Natural Language Processing
Sequence labeling

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Credit to Yulia Tsvetkov and Noah Smith for slides

Announcements

- A2 is out for < 10 more full days! Please start early!
- A1 grades will be released sometime today(?)
  - We'll be accepting regrade requests for A1 for a week (Feb. 8 through Feb. 15)
- Quiz 4 will go out at 2:20pm today
  - 5 multiple-choice questions
  - Will cover lexical semantics, neural networks we've seen so far, and sequence labeling content up through the end of Monday's lecture
  - Remember that you're allowed to use your notes
  - From now on (including this quiz), you'll have **15 minutes** to complete the quiz
  - From now on (including this quiz), quizzes will be available from 2:20pm on Wednesdays to 2:20pm on **Fridays**

Midterm eval feedback: Takeaways

What's working:

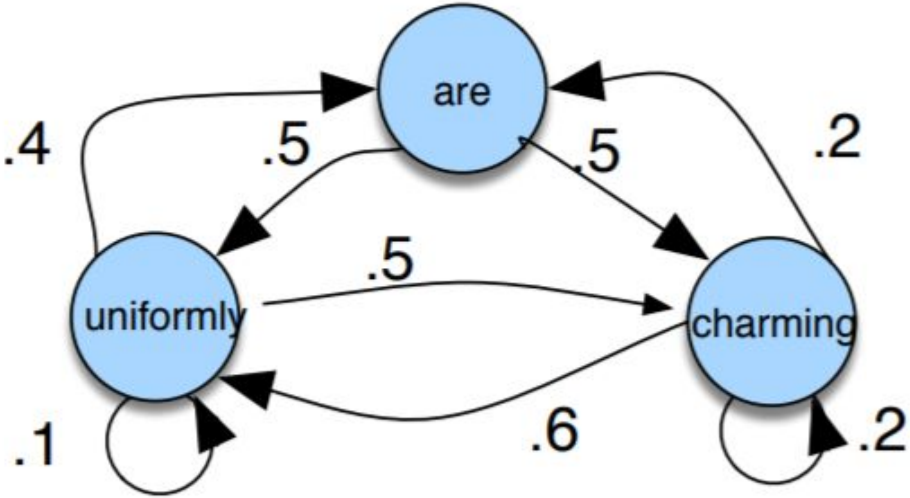
- Lectures
- Asynchronous availability of slides/lecture recordings

What could use work:

- Quizzes– quiz-taking time window was the repeated issue that came up here
- Walking through equations in a bit more detail/using more visualizations when possible
- Computing setup instructions that assume less familiarity with git, etc.

(Back to) Generative sequence labeling: Hidden Markov Models

Markov Chain: words

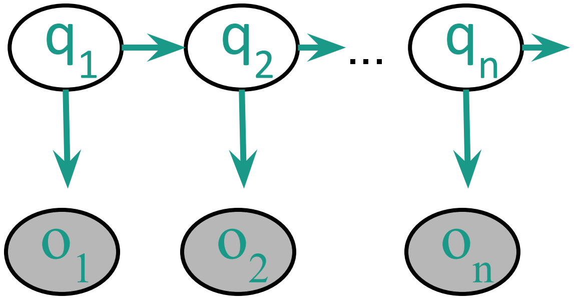


$$\pi = [0.1, 0.7, 0.2]$$

the future is independent of the past given the present

Hidden Markov Models

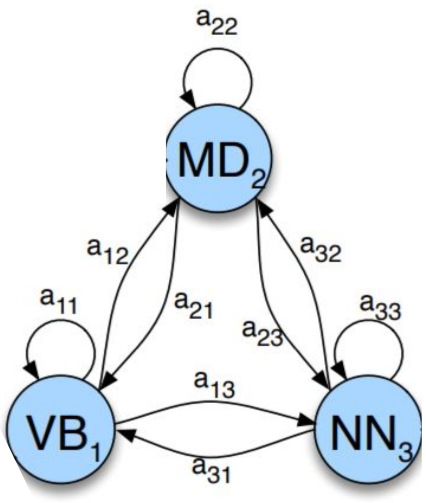
- In the real world many events are not observable
- Speech recognition: we observe acoustic features but not the phones
- POS tagging: we observe words but not the POS tags



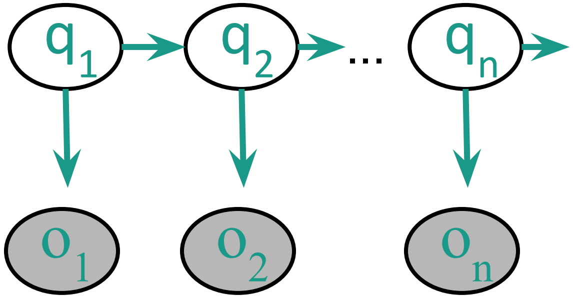
Markov Assumption: $P(q_i|q_1...q_{i-1}) = P(q_i|q_{i-1})$

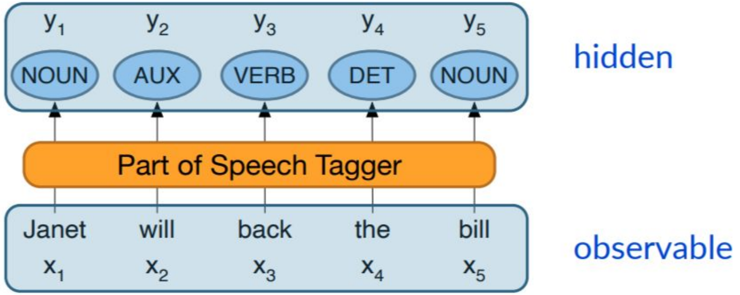
Output Independence: $P(o_i|q_1 \ldots q_i, \ldots, q_T, o_1, \ldots, o_i, \ldots, o_T) = P(o_i|q_i)$

