POS tagging using Generative Model

- Make an inference based on a trained model and some observed data
- Answer the question
- What is the choice of states such that the joint probability reaches maximum?

$$X_{0:T}^* = \underset{X_{0:T}}{\operatorname{argmax}} P[X_{0:T} | Y_{0:T}]$$

To find best set of states we use following recursive formula

$$\mu(X_k) = \max_{X_{0:k-1}} P[X_{0:k}, Y_{0:k}] = \max_{X_{k-1}} \mu(X_{k-1}) P[X_k | X_{k-1}] P[Y_k | X_k]$$

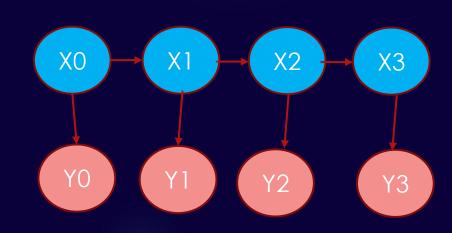
♣ Let us substitute k=1,2,3

$$\mu(X_0) = P[Y_0|X_0]P[X_0]$$

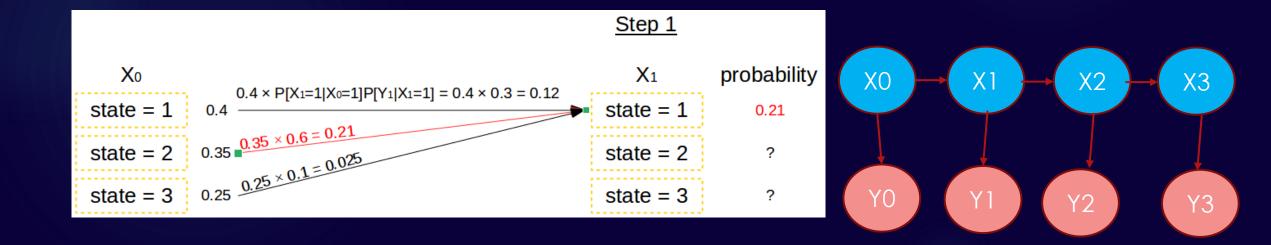
$$\mu(X_1) = \max_{X_0} \mu(X_0)P[X_1|X_0]P[Y_1|X_1]$$

$$\mu(X_2) = \max_{X_1} \mu(X_1)P[X_2|X_1]P[Y_2|X_2]$$

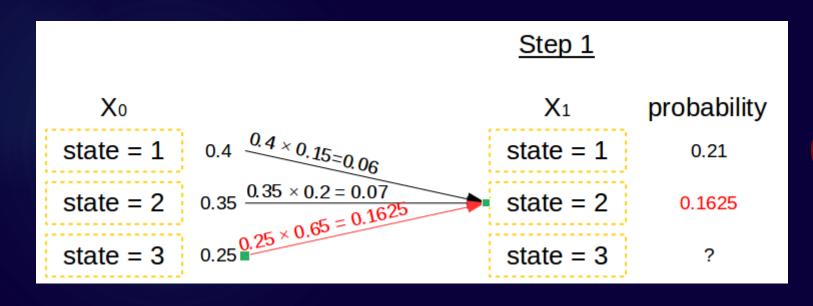
$$\mu(X_3) = \max_{X_2} \mu(X_2)P[X_3|X_2]P[Y_3|X_3]$$

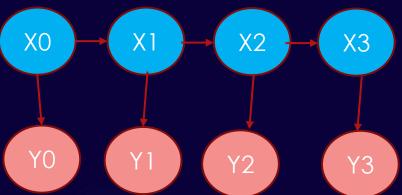


- Assume there are 3 possible states at each step
- At each step maximize the probability
- ❖ For X1, state=1, the best possible state at X0, state=2 is chosen

