CS447: Natural Language Processing
http://courses.engr.illinois.edu/cs447

Lecture 9: Sequence Labeling

Julia Hockenmaier
juliahmr@illinois.edu
3324 Siebel Center

Friday's key concepts (I)

The Forward algorithm:

Computes $P(\mathbf{w})$ by replacing Viterbi's $\max()$ with $\mathrm{sum}()$

Learning HMMs from raw text with the EM algorithm:

- We have to replace the observed counts (from labeled data) with expected counts (according to the current model)
- Renormalizing these expected counts will give a new model
- This will be "better" than the previous model, but we will have to repeat this multiple times to get to decent model

The Forward-Backward algorithm:

A dynamic programming algorithm for computing the expected counts of tag bigrams and word-tag occurrences in a sentence under a given HMM

Expected counts

Emission probabilities with *observed* counts $C(w, t)$

$$P(w \mid t) = C(w, t) / \sum_{w'} C(t) = C(w, t) / \sum_{w'} C(w', t)$$

Emission probabilities with *expected* counts $\langle C(w, t) \rangle$

$$P(w \mid t) = \langle C(w, t) \rangle / \sum_{w'} \langle C(t) \rangle = \langle C(w, t) \rangle / \sum_{w'} \langle C(w', t) \rangle$$

$\langle C(w, t) \rangle$: How often do we expect to see word w with tag t in our training data (under a given HMM)?

We know how often the word w appears in the data, but we don't know how often it appears with tag t

We need to sum up $\langle C(w^{(i)}{=}w, t) \rangle$ for any occurrence of w

We can show that $\langle C(w^{(i)}{=}w, t) \rangle = P(t^{(i)}{=}t \mid \mathbf{w})$

(NB: Transition counts $\langle C(t^{(i)}{=}t, t^{(i+1)}{=}t') \rangle$ work in a similar fashion)

Forward-Backward: $P(\mathrm{t}^{(i)}=\mathrm{t} \mid \mathbf{w}^{(1)..(N)})$

$P(\ \mathrm{t}^{(i)}=t \mid \mathbf{w}^{(1)\ldots(N)}) \ = \ P(\ \mathrm{t}^{(i)}=t,\ \mathbf{w}^{(1)\ldots(N)})\ /\ P(\mathbf{w}^{(1)\ldots(N)})$

$\mathbf{w}^{(1)\ldots(N)} = \mathbf{w}^{(1)\ldots(i)}\mathbf{w}^{(i+1)\ldots(N)}$

Due to HMM's independence assumptions:

$P(\ \mathrm{t}^{(i)}=t,\ \mathbf{w}^{(1)\ldots(N)}) = P(\mathrm{t}^{(i)}=t,\ \mathbf{w}^{(1)\ldots(i)}) \times P(\mathbf{w}^{(i+1)\ldots(N)} \mid t^{(i)} = t)$

The forward algorithm gives $P(\mathbf{w}^{(1)\ldots(N)}) = \sum_t \mathrm{forward}[N][t]$

Forward trellis: $\mathrm{forward}[i][t] = P(\mathrm{t}^{(i)}=t,\ \mathbf{w}^{(1)\ldots(i)})$

Gives the total probability mass of the **prefix** $\mathbf{w}^{(1)\ldots(i)}$, summed over all tag sequences $\mathbf{t}^{(1)\ldots(i)}$ that end in tag $\mathrm{t}^{(i)}=t$

Backward trellis: $\mathrm{backward}[i][t] = P(\mathbf{w}^{(i+1)\ldots(N)} \mid \mathrm{t}^{(i)}=t)$

Gives the total probability mass of the **suffix** $\mathbf{w}^{(i+1)\ldots(N)}$, summed over all tag sequences $\mathbf{t}^{(i+1)\ldots(N)}$, if we assign tag $\mathrm{t}^{(i)}=t$ to $\mathrm{w}^{(i)}$

The Backward algorithm

The backward trellis is filled from right to left.