Hidden Markov Models



Hidden Markov Models





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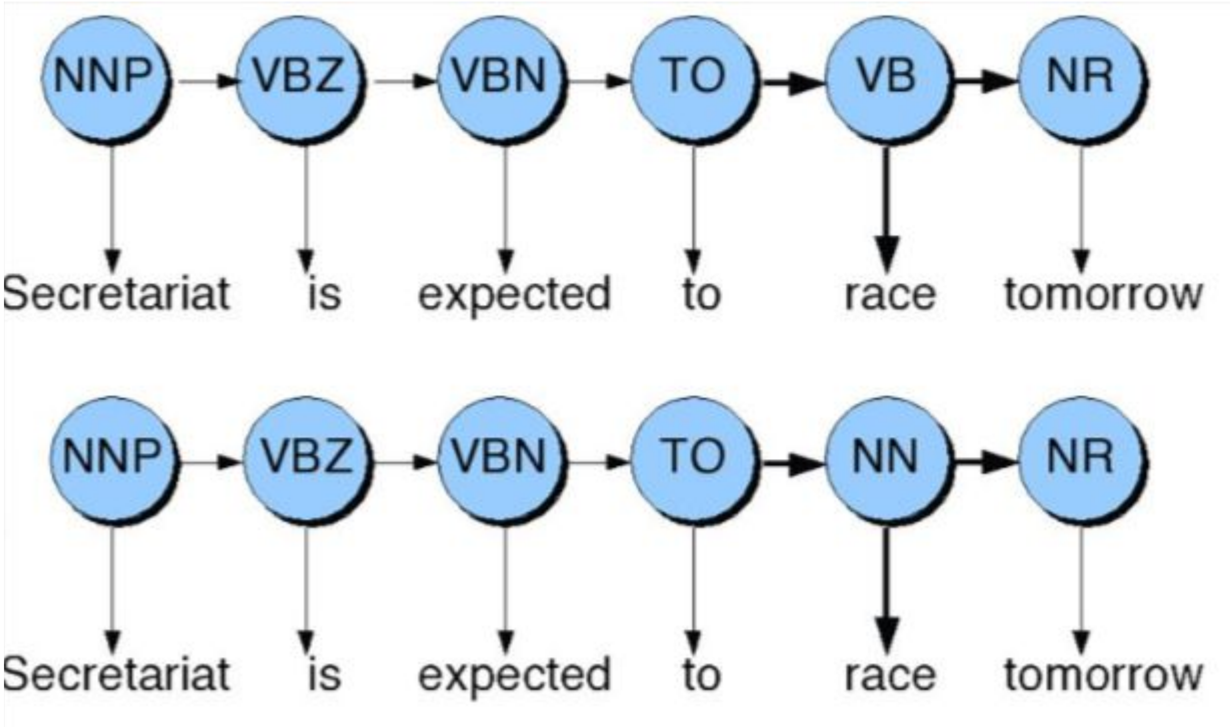
Hidden Markov Models (HMMs)

$Q = q_1 q_2 \ldots q_N$	a set of N **states**
$A = a_{11} \ldots a_{ij} \ldots a_{NN}$	a **transition probability matrix** A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{N} a_{ij} = 1 \quad \forall i$
$O = o_1 o_2 \ldots o_T$	a sequence of T **observations**, each one drawn from a vocabulary $V = v_1, v_2, \ldots, v_V$
$B = b_i(o_t)$	a sequence of **observation likelihoods**, also called **emission probabilities**, each expressing the probability of an observation o_t being generated from a state q_i
$\pi = \pi_1, \pi_2, \ldots, \pi_N$	an **initial probability distribution** over states. π_i is the probability that the Markov chain will start in state i. Some states j may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{n} \pi_i = 1$

POS tagging with HMMs



HMM parameters

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HMMs: algorithms

Forward

Viterbi

Problem 1 (Likelihood):	Given an HMM $\lambda = (A, B)$ and an observation sequence O, determine the likelihood $P(O\|\lambda)$.
Problem 2 (Decoding):	Given an observation sequence O and an HMM $\lambda = (A, B)$, discover the best hidden state sequence Q.
Problem 3 (Learning):	Given an observation sequence O and the set of states in the HMM, learn the HMM parameters A and B.

HMM tagging as decoding

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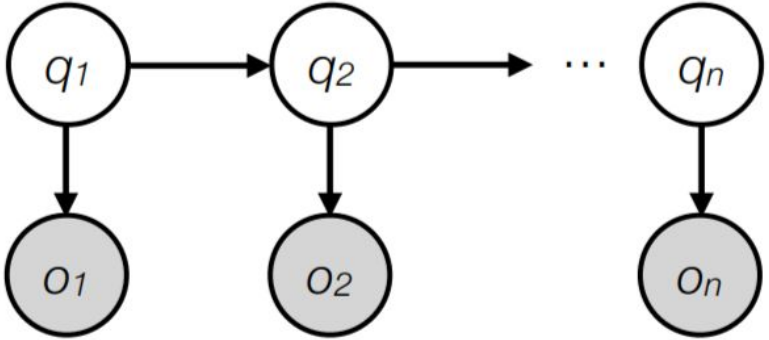
	Problem 3 (Learning):	Given an observation sequence O and the set of states in the HMM, learn the HMM parameters A and B.

"What is the best sequence of tags (given the parameters of this HMM) that corresponds to 'Janet will back the bill?'"

