

HMM (2)

LING 570

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Three fundamental questions for HMMs

- Training an HMM: given a set of observation sequences, learn its distribution, i.e. learn the transition and emission probabilities
- HMM as a parser: Finding the best state sequence for a given observation
- HMM as an LM: compute the probability of a given observation

Training an HMM: estimating the probabilities

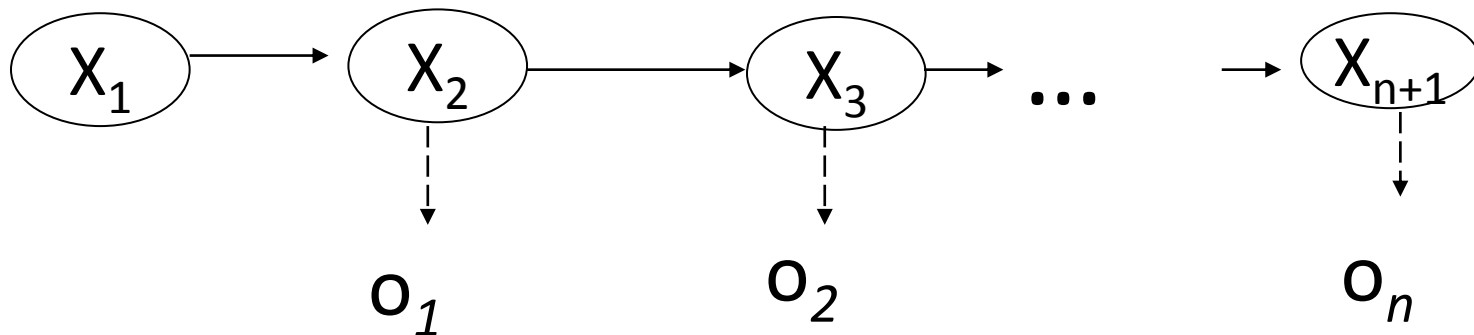
- Supervised learning:
 - The state sequences in the training data are known
 - ML estimation
- Unsupervised learning:
 - The state sequences in the training data are unknown
 - forward-backward algorithm

HMM as a parser

HMM as a parser:

Finding the best state sequence

- Given the observation $O_{1,T}=o_1...o_T$, find the state sequence $X_{1,T+1}=X_1 ... X_{T+1}$ that maximizes $P(X_{1,T+1} | O_{1,T})$.



➔ Viterbi algorithm

“time flies like an arrow”

