rangle, \langle t_i, w_{i-1}\rangle, \langle t_i, w_i\rangle, \langle t_i, w_{i+1}\rangle, \langle t_i, w_{i+2}\rangle$$
$$\langle t_i, t_{i-1}\rangle, \langle t_i, t_{i-2}, t_{i-1}\rangle,$$
$$\langle t_i, t_{i-1}, w_i\rangle, \langle t_i, w_{i-1}, w_i\rangle \langle t_i, w_i, w_{i+1}\rangle,$$

Feature templates

t_i = VB and w_{i-2} = Janet

t_i = VB and w_{i-1} = will

t_i = VB and w_i = back

t_i = VB and w_{i+1} = the

t_i = VB and w_{i+2} = bill

t_i = VB and t_{i-1} = MD

t_i = VB and t_{i-1} = MD and t_{i-2} = NNP

t_i = VB and w_i = back and w_{i+1} = the

Features (binary)

Features in an MEMM

Incorrect	DT	JJ	NN	DT	NN
Correct	DT	NN	VB	DT	NN
	The	old	man	the	boat
	w_{i-1}	w_i	w_{i+1}	w_{i+2}	w_{i+3}

Which of these feature templates would help most to tag 'old' correctly?

A) $\langle t_i, t_{i-1}, w_i, w_{i-1}, w_{i+1} \rangle$

B) $\langle t_i, t_{i-1}, w_i, w_{i-1} \rangle$

C) $\langle t_i, w_i, w_{i-1}, w_{i+1} \rangle$

D) $\langle t_i, w_i, w_{i-1}, w_{i+1}, w_{i+2} \rangle$

t_i = tags (states)

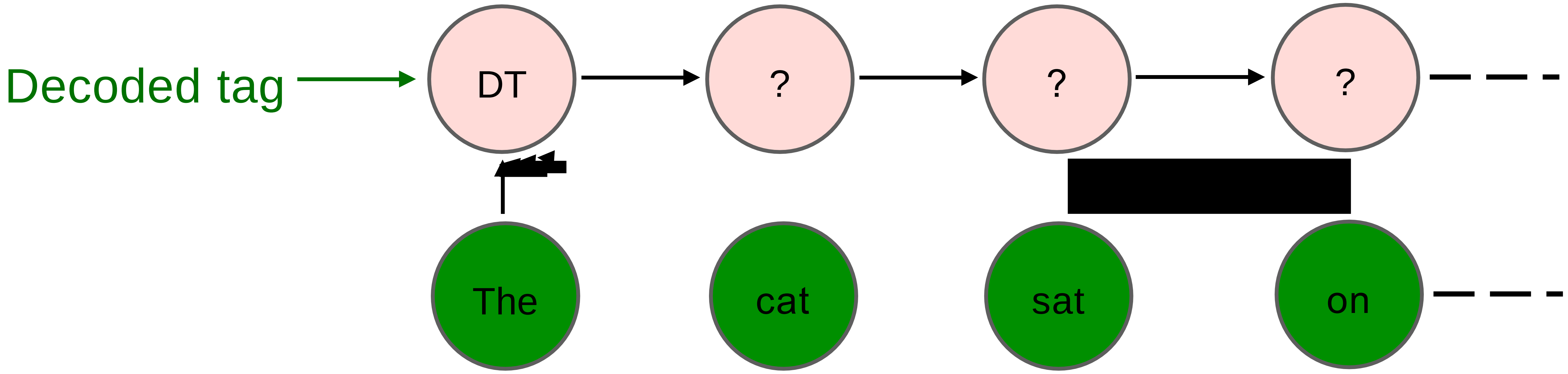
w_i = words (observations)

The answer is (D)

MEMMs: Decoding

- Bigram MEMM:

- Greedy decoding:

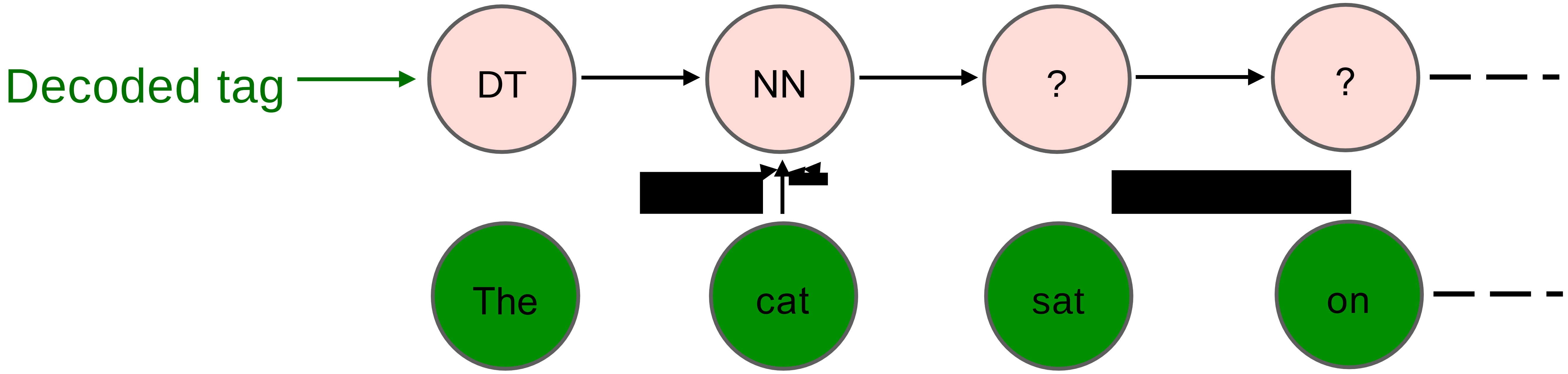


$$\hat{s}_1 = \arg\max_s P(s_i = s \mid \emptyset, O) = \arg\max_s \mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1} = \emptyset, O) = \text{DT}$$

MEMMs: Decoding

- Bigram MEMM:

- Greedy decoding:

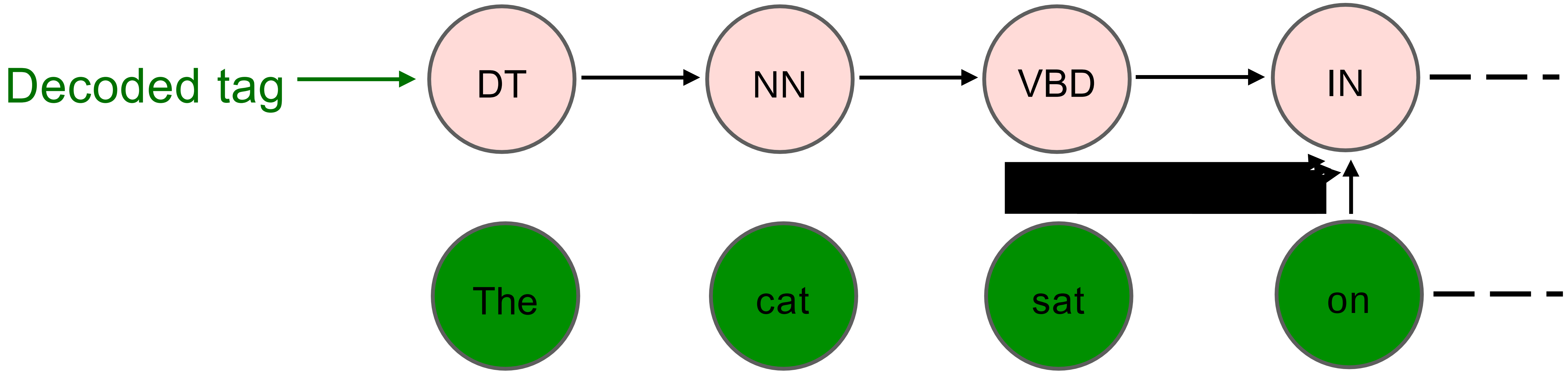


$$\hat{s}_2 = \arg\max_{s} P(s_i = s \mid \text{DT}, O) = \text{NN}$$

MEMMs: Decoding

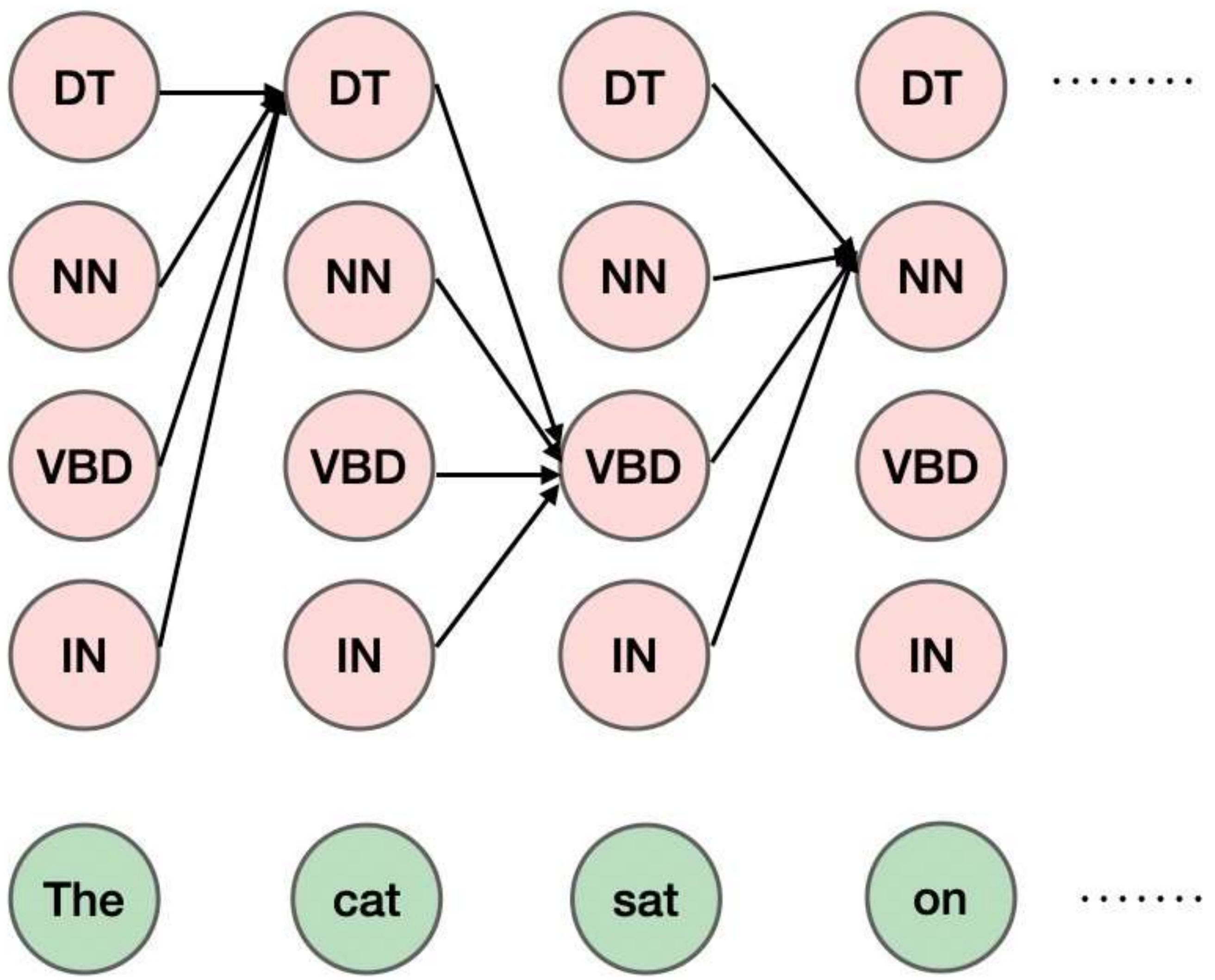
- Bigram MEMM:

- Greedy decoding:



$$\hat{s}_i = \arg\max_{s} P(s_i = s \mid \hat{s}_{i-1}, O)$$

Viterbi decoding for MEMMs



$M[i, j]$ stores joint probability of most probable sequence of states ending with state j at time i

$$M[i, j] = \max_k M[i-1, k] \; P(s_i = j \mid s_{i-1} = k, O) \qquad 1 \le k \le K \quad 1 \le i \le n$$

Backward: Pick $\max_k M[n, k]$ and backtrack using B

MEMM: Decoding

How would you compare the computational complexity of Viterbi decoding for bigram MEMMs compared to decoding for bigram HMMs?

A) More operations in MEMM
B) More operations in HMM
C) Equal
D) Depends on number of features in MEMM

The answer is (D)

MEMM: $M[i,j] = \max_k M[i-1,k] \, P(s_i = j \mid s_{i-1} = k, O) \quad 1 \leq k \leq K \quad 1 \leq i \leq n$

HMM: $M[i,j] = \max_k M[i-1,k] \, P(s_j \mid s_k) \, P(o_i \mid s_j) \quad 1 \leq k \leq K \quad 1 \leq i \leq n$

MEMM: Learning

- **Gradient descent:** similar to logistic regression!

$$P(s_i = s \mid s_{i-1}, O) = \frac{\exp(\mathbf{w} \cdot \mathbf{f}(s_i = s, s_{i-1}, O, i))}{\sum_{s'} \exp(\mathbf{w} \cdot \mathbf{f}(s_i = s', s_{i-1}, O, i))}$$

- **Given:** annotated pairs of (S, O) where each $S = \langle s_1, s_2, \ldots, s_n \rangle$

Loss for one sequence, $L = -\sum_{i=1}^{n} \log P(s_i \mid s_{i-1}, O)$

- Compute gradients with respect to weights and update

MEMM vs HMM

- HMM models the joint $P(S, O)$ while MEMM models the required prediction $P(S \mid O)$
- MEMM has more expressivity
  - accounts for dependencies between neighboring states and **entire observation** sequence
  - allows for **more flexible features**
- HMM may hold an advantage if the dataset is small

Conditional Random Fields (CRFs)