HMM tagging as decoding

Decoding: Given as input an HMM $\lambda = (A, B)$ and sequence of observations $O = o_1, o_2, \ldots, o_n$, find the most probable sequence of states $Q = q_1, q_2, \ldots, q_n$

$$\hat{t}_1^n = \underset{t_1^n}{\operatorname{argmax}} P(t_1^n \mid w_1^n)$$



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simplifying assumptions:

HMM tagging as decoding

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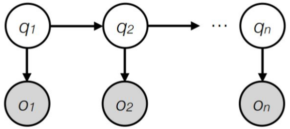

simplifying assumptions:

$$P(w_1^n \mid t_1^n) \approx \prod_{i=1}^{n} P(w_i \mid t_i)$$

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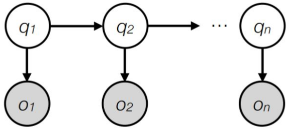

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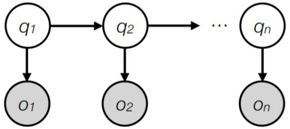


HMM tagging as decoding

Decoding: Given as input an HMM $\lambda = (A, B)$ and sequence of observations $O = o_1, o_2, \ldots, o_n$, find the most probable sequence of states $Q = q_1, q_2, \ldots, q_n$

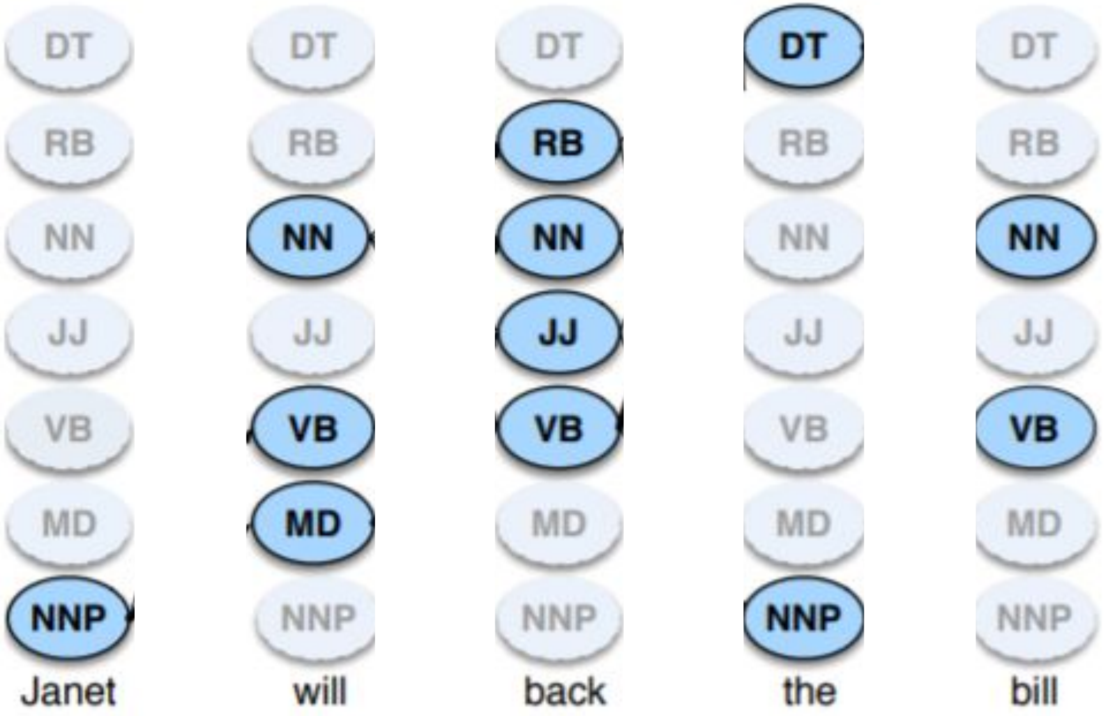
emission, B transition, A

$$\hat{t}_1^n = \underset{t_1^n}{\operatorname{argmax}} P(t_1^n \mid w_1^n) \approx \underset{t_1^n}{\operatorname{argmax}} \prod_{i=1}^{n} P(w_i \mid t_i) P(t_i \mid t_{i-1})$$

How many possible choices?

Could we brute force this?

(Imagine all these circles are colored in)