backward[i][t] provides $P(\boldsymbol{w}^{(i+1)\ldots(N)} \mid t^{(i)} = t)$

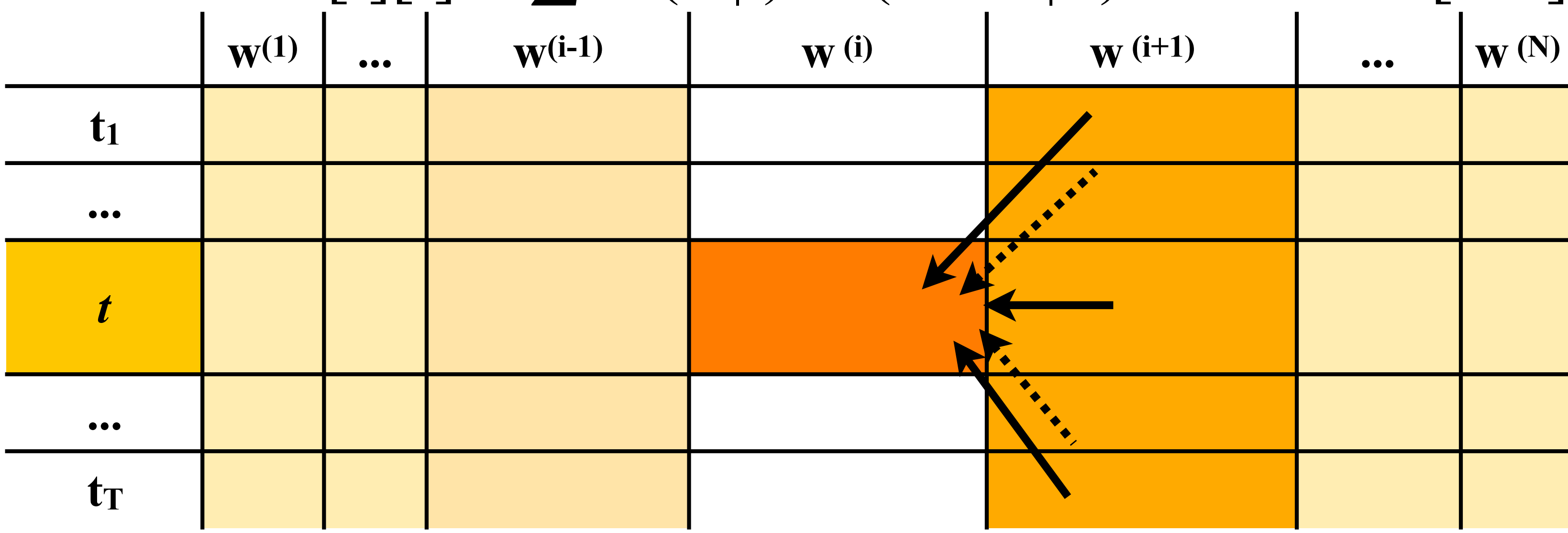
NB: $\sum_t \text{backward}[1][t] = P(\boldsymbol{w}^{(i+1)\ldots(N)}) = \sum_t \text{forward}[N][t]$

Initialization (last column):