ICML 2001

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

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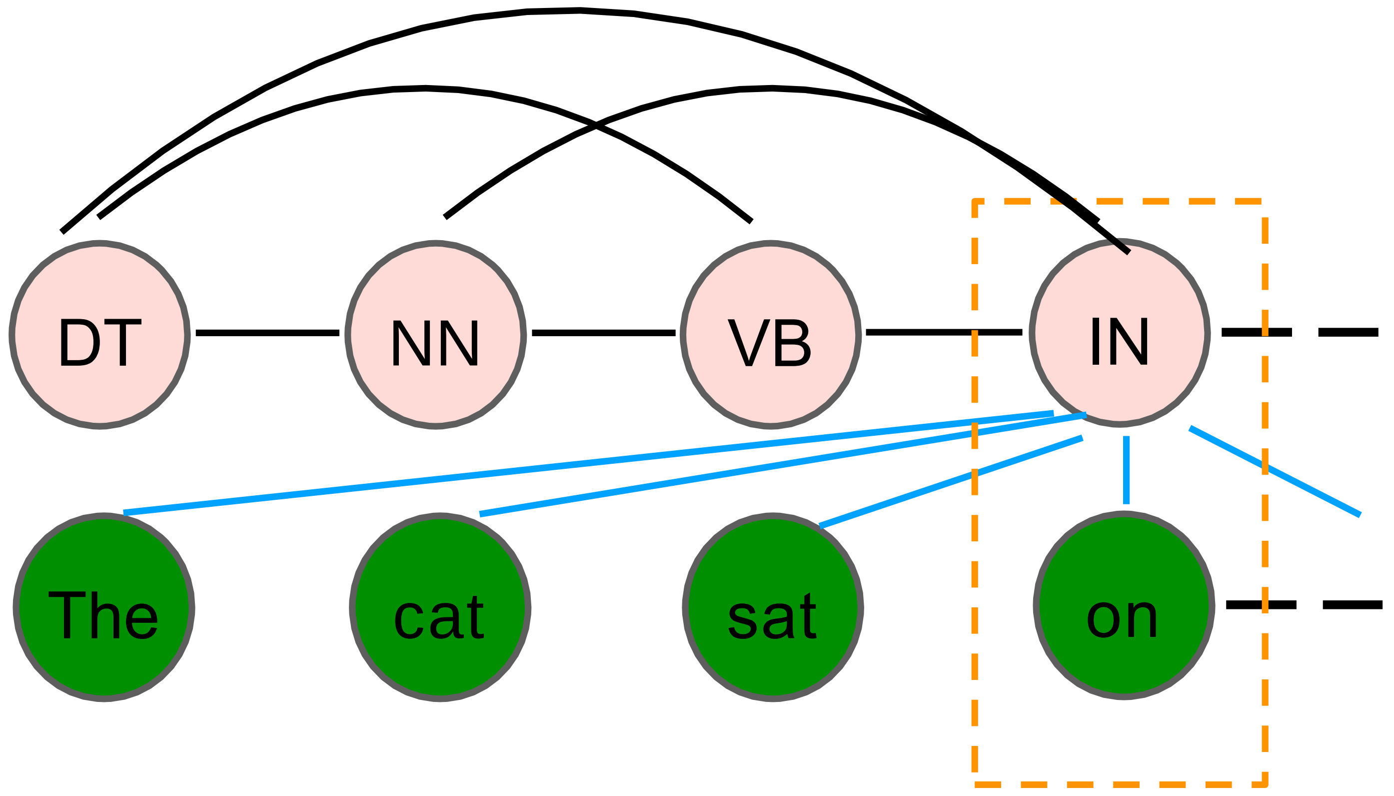
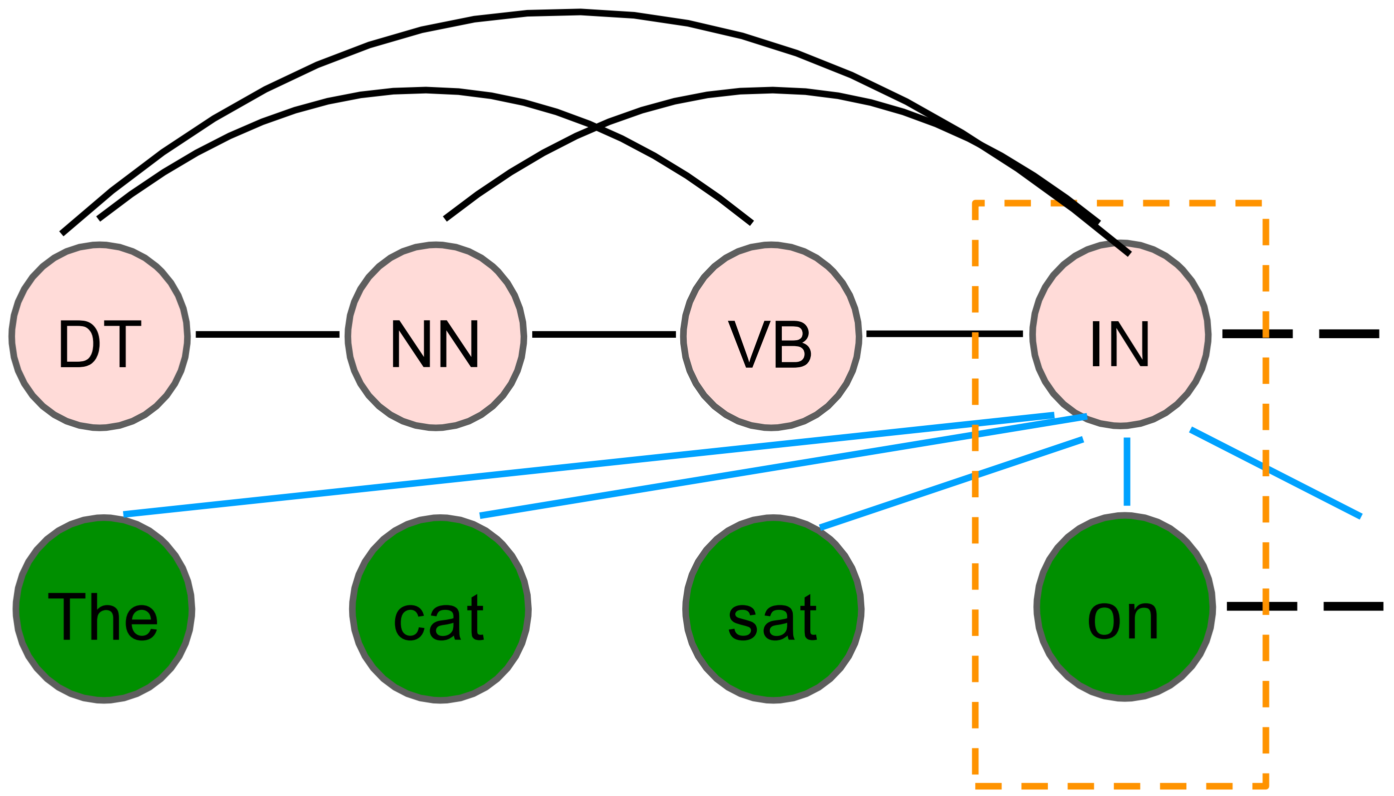
Conditional Random Field