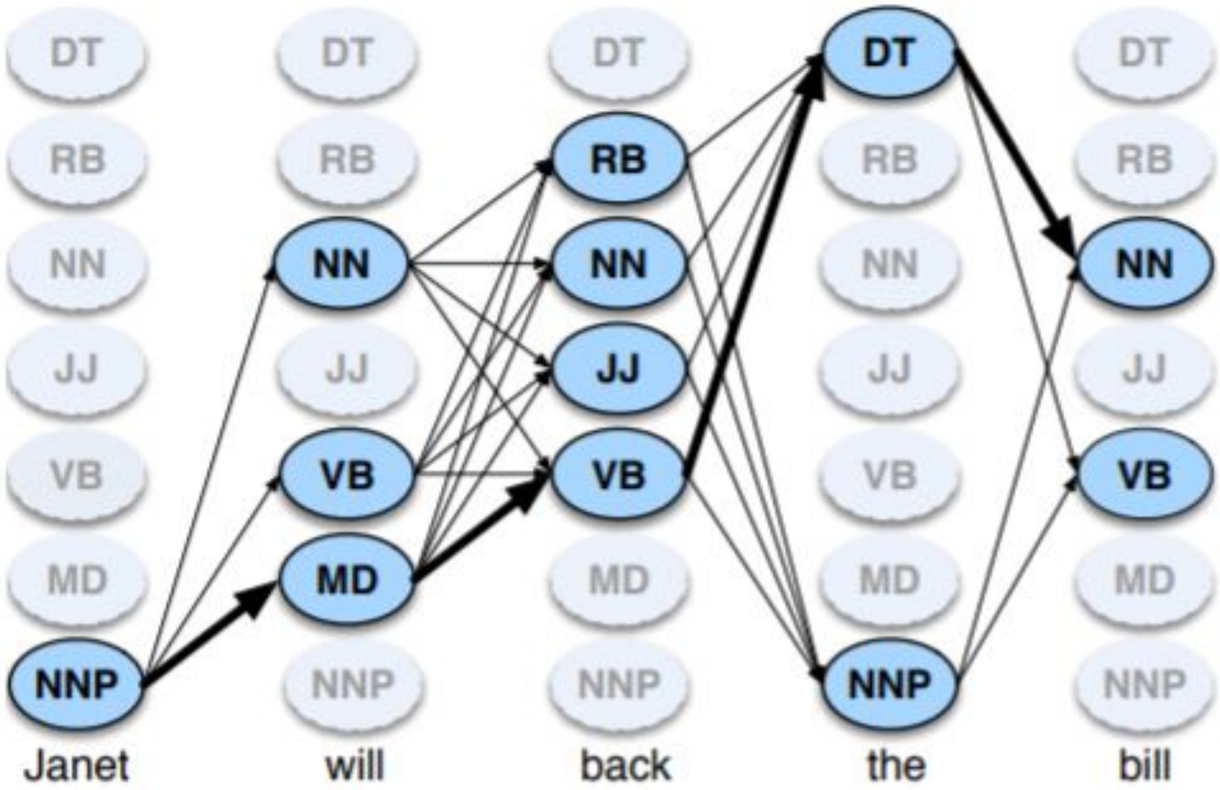
Part of speech tagging example

	I	suspect	the	present	forecast	is	pessimistic	.
noun	•	•	•	•	•	•		
adj.		•		•	•		•	
adv.				•				
verb		•		•	•	•		
num.	•							
det.			•					
punc.								•

With this very simple tag set, $7^8 = 5.7$ million labelings.
(Even restricting to the possibilities above, 288 labelings.)

The Viterbi algorithm

The Viterbi algorithm



Building up the Viterbi algorithm

The best possible paths ending
in any specific tag at position i

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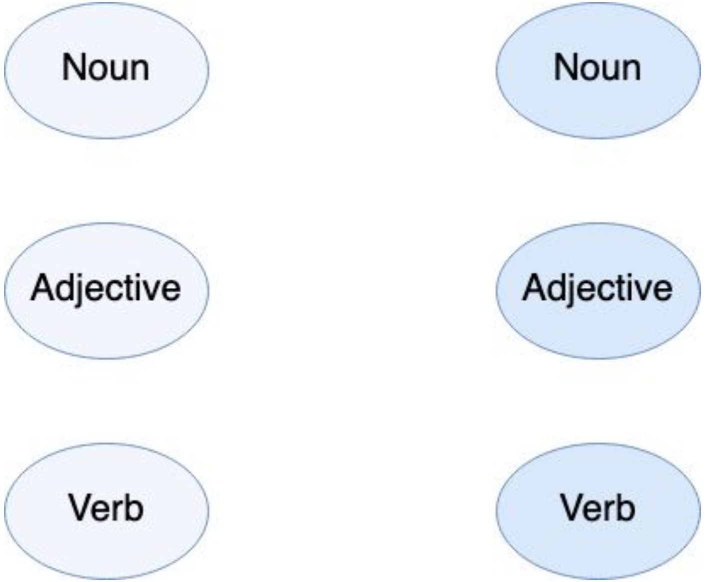
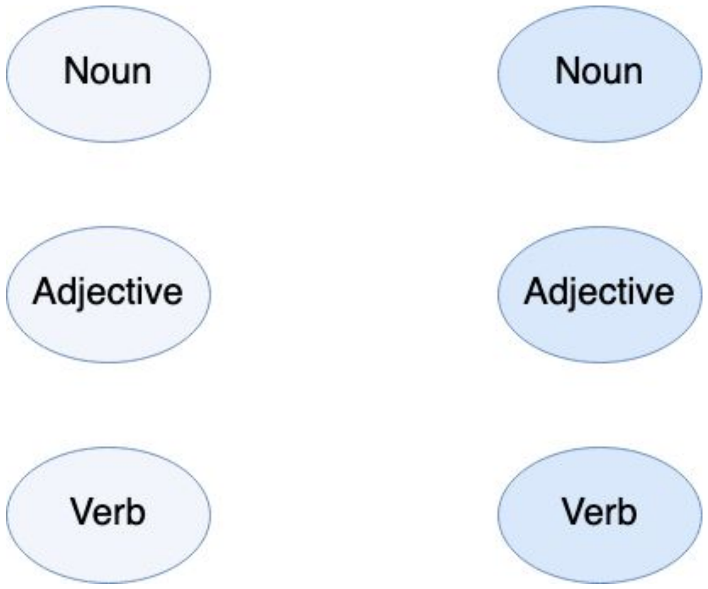


How do we use those to assemble the best possible paths ending in any specific tag at position i + 1?

Building up the Viterbi algorithm

The best possible paths ending
in any specific tag at position i



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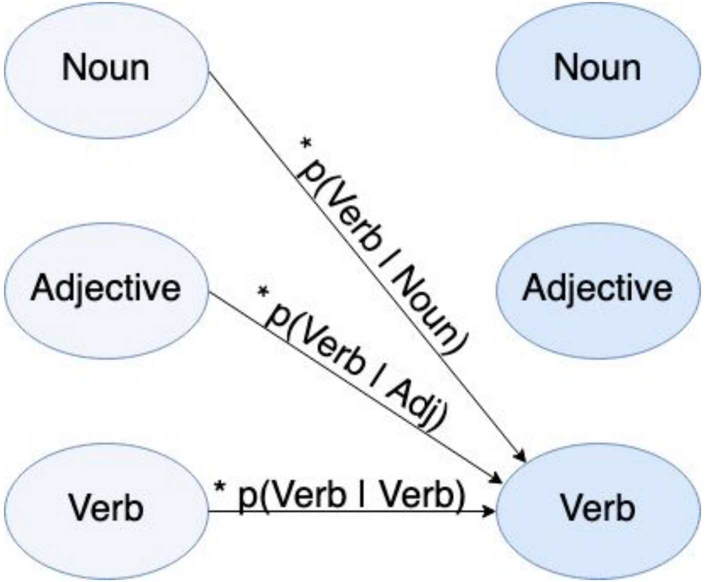