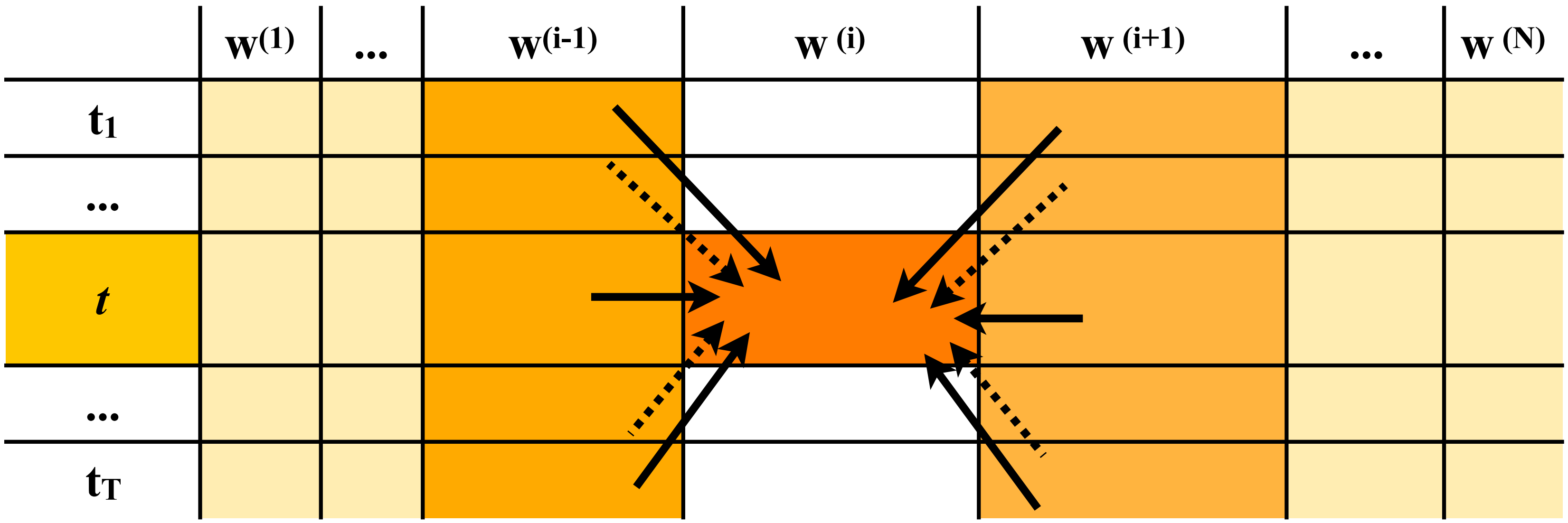
backward[N][t] = 1

Recursion (any other column):

$\text{backward}[i][t] = \sum_{t'} P(t' \mid t) \times P(w^{(i+1)} \mid t') \times \text{backward}[i+1][t']$



How do we compute $\langle C(t_i) \mid w_j \rangle$



$$\langle C(t, w^{(i)}) \mid \boldsymbol{w} \rangle = P(t^{(i)} = t, \boldsymbol{w}) / P(\boldsymbol{w})$$

with

$$P(t^{(i)} = t, \boldsymbol{w}) = \text{forward[i][t] backward[i][t]}$$

$$P(\boldsymbol{w}) \qquad = \textstyle\sum_t \text{forward[N][t]}$$

The importance of tag dictionaries

Forward-Backward assumes that each tag can be assigned to any word.

- No guarantee that the learned HMM bears any resemblance to the tags we want to get out of a POS tagger.

A tag dictionary lists the possible POS tags for words.

- Even a partial dictionary that lists only the tags for the most common words and contains at least a few words for each tag provides enough constraints to get significantly closer to a model that produces linguistically correct (and hence useful) POS tags.

a	DT	back	JJ, NN, VB, VBP, RP
an	DT	bank	NN, VB, VBP
and	CC	…	…
America	NNP	zebra	NN

Sequence labeling

POS tagging

```
Pierre Vinken , 61 years old , will join IBM 's board
as a nonexecutive director Nov. 29 .
```

```
Pierre_NNP Vinken_NNP ,_, 61_CD years_NNS old_JJ ,_,
will_MD join_VB IBM_NNP 's_POS board_NN as_IN a_DT
nonexecutive_JJ director_NN Nov._NNP 29_CD ._.
```

Task: assign POS tags to words

Noun phrase (NP) chunking

```
Pierre Vinken , 61 years old , will join IBM ‘s board
as a nonexecutive director Nov. 29 .
```

```
[NP Pierre Vinken] , [NP 61 years] old , will join
[NP IBM] ‘s [NP board] as [NP a nonexecutive director]
[NP Nov. 2] .
```

Task: identify all non-recursive NP chunks

The BIO encoding

We define three new tags:

– **B-NP**: beginning of a noun phrase chunk
– **I-NP**: inside of a noun phrase chunk
– **O**: outside of a noun phrase chunk

```
[NP Pierre Vinken] , [NP 61 years] old , will join
[NP IBM] ‘s [NP board] as [NP a nonexecutive director]
[NP Nov. 2] .
```

```
Pierre_B-NP Vinken_I-NP ,_O 61_B-NP years_I-NP
old_O ,_O will_O join_O IBM_B-NP ‘s_O board_B-NP as_O
a_B-NP nonexecutive_I-NP director_I-NP Nov._B-NP
29_I-NP ._O
```