- Model $P(s_1, ..., s_n \mid o_1, ..., o_n)$ directly
- No Markov assumption
  - Map entire sequence of states S and observations O to a **global** feature vector
- Normalize over entire sequences



Features



$$P(S \mid O) = \frac{\exp(\mathbf{w} \cdot \mathbf{f}(S, O))}{\sum_{S'} \exp(\mathbf{w} \cdot \mathbf{f}(S', O))}$$

$\mathbb{1}\{x_i = \textit{the},\ y_i = \text{DET}\}$
$\mathbb{1}\{y_i = \text{PROPN},\ x_{i+1} = \textit{Street},\ y_{i-1} = \text{NUM}\}$
$\mathbb{1}\{y_i = \text{VERB},\ y_{i-1} = \text{AUX}\}$

- Each F_k in $\mathbf{f}$ is a **global** feature function

$$P(S \mid O) = \frac{\exp(\sum_{k=1}^{m} w_k \cdot F_k(S, O))}{\sum_{S'} \exp(\sum_{k=1}^{m} w_k \cdot F_k(S', O))}$$

- Can be computed as a combination of local features: $F_k = \sum_{i=1}^{n} f_k(s_{i-1}, s_i, O, i)$

- Each local feature only depends on previous and current states

CRF: Decoding

- $$\hat{S} = \arg\max_S P(S\,|\,O) = \arg\max_S \frac{\exp(\mathbf{w}\cdot\mathbf{f}(S,O))}{Z(O)}$$

$$= \arg\max_S \exp(\mathbf{w}\cdot\mathbf{f}(S,O))$$

$$= \arg\max_S \sum_{k=1}^{m}\sum_{i=1}^{n} w_k f_k(s_{i-1}, s_i, O, i)$$

- Use Viterbi similar to HMM and MEMM

CRF: Learning

Log-Linear Models, MEMMs, and CRFs

Michael Collins

$$P(S \mid O) = \frac{\exp(\sum_{k=1}^{m} \sum_{i=1}^{n} w_k f_k(s_{i-1}, s_i, O, i))}{Z(O)}$$

$$= \frac{\exp(\sum_{k=1}^{m} \sum_{i=1}^{n} w_k f_k(s_{i-1}, s_i, O, i))}{\sum_{s'_1,\ldots,s'_n} \exp(\sum_{k=1}^{m} \sum_{i=1}^{n} w_k f_k(s'_{i-1}, s'_i, O, i))}$$

$$-\log P(S \mid O) = -\sum_{k=1}^{m} \sum_{i=1}^{n} w_k f_k(s_{i-1}, s_i, O, i)) + \log \sum_{s'_1,\ldots,s'_n} \exp(\sum_{k=1}^{m} \sum_{i=1}^{n} w_k f_k(s'_{i-1}, s'_i, O, i))$$