\init

BOS 1.0

\transition

BOS N 0.5

BOS DT 0.4

BOS V 0.1

DT N 1.0

N N 0.2

N V 0.7

N P 0.1

V DT 0.4

V N 0.4

V P 0.1

V V 0.1

P DT 0.6

P N 0.4

\emission

N time 0.1

V time 0.1

N flies 0.1

V flies 0.2

V like 0.2

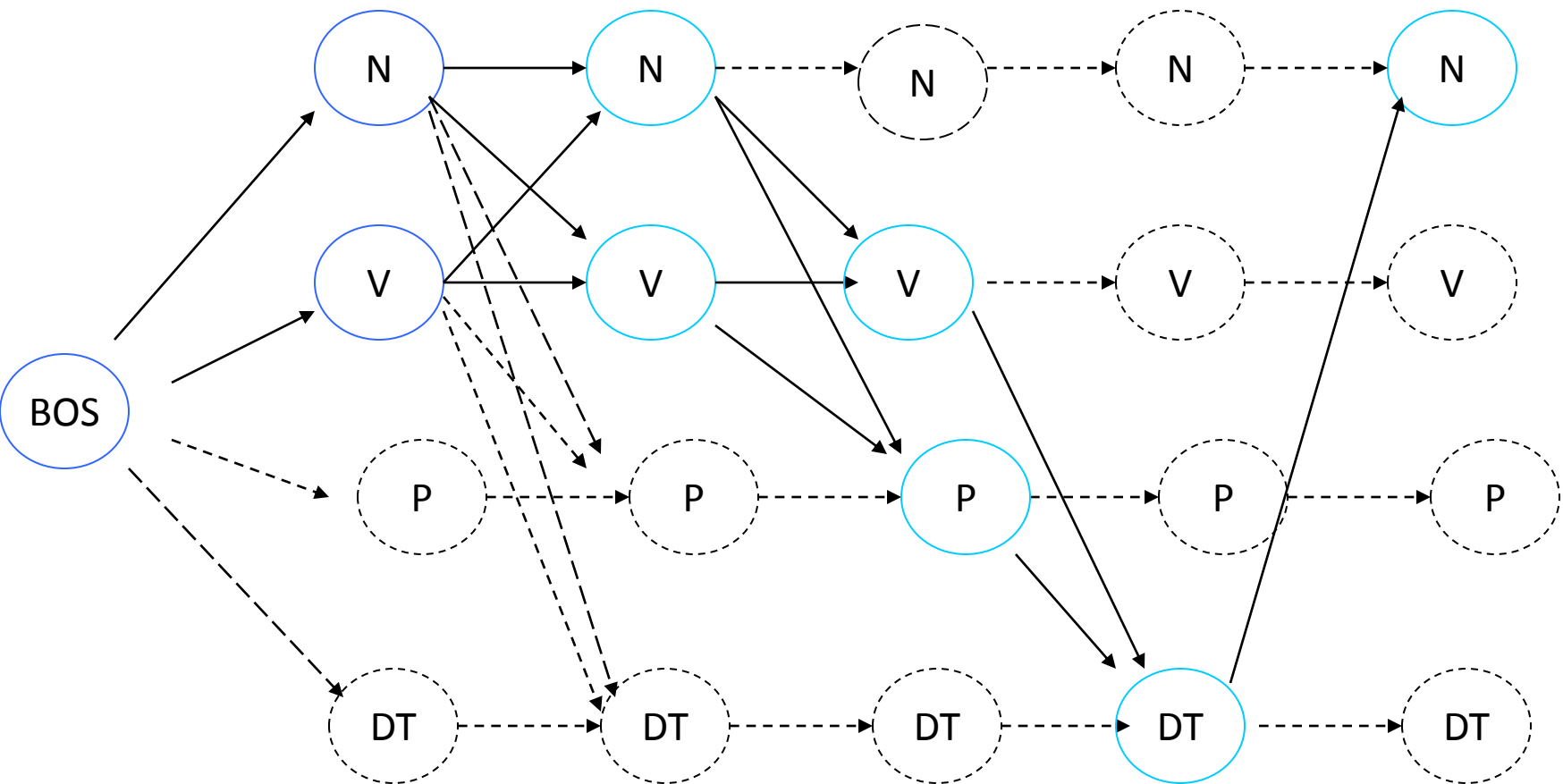
P like 0.1

DT an 0.3

N arrow 0.1