Shallow parsing

```
Pierre Vinken , 61 years old , will join IBM ‘s board
as a nonexecutive director Nov. 29 .
```

```
[NP Pierre Vinken] , [NP 61 years] old , [VP will join]
[NP IBM] ‘s [NP board] [PP as] [NP a nonexecutive
director] [NP Nov. 2] .
```

Task: identify all non-recursive NP, verb (“VP”) and preposition (“PP”) chunks

The BIO encoding for shallow parsing

We define several new tags:

– **B-NP B-VP B-PP**: beginning of an NP, “VP”, “PP” chunk

– **I-NP I-VP I-PP**: inside of an NP, “VP”, “PP” chunk

– **O**: outside of any chunk

```
[NP Pierre Vinken] , [NP 61 years] old , [VP will join]
[NP IBM] ‘s [NP board] [PP as] [NP a nonexecutive
director] [NP Nov. 2] .
```

```
Pierre_B-NP Vinken_I-NP ,_O 61_B-NP years_I-NP
old_O ,_O will_B-VP join_I-VP IBM_B-NP ‘s_O board_B-NP
as_B-PP a_B-NP nonexecutive_I-NP director_I-NP Nov._B-
NP 29_I-NP ._O
```

Named Entity Recognition

```
Pierre Vinken , 61 years old , will join IBM ‘s board
as a nonexecutive director Nov. 29 .
```

```
[PERS Pierre Vinken] , 61 years old , will join
[ORG IBM] ‘s board as a nonexecutive director
[DATE Nov. 2] .
```

Task: identify all mentions of named entities (people, organizations, locations, dates)

The BIO encoding for NER

We define many new tags:

– **B-PERS**, **B-DATE, …:** beginning of a mention of a person/date...
– **I-PERS**, **I-DATE, …:** inside of a mention of a person/date...
– **O**: outside of any mention of a named entity

```
[PERS Pierre Vinken] , 61 years old , will join
[ORG IBM] ‘s board as a nonexecutive director
[DATE Nov. 2] .
```

```
Pierre_B-PERS Vinken_I-PERS ,_O 61_O years_O old_O ,_O
will_O join_O IBM_B-ORG ‘s_O board_O as_O a_O
nonexecutive_O director_O Nov._B-DATE 29_I-DATE ._O
```

Many NLP tasks are sequence labeling tasks

Input: a sequence of tokens/words:

`Pierre Vinken , 61 years old , will join IBM ‘s board as a nonexecutive director Nov. 29 .`

Output: a sequence of **labeled** tokens/words:

POS-tagging: Pierre_**NNP** Vinken_**NNP** ,_**,** 61_**CD** years_**NNS** old_**JJ** ,_**,** will_**MD** join_**VB** IBM_**NNP** ‘s_**POS** board_**NN** as_**IN** a_**DT** nonexecutive_**JJ** director_**NN** Nov._**NNP** 29_**CD** ._**.**

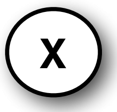
Named Entity Recognition: Pierre_**B-PERS** Vinken_**I-PERS** ,_**O** 61_**O** years_**O** old_**O** ,_**O** will_**O** join_**O** IBM_**B-ORG** ‘s_**O** board_**O** as_**O** a_**O** nonexecutive_**O** director_**O** Nov._**B-DATE** 29_**I-DATE** ._**O**

Graphical models for sequence labeling

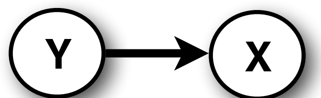
Directed graphical models

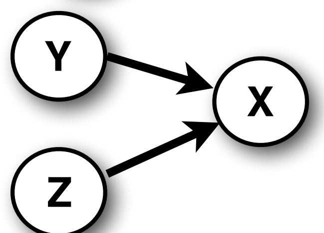
Graphical models are a **notation for probability models**.

In a **directed** graphical model, **each node** represents a distribution over a random variable:

– $P(X)$ = 

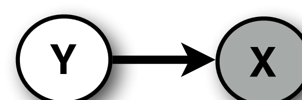
Arrows represent dependencies (they define what other random variables the current node is conditioned on)

– $P(Y)\ P(X \mid Y)$ = 

– $P(Y)\ P(Z)\ P(X \mid Y, Z)$ = 

Shaded nodes represent observed variables.