$\frac{-\partial \log P(S \mid O)}{\partial w_k}$ can be done efficiently using dynamic programming

CRF vs MEMM

- MEMM models the required prediction $P(S|O)$ using the Markov assumption, while the CRF does not

- CRF uses global features while MEMM features are localized

- Feature design is flexible in both models

- CRF is computationally more complex

History of CRFs

- Very popular in the 2000s
- Wide variety of applications:
  - Information extraction
  - Summarization
  - Image labeling/segmentation

Information extraction from research papers using conditional random fields ☆

Fuchun Peng [a], Andrew McCallum [b]

Multiscale conditional random fields for image labeling

Publisher: IEEE   Cite This   PDF

Xuming He ; R.S. Zemel ; M.A. Carreira-Perpinan   **All Authors**

Document Summarization using Conditional Random Fields

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- Wide variety of applications:
  - Information extraction
  - Summarization
  - Image labeling/segmentation

Software [edit]

This is a partial list of software that implement generic CRF tools.

- RNNSharp CRFs based on recurrent neural networks (C#, .NET)
- CRF-ADF Linear-chain CRFs with fast online ADF training (C#, .NET)
- CRFSharp Linear-chain CRFs (C#, .NET)
- GCO CRFs with submodular energy functions (C++, Matlab)
- DGM General CRFs (C++)
- GRMM General CRFs (Java)
- factorie General CRFs (Scala)
- CRFall General CRFs (Matlab)
- Sarawagi's CRF Linear-chain CRFs (Java)
- HCRF library Hidden-state CRFs (C++, Matlab)
- Accord.NET Linear-chain CRF, HCRF and HMMs (C#, .NET)
- Wapiti Fast linear-chain CRFs (C)[15]
- CRFSuite Fast restricted linear-chain CRFs (C)
- CRF++ Linear-chain CRFs (C++)
- FlexCRFs First-order and second-order Markov CRFs (C++)
- crf-chain1 First-order, linear-chain CRFs (Haskell)
- imageCRF CRF for segmenting images and image volumes (C++)
- MALLET Linear-chain for sequence tagging (Java)

CRFs in deep learning era

Conditional Random Fields as Recurrent Neural Networks

Shuai Zheng, Sadeep Jayasumana, Bernardino Romera-Paredes, Vibhav Vineet, Zhizhong Su, Dalong Du, Chang Huang, Philip H. S. Torr; Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2015, pp. 1529-1537

Neural Architectures for Named Entity Recognition

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Bidirectional LSTM-CRF Models for Sequence Tagging