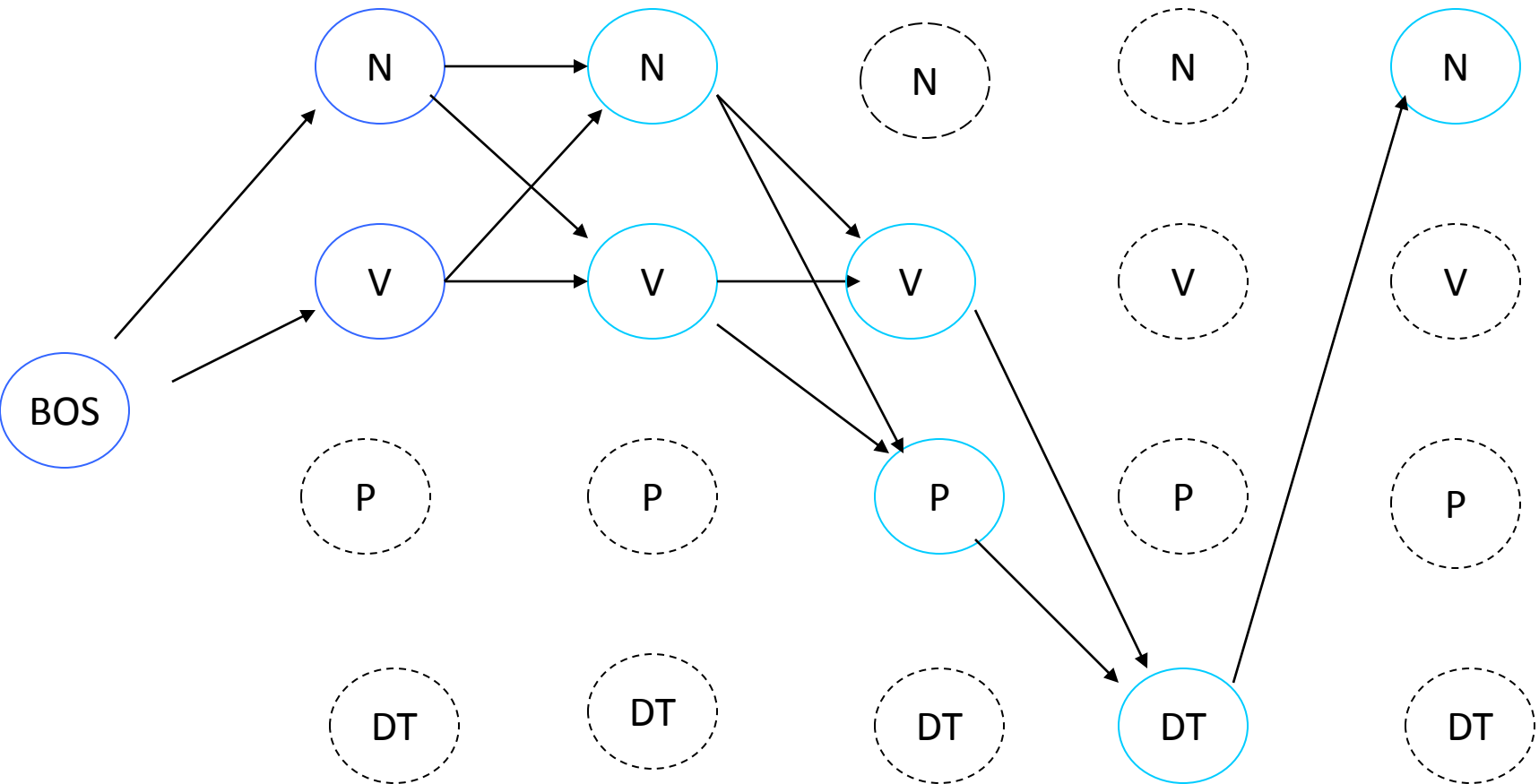
Finding all the paths: to build the trellis

time flies like an arrow



Finding all the paths (cont)

time flies like an arrow



Viterbi algorithm

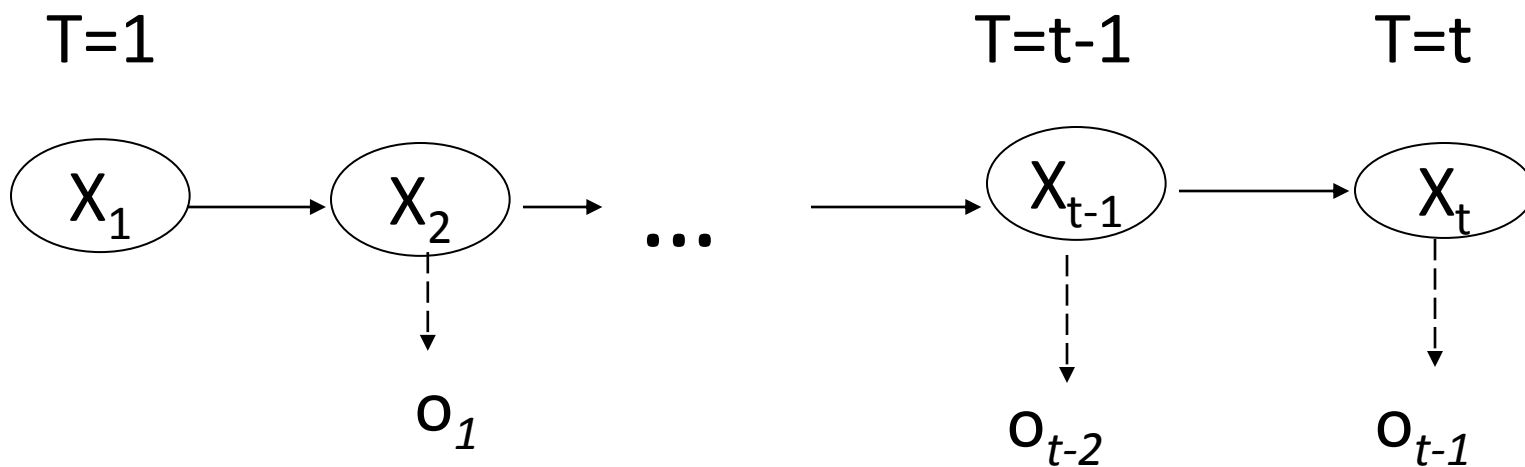
The probability of the best path that produces $O_{1,t-1}$ while ending up in state s_j :