White nodes represent hidden variables

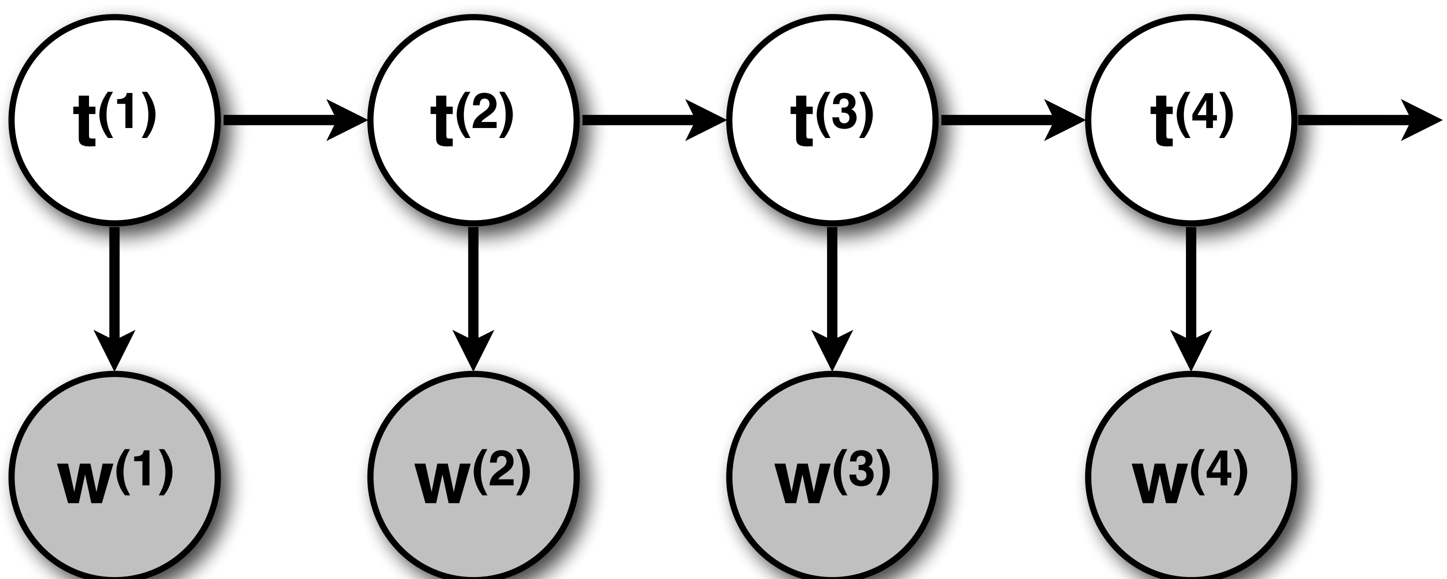
– $P(Y)\ P(X \mid Y)$ with Y hidden and X observed = 

HMMs as graphical models

HMMs are **generative** models of the observed input string **w**

They 'generate' **w** with $P(\mathbf{w},\mathbf{t}) = \prod_i P(t^{(i)} | t^{(i-1)}) P(w^{(i)} | t^{(i)})$

When we use an HMM to tag, we observe **w**, and need to find **t**



Models for sequence labeling

Sequence labeling: Given an input sequence $\mathbf{w} = w^{(1)} \ldots w^{(n)}$, predict the best (most likely) label sequence $\mathbf{t} = t^{(1)} \ldots t^{(n)}$

$$\underset{\mathbf{t}}{\operatorname{argmax}} P(\mathbf{t}|\mathbf{w})$$

Generative models use Bayes Rule:

$$\begin{aligned} \underset{\mathbf{t}}{\operatorname{argmax}} P(\mathbf{t}|\mathbf{w}) &= \underset{\mathbf{t}}{\operatorname{argmax}} \frac{P(\mathbf{t},\mathbf{w})}{P(\mathbf{w})} \\ &= \underset{\mathbf{t}}{\operatorname{argmax}} P(\mathbf{t},\mathbf{w}) \\ &= \underset{\mathbf{t}}{\operatorname{argmax}} P(\mathbf{t})P(\mathbf{w}|\mathbf{t}) \end{aligned}$$

Discriminative (conditional) models model $P(\mathbf{t}|\mathbf{w})$ directly

Advantages of discriminative models

We're usually not really interested in $P(\mathbf{w} \mid \mathbf{t})$.