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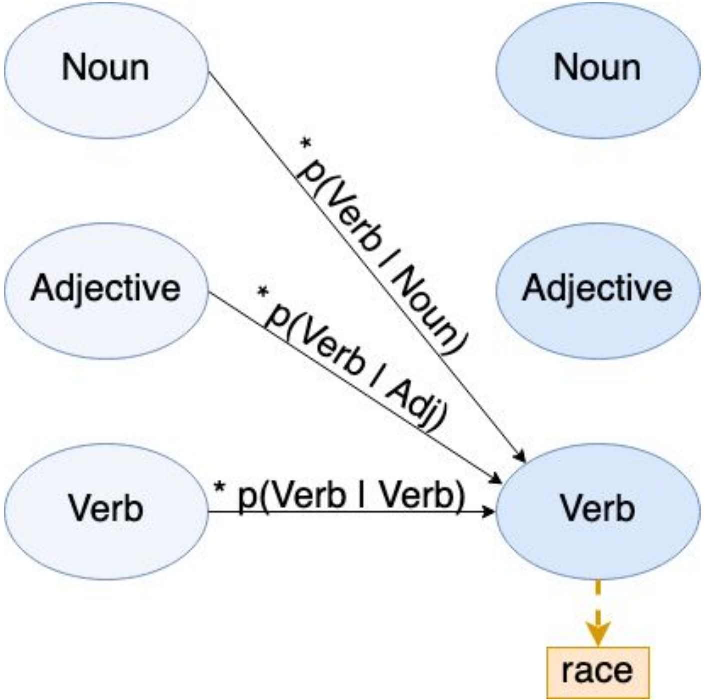

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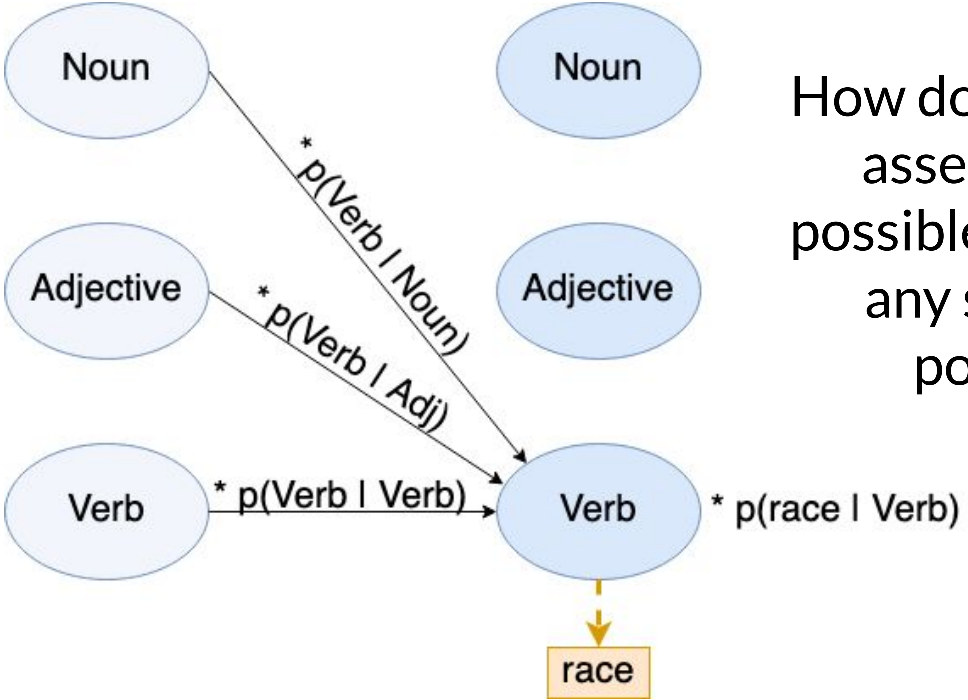

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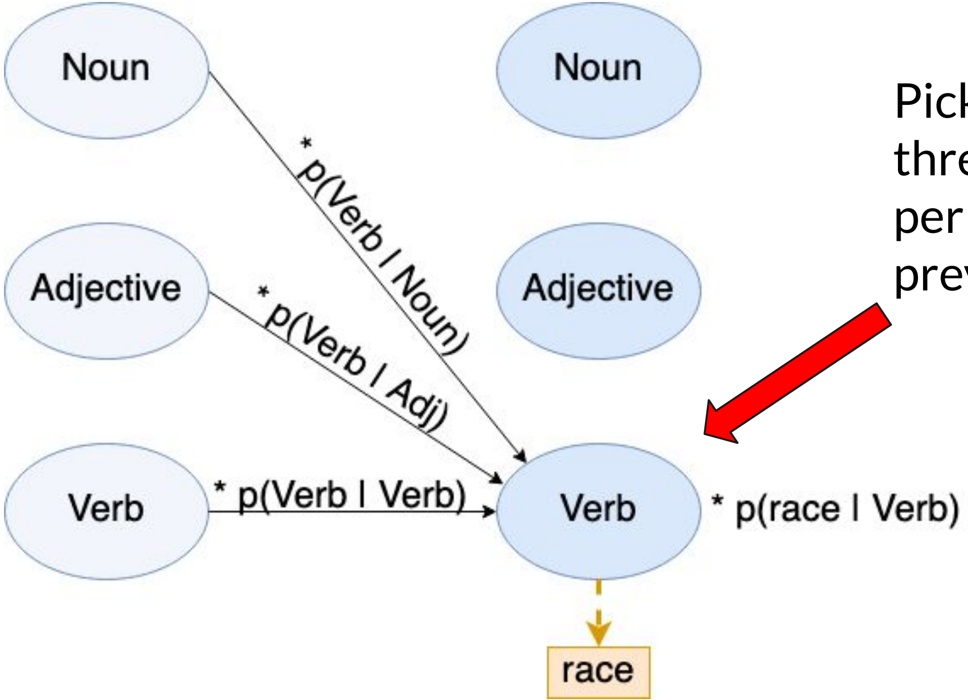
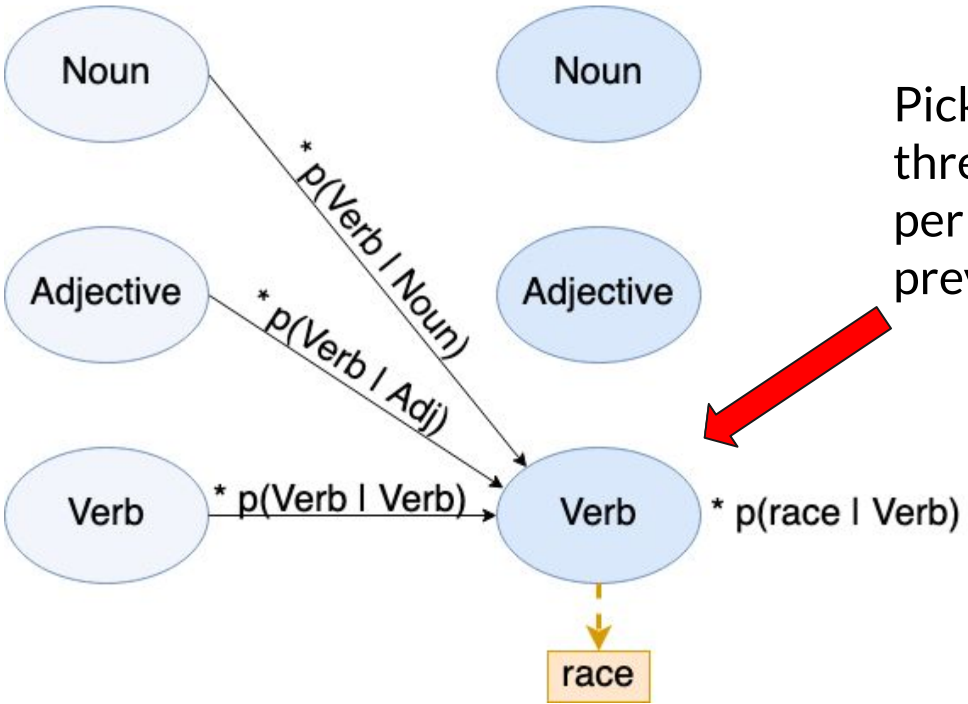