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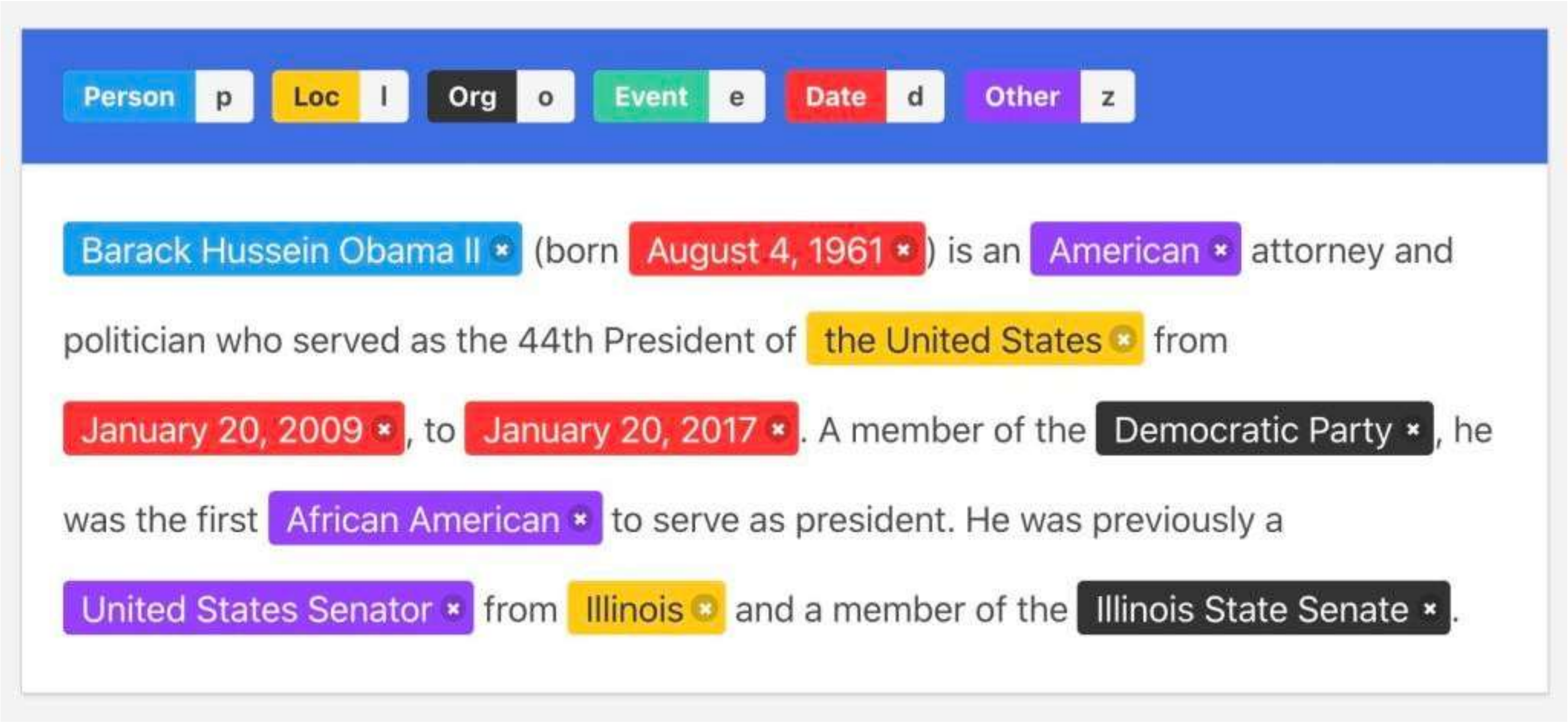
- Use CRFs on top of neural representations (instead of features and weights)
- Joint sequence prediction without the need for defining features!
- Recent architectures such as seq2seq w/ attention or Transformer may implicitly do the job

Named entity recognition (NER)

Named entity recognition



Named entities

- Named entity, in its core usage, means anything that can be referred to with a proper name.
- NER is the task of 1) finding spans of text that constitute proper names; 2) tagging the type of the entity
- Most common 4 tags:
  - **PER** (Person): “Marie Curie”
  - **LOC** (Location): “New York City”
  - **ORG** (Organization): “Princeton University”
  - **MISC** (Miscellaneous): nationality, events, ..

Only	France	and	Britain	backed	Fischler	's	proposal	.
O	LOC	O	LOC	O	PER	O	O	O

Steve	Jobs	founded	Apple	with	Steve	Wozniak	.
PER	PER	O	ORG	O	PER	PER	.

O = not an entity

If multiple words constitute a named entity, they will be labeled with the same tag.

NER: BIO Tagging

[PER Jane Villanueva] of [ORG United] , a unit of [ORG United Airlines Holding] , said the fare applies to the [LOC Chicago] route.

Words	BIO Label
Jane	B-PER
Villanueva	I-PER
of	O
United	B-ORG
Airlines	I-ORG
Holding	I-ORG
discussed	O
the	O
Chicago	B-LOC
route	O
.	O

B: token that begins a span

I: tokens that inside a span

O: tokens outside of a span