– $\mathbf{w}$ is given. We don't need to predict it!

Why not model what we're actually interested in: $P(\mathbf{t} \mid \mathbf{w})$

Modeling $P(\mathbf{w} \mid \mathbf{t})$ well is quite difficult:

– Prefixes (capital letters) or suffixes are good predictors for certain classes of $\mathbf{t}$ (proper nouns, adverbs,…)

– These features may also help us deal with unknown words

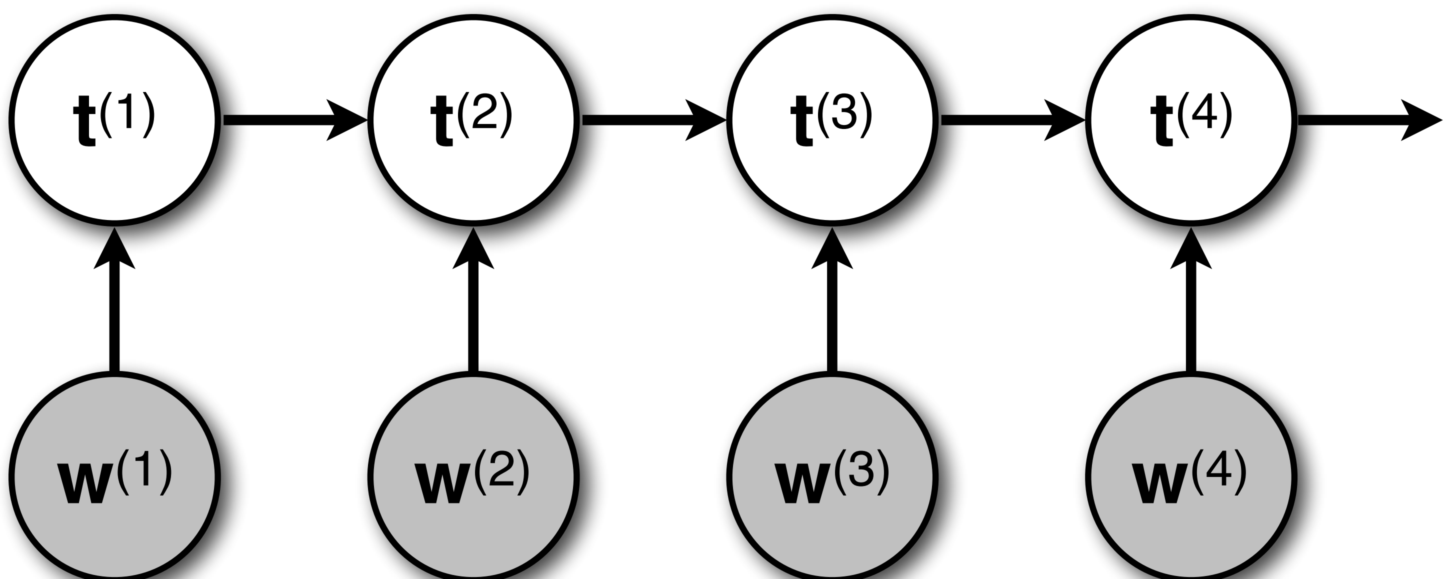
– But these features may not be independent (e.g. they are overlapping)

Modeling $P(\mathbf{t} \mid \mathbf{w})$ should be easier:

– Now we can incorporate arbitrary features of the word, because we don't need to predict $\mathbf{w}$ anymore

Discriminative probability models

A discriminative or **conditional** model of the labels **t** given the observed input string **w** models $P(\mathbf{t} \mid \mathbf{w}) = \prod_i P(t^{(i)} \mid w^{(i)}, t^{(i-1)})$ directly.