Pick the **max** of those three quantities (one per path from the previous timestep)

Building up the Viterbi algorithm

The best possible paths ending in any specific tag at position i



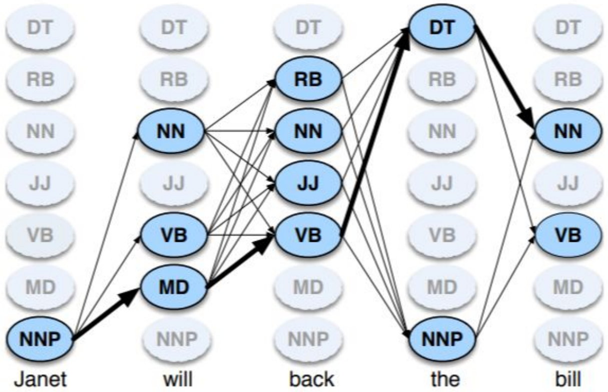
Pick the **max** of those three quantities (one per path from the previous timestep)

Store:

- That max score
- AND the preceding tag that was used to produce that max score ("**backpointer**")

The Viterbi algorithm

$v_{t-1}(i)$	the **previous Viterbi path probability** from the previous time step
a_{ij}	the **transition probability** from previous state q_i to current state q_j
$b_j(o_t)$	the **state observation likelihood** of the observation symbol o_t given the current state j



$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i) a_{ij} b_j(o_t)$$

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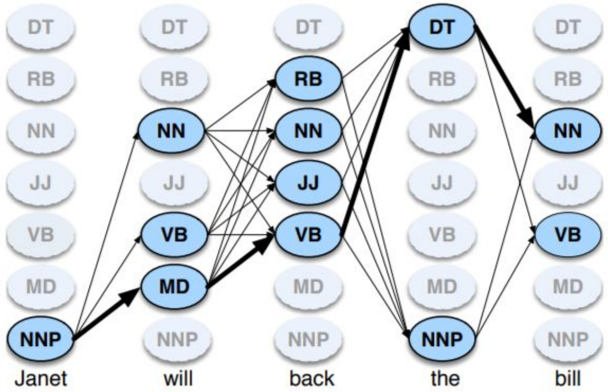

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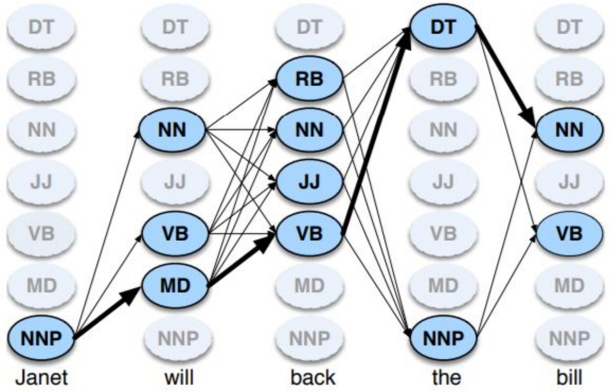

transition probability

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)\, a_{ij}\, b_j(o_t)$$

previous Viterbi path probability

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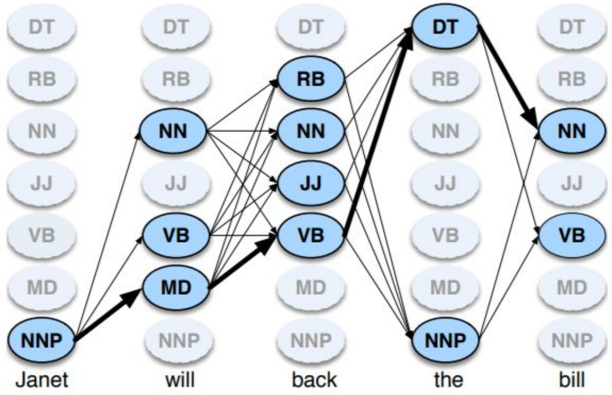