$$\delta_j(t) \stackrel{def}{=} \max_{X_{1,t-1}} P(X_{1,t-1}, O_{1,t-1}, X_t = j)$$

Initialization: $\delta_j(1) = \pi_j$

Induction: $\delta_j(t+1) = \max_i \delta_i(t) a_{ij} b_{jo_t}$

→ Modify it to allow ϵ -emission



$$\delta_j(t) \stackrel{def}{=} \max_{X_{1,t-1}} P(X_{1,t-1}, O_{1,t-1}, X_t = j)$$

$$\delta_j(1) = \pi_j$$

$$\delta_j(t+1) = \max_i \delta_i(t) a_{ij} b_{jo_t}$$

Proof of the recursive function**

$$\begin{aligned}\delta_j(t+1) &= \max_{X_{1,t}} P(X_{1,t}, O_{1,t}, X_{t+1} = j) \\&= \max_{X_{1,t}} P(X_{1,t-1}, O_{1,t-1}, O_t, X_t, X_{t+1} = j) \\&= \max_{X_t=i} \max_{X_{1,t-1}} P(X_{1,t-1}, O_{1,t-1}, X_t = i) P(o_t, X_{t+1} = j \mid X_{1,t-1}, O_{1,t-1}, X_t = i) \\&= \max_{X_t=i} \max_{X_{1,t-1}} P(X_{1,t-1}, O_{1,t-1}, X_t = i) a_{ij} b_{jo_t} \\&= \max_{X_t=i} a_{ij} b_{jo_t} (\max_{X_{1,t-1}} P(X_{1,t-1}, O_{1,t-1}, X_t = i)) \\&= \max_{X_t=i} \delta_i(t) a_{ij} b_{jo_t}\end{aligned}$$

Viterbi algorithm: calculating $\delta_j(t)$

N is the number of states in the HMM structure

observ is the observation O, and leng is the length of observ.


Initialize $\text{delta}[0..\text{leng}][0..N-1]$ to 0

for each state j

$\text{delta}[0][j] = \pi[j]$ 

$\text{back-pointer}[0][j] = -1$ # dummy

for (t=0; t<leng; t++)

 for (j=0; j<N; j++) 

$k = \text{observ}[t]$ # the symbol at time t

$\text{delta}[t+1][j] = \max_i \text{delta}[t][i] a_{ij} b_{jk}$

$\text{back-pointer}[t+1][j] = \arg \max_i \text{delta}[t][i] a_{ij} b_{jk}$

Viterbi algorithm: retrieving the best path

```
# find the best path
```

```
best_final_state = arg maxj delta[leng] [j]
```

```
# start with the last state in the sequence
```

```
j = best_final_state
```

```
push(arr, j);
```

```
for (t=leng; t>0; t--)
```

```
    i = back-pointer[t] [j]
```

```
    push(arr, i)
```

```
    j = i
```

```
return reverse(arr)
```

Implementation issue storing HMM

Approach #1:

- π_i : π_i {state_str}
- a_{ij} : a {from_state_str} {to_state_str}
- b_{jk} : b {state_str} {symbol}

Approach #2:

- $\text{state2idx}\{\text{state_str}\} = \text{state_idx}$
- $\text{symbol2idx}\{\text{symbol_str}\} = \text{symbol_idx}$
- π_i : π_i [state_idx] = prob
- a_{ij} : a [from_state_idx] [to_state_idx] = prob
- b_{jk} : b [state_idx] [symbol_idx] = prob
- $\text{idx2state}[\text{state_idx}] = \text{state_str}$
- $\text{idx2symbol}[\text{symbol_idx}] = \text{symbol_str}$

Storing HMM: sparse matrix

- a_{ij} : $a[i][j] = \text{prob}$
- b_{jk} : $b[j][k] = \text{prob}$
- a_{ij} : $a[i] = \text{"j1 p1 j2 p2 ..."}"$
- a_{ij} : $a[j] = \text{"i1 p1 i2 p2 ..."}"$
- b_{jk} : $b[j] = \text{"k1 p1 k2 p2"}"$
- b_{jk} : $b[k] = \text{"j1 p1 j2 p2 ..."}"$

Other implementation issues

- Index starts from 0 in programming, but often starts from 1 in algorithms
- The sum of logprob is used in practice to replace the product of prob.
- Check constraints and print out warning if the constraints are not met.

HMM as LM

HMM as an LM: computing $P(o_1, \dots, o_T)$

$$P(o_1, \dots, o_T) = \sum_{X_1, \dots, X_{T+1}} P(o_1, \dots, o_T, X_1, \dots, X_{T+1})$$

1st try:

- enumerate all possible paths
- add the probabilities of all paths

Forward probabilities

- Forward probability: the probability of producing $O_{1,t-1}$ while ending up in state s_i :

$$\alpha_i(t) \stackrel{def}{=} P(O_{1,t-1}, X_t = i)$$

$$P(O) = \sum_{i=1}^N \alpha_i(T+1)$$

Calculating forward probability

Initialization: $\alpha_j(1) = \pi_j$

Induction:

$$\alpha_j(t+1) = P(O_{1,t}, X_{t+1} = j)$$
$$= \sum_i \alpha_i(t) a_{ij} b_{jo_t}$$

$$\alpha_j(t+1) = P(O_{1,t}, X_{t+1} = j)$$

$$= \sum_i P(O_{1,t}, X_t = i, X_{t+1} = j)$$

$$= \sum_i P(O_{1,t-1}, X_t = i) * P(o_t, X_{t+1} = j \mid O_{1,t-1}, X_t = i)$$

$$= \sum_i P(O_{1,t-1}, X_t = i) * P(o_t, X_{t+1} = j \mid X_t = i)$$

$$= \sum_i \alpha_i(t) a_{ij} b_{jo_t}$$

Summary

- Definition: hidden states, output symbols
- Properties: Markov assumption
- Applications: POS-tagging, etc.
- Three basic questions in HMM
 - Find the probability of an observation: forward probability
 - Find the best sequence: Viterbi algorithm
 - Estimate probability: MLE
- Bigram POS tagger: decoding with Viterbi algorithm

Hw7

- Q1: Viterbi algorithm
 - `viterbi.sh` `hmm` `test_file` `output_file`
 - HMM: the same format as in Hw6
 - `test_file`: “ $o_1 o_2 \dots o_k$ ”
 - `output_file`: “ $o_1 o_2 \dots o_k \Rightarrow x_1 x_2 \dots x_{k+1} \text{ logprob}$ ”
 - `logprob` is $\lg P(o_1 o_2 \dots o_k, x_1 x_2 \dots x_{k+1})$
 - Do not try to smooth the input HMM. It might have been smoothed already.
 - You can reuse some code from `check_hmm.sh` in Hw6

Q2: trigram POS tagger with HMM

- training:
 - `cat wsj sec0.word pos | create_3gram_hmm.sh hmm1 1.0 0 0 unk_prob_sec22`
- decoding: “w1 w2 ... => x1 x2 ... logprob”
 - `viterbi.sh hmm1 test.word sys1`
- convert format: “w1/t1 w2/t2 ...”
 - `cat sys1 | conv format.sh > sys1 res`
- evaluation
 - `calc tagging accuracy.pl test.word pos sys1 res > sys1 res.acc 2>&1`