Discriminative models

There are two main types of discriminative probability models:

- Maximum Entropy Markov Models (MEMMs)
- Conditional Random Fields (CRFs)

MEMMs and CRFs:

- are both based on logistic regression
- have the same graphical model
- require the Viterbi algorithm for tagging
- differ in that MEMMs consist of independently learned distributions, while CRFs are trained to maximize the probability of the entire sequence

Probabilistic classification

Classification:

Predict a class (label) c for an input $\mathbf{x}$

There are only a (small) finite number of possible class labels

Probabilistic classification:

– Model the probability $P(c \mid \mathbf{x})$

$P(c|\mathbf{x})$ is a probability if $0 \leq P(c_i \mid \mathbf{x}) \leq 1$, and $\sum_i P(c_i \mid \mathbf{x}) = 1$

– Return the class $c^* = \text{argmax}_i\, P(c_i \mid \mathbf{x})$ that has the highest probability

There are different ways to model $P(c \mid \mathbf{x})$.
MEMMs and CRFs are based on logistic regression

Using features

Think of feature functions as useful questions you can ask about the input $\mathbf{x}$:

– **Binary feature functions**:

$f_{\text{first-letter-capitalized}}(\textbf{Urbana}) = 1$

$f_{\text{first-letter-capitalized}}(\textbf{computer}) = 0$

– **Integer (or real-valued) features**:

$f_{\text{number-of-vowels}}(\textbf{Urbana}) = 3$

Which specific feature functions are useful will depend on your task (and your training data).

From features to probabilities

We associate a real-valued weight w_{ic} with each feature function $f_i(\mathbf{x})$ and output class c

Note that the feature function $f_i(\mathbf{x})$ does not have to depend on c as long as the weight does (note the double index w_{ic})

This gives us a real-valued score for predicting class c for input $\mathbf{x}$: $\text{score}(\mathbf{x},c) = \sum_i w_{ic} f_i(\mathbf{x})$

This score could be negative, so we exponentiate it:
$\text{score}(\mathbf{x},c) = \exp(\sum_i w_{ic} f_i(\mathbf{x}))$

To get a probability distribution over all classes c, we renormalize these scores:

$$P(c \mid \mathbf{x}) = \text{score}(\mathbf{x},c) / \sum_j \text{score}(\mathbf{x},c_j)$$
$$= \exp(\sum_i w_{ic} f_i(\mathbf{x})) / \sum_j \exp(\sum_i w_{ij} f_i(\mathbf{x}))$$

Learning: finding *w*

Learning = finding weights ***w***

We use conditional maximum likelihood estimation

(and standard convex optimization algorithms)

to find/learn ***w***

(for more details, attend CS446 and CS546)

The conditional MLE training objective:

Find the **w** that assigns highest probability to all observed outputs c_i given the inputs $\mathbf{x}_i$

$$\hat{\mathbf{w}} = \arg\max_{\mathbf{w}} \prod_i P(c_i | \mathbf{x}_i, \mathbf{w})$$

Terminology

Models that are of the form

$$P(c \mid \mathbf{x}) = \text{score}(\mathbf{x},c) / \sum_j \text{score}(\mathbf{x},c_j)$$
$$= \exp(\sum_i w_{ic} f_i(\mathbf{x})) / \sum_j \exp(\sum_i w_{ij} f_i(\mathbf{x}))$$

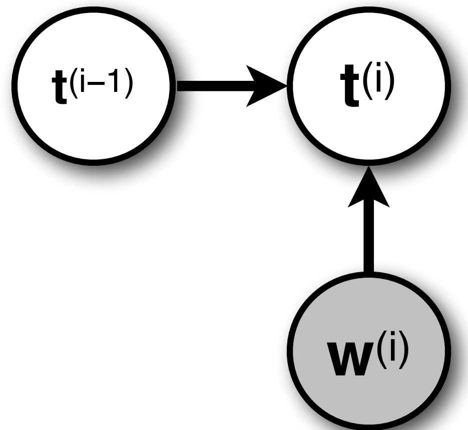
are also called loglinear models, Maximum Entropy (MaxEnt) models, or multinomial logistic regression models.

CS446 and CS546 should give you more details about these.