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state observation likelihood

previous Viterbi path probability

The Viterbi algorithm

function VITERBI(*observations* of len T, *state-graph* of len N) **returns** *best-path*, *path-prob*

create a path probability matrix *viterbi[N,T]*
for each state s **from** 1 **to** N **do**
$\quad viterbi[s,1] \leftarrow \pi_s * b_s(o_1)$
$\quad backpointer[s,1] \leftarrow 0$
for each time step t **from** 2 **to** T **do**
$\quad$**for** each state s **from** 1 **to** N **do**
$$viterbi[s,t] \leftarrow \max_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$$
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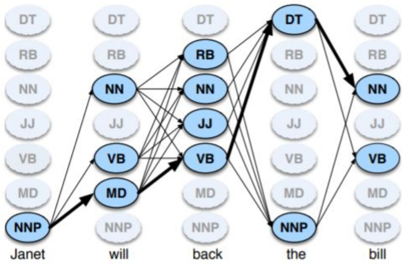

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initialization

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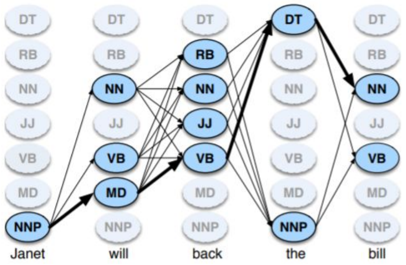

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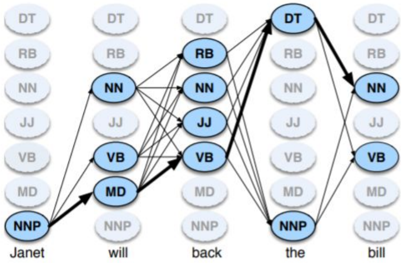
initialization

recursion



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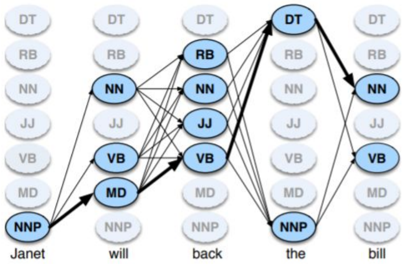

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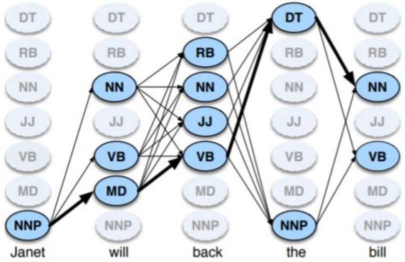
  $backpointer[s,1] \leftarrow 0$
for each time step *t* **from** 2 **to** *T* **do**   recursion
  for each state *s* **from** 1 **to** *N* **do**
   $viterbi[s,t] \leftarrow \max_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$ ← $v_t(j) = \max_{i=1}^{N} v_{t-1}(i) a_{ij} b_j(o_t)$
   $backpointer[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$

$bestpathprob \leftarrow \max_{s=1}^{N} viterbi[s,T]$

$bestpathpointer \leftarrow \operatorname{argmax}_{s=1}^{N} viterbi[s,T]$

bestpath ← the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time
return *bestpath*, *bestpathprob*

The Viterbi algorithm



function VITERBI(*observations* of len *T*,*state-graph* of len *N*) **returns** *best-path*, *path-prob*

create a path probability matrix *viterbi[N,T]*
for each state *s* **from** 1 **to** *N* **do**
    $viterbi[s,1] \leftarrow \pi_s * b_s(o_1)$
    $backpointer[s,1] \leftarrow 0$

initialization

for each time step *t* **from** 2 **to** *T* **do**
  for each state *s* **from** 1 **to** *N* **do**

recursion

    $viterbi[s,t] \leftarrow \max_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$ ← $v_t(j) = \max_{i=1}^{N} v_{t-1}(i) a_{ij} b_j(o_t)$
    $backpointer[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$

$bestpathprob \leftarrow \max_{s=1}^{N} viterbi[s,T]$
$bestpathpointer \leftarrow \operatorname{argmax}_{s=1}^{N} viterbi[s,T]$

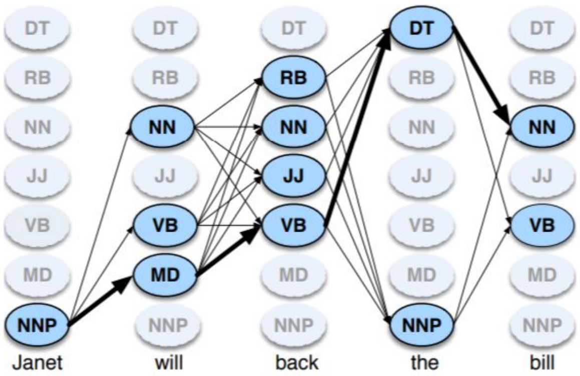
termination

bestpath ← the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time
return *bestpath*, *bestpathprob*

The Viterbi algorithm

	NNP	MD	VB	JJ	NN	RB	DT
$<s>$	0.2767	0.0006	0.0031	0.0453	0.0449	0.0510	0.2026
NNP	0.3777	0.0110	0.0009	0.0084	0.0584	0.0090	0.0025
MD	0.0008	0.0002	0.7968	0.0005	0.0008	0.1698	0.0041
VB	0.0322	0.0005	0.0050	0.0837	0.0615	0.0514	0.2231
JJ	0.0366	0.0004	0.0001	0.0733	0.4509	0.0036	0.0036
NN	0.0096	0.0176	0.0014	0.0086	0.1216	0.0177	0.0068
RB	0.0068	0.0102	0.1011	0.1012	0.0120	0.0728	0.0479
DT	0.1147	0.0021	0.0002	0.2157	0.4744	0.0102	0.0017

	Janet	will	back	the	bill
NNP	0.000032	0	0	0.000048	0
MD	0	0.308431	0	0	0
VB	0	0.000028	0.000672	0	0.000028
JJ	0	0	0.000340	0	0
NN	0	0.000200	0.000223	0	0.002337
RB	0	0	0.010446	0	0
DT	0	0	0	0.506099	0



A

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i) a_{ij} b_j(o_t)$$

B

Details about finishing Viterbi

- Transitioning to an end state
  - Not all POS tags are equally likely to end a sequence! (For example, DET (corresponding to words like “the”))
  - Our algorithm should account for that!
  - Solution? Multiply candidate best paths at last time step by p(<EOS> | tag)
- Assembling your best tag sequence using that max score at the last timestep
  - Here’s where we use our backpointers!
  - Just trace backwards by using the backpointers (that extra piece of information that we stored about how we got to our current tag at timestep i + 1) :)

The Viterbi algorithm

function VITERBI(*observations* of len T,*state-graph* of len N) **returns** *best-path*, *path-prob*

create a path probability matrix *viterbi[N,T]*
for each state s **from** 1 **to** N **do**
    $viterbi[s,1] \leftarrow \pi_s * b_s(o_1)$
    $backpointer[s,1] \leftarrow 0$
for each time step t **from** 2 **to** T **do**
  for each state s **from** 1 **to** N **do**
    $viterbi[s,t] \leftarrow \max_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
    $backpointer[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$
$bestpathprob \leftarrow \max_{s=1}^{N} viterbi[s,T]$
$bestpathpointer \leftarrow \operatorname{argmax}_{s=1}^{N} viterbi[s,T]$
bestpath ← the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time
return *bestpath*, *bestpathprob*

Computational complexity in N and T?

HMMs: algorithms

Forward	**Problem 1 (Likelihood):**	Given an HMM $\lambda = (A,B)$ and an observation sequence O, determine the likelihood $P(O\|\lambda)$.
Viterbi	**Problem 2 (Decoding):**	Given an observation sequence O and an HMM $\lambda = (A,B)$, discover the best hidden state sequence Q.
	Problem 3 (Learning):	Given an observation sequence O and the set of states in the HMM, learn the HMM parameters A and B.

"What is the best sequence of tags (given the parameters of this HMM) that corresponds to 'Janet will back the bill?'"

From J&M

HMMs: algorithms

Forward	**Problem 1 (Likelihood):**	Given an HMM $\lambda = (A, B)$ and an observation sequence O, determine the likelihood $P(O\|\lambda)$.
Viterbi	**Problem 2 (Decoding):**	Given an observation sequence O and an HMM $\lambda = (A, B)$, discover the best hidden state sequence Q.
	Problem 3 (Learning):	Given an observation sequence O and the set of states in the HMM, learn the HMM parameters A and B.

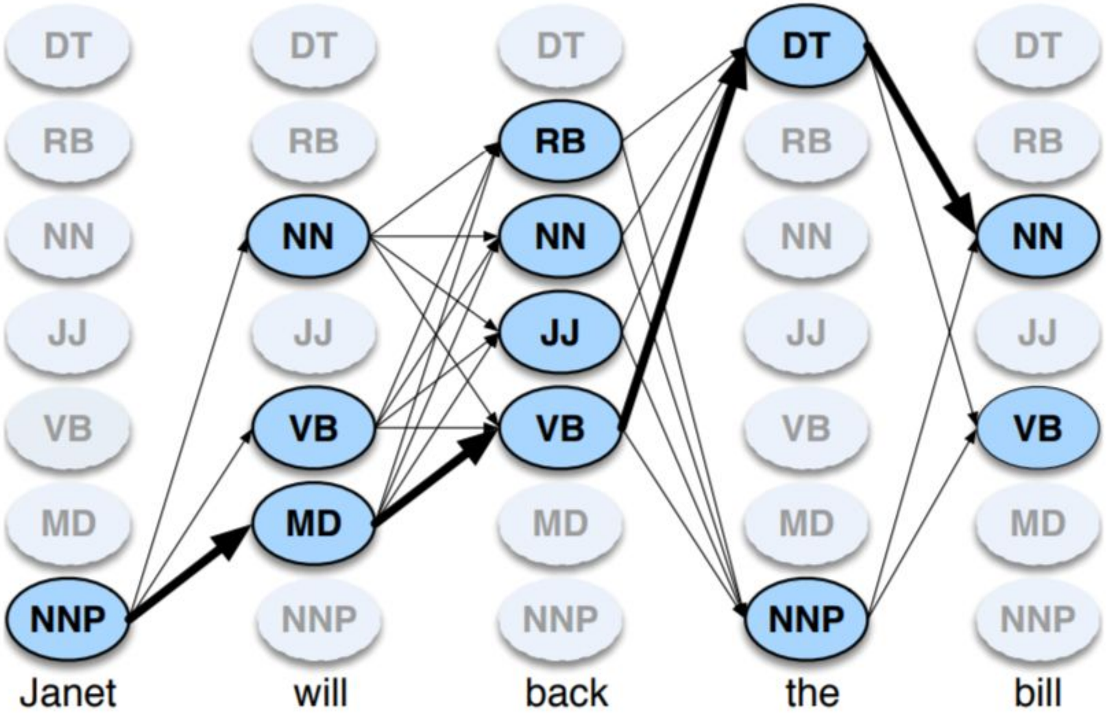
“What is the probability (given the parameters of this HMM) of observing the text ‘Janet will back the bill?’”

From J&M

The Forward algorithm

- Just sum instead of max!

$$\alpha_t(j) = \sum_{i=1}^{N} \alpha_{t-1}(i) a_{ij} b_j(o_t)$$



Viterbi

- n-best decoding
- relationship to sequence alignment

Citation	Field
Viterbi (1967)	information theory
Vintsyuk (1968)	speech processing
Needleman and Wunsch (1970)	molecular biology
Sakoe and Chiba (1971)	speech processing
Sankoff (1972)	molecular biology
Reichert et al. (1973)	molecular biology
Wagner and Fischer (1974)	computer science