The normalizing term $\sum_j \exp(\sum_i w_{ij} f_i(\mathbf{x}))$ is also called the partition function and is often abbreviated as Z

Maximum Entropy Markov Models

MEMMs use a MaxEnt classifier for each $P(t^{(i)} | w^{(i)}, t^{(i-1)})$:



Since we use w to refer to words, let's use λ_{jk} as the weight for the feature function $f_j(t^{(i-1)}, w^{(i)})$ when predicting tag t_k:

$$P(t^{(i)} = t_k \mid t^{(i-1)}, w^{(i)}) = \frac{\exp(\sum_j \lambda_{jk} f_j(t^{(i-1)}, w^{(i)}))}{\sum_l \exp(\sum_j \lambda_{jl} f_j(t^{(i-1)}, w^{(i)}))}$$

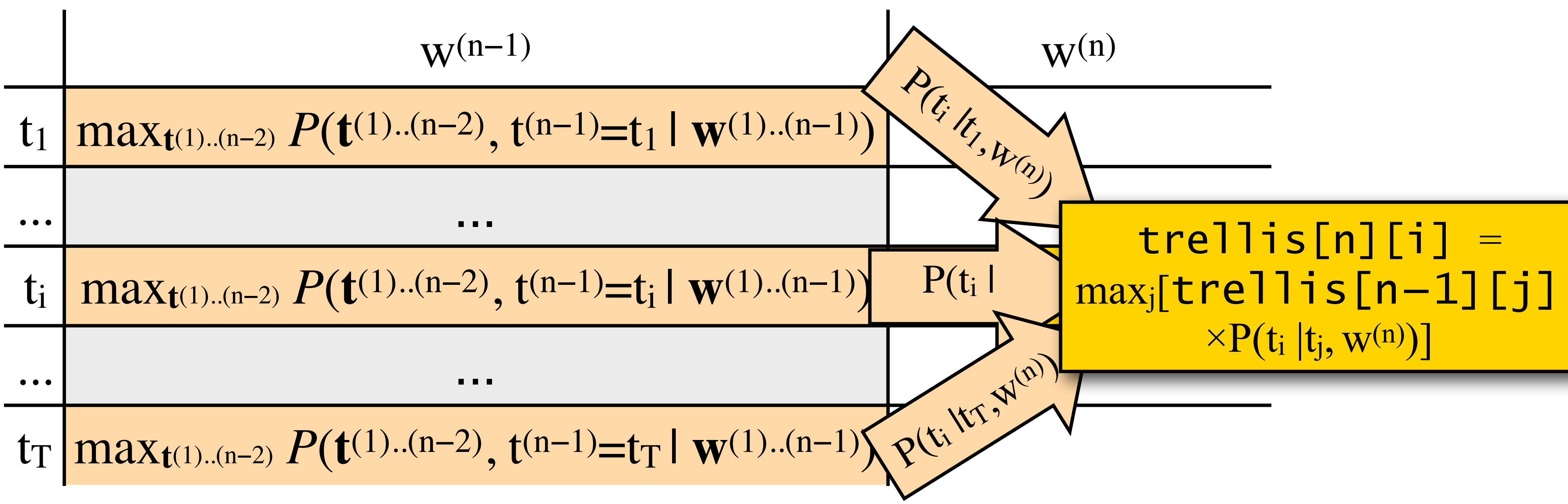
Viterbi for MEMMs

`trellis[n][i]` stores the probability of the most likely (Viterbi) tag sequence $\mathbf{t}^{(1)\ldots(n)}$ that ends in tag t_i for the prefix $w^{(1)}\ldots w^{(n)}$
Remember that we do not generate $\mathbf{w}$ in MEMMs. So:

$$\texttt{trellis[n][i]} = \max_{\mathbf{t}^{(1)..(n-1)}}[\, P(\mathbf{t}^{(1)\ldots(n-1)}, t^{(n)}{=}t_i \mid \mathbf{w}^{(1)\ldots(n)})\,]$$

$$= \max_j [\, \texttt{trellis[n-1][j]} \times P(t_i \mid t_j, w^{(n)})\,]$$

$$= \max_j [\max_{\mathbf{t}^{(1)..(n-2)}}[P(\mathbf{t}^{(1)..(n-2)}, t^{(n-1)}{=}t_j \mid \mathbf{w}^{(1)..(n-1)})] \times P(t_i \mid t_j, w^{(n)})]$$



Today's key concepts

Sequence labeling tasks:

- POS tagging
- NP chunking
- Shallow Parsing
- Named Entity Recognition

Discriminative models:

- Maximum Entropy classifiers
- MEMMs