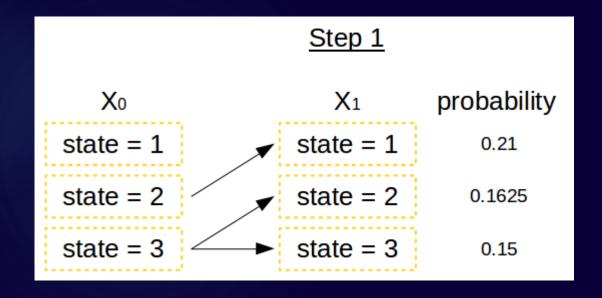


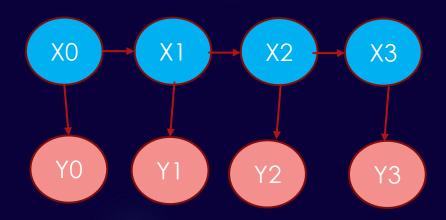
❖ For X1, state=2, the best possible state at X0, state=3 chosen



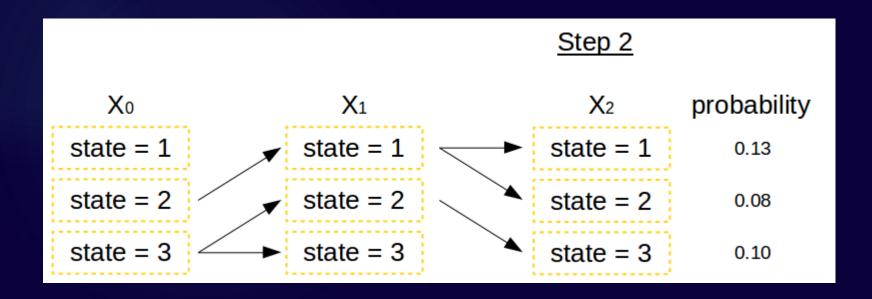


For X1, state=3 also calculation is done and we get max value 0.15

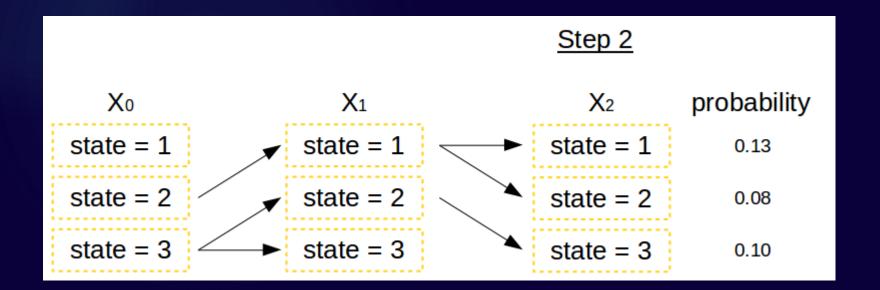




- \*Repeat same steps to get to step 2
- if we end the inference at step 2, then the most likely ending state would be state = 1



- Rest of the previous states could be back-traced through the arrows, which are
- state 2 at time 0,
- state 1 at time 1,
- and state 1 at time 2
- ❖The second likely path is 3–2–3, and the least likely path is 2–1–
  2. It is very unlikely that the path starts with state 1



# Example 2

# POS Tagging -Viterbi Algorithm

The fans watch the race



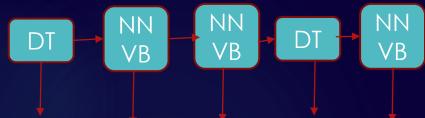




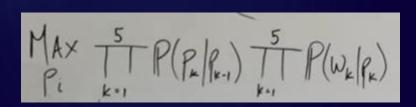








The fans watch the race



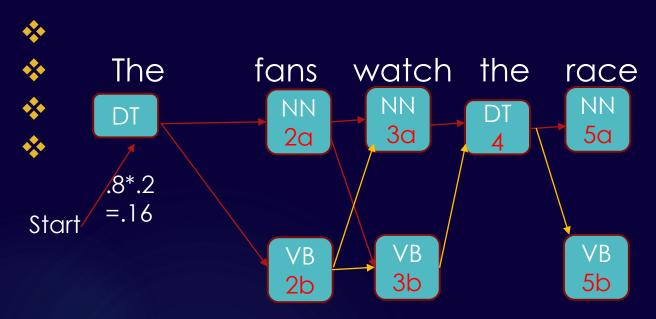
### **Emission Probability**

	The	Fans	Watc h	Race
DT	0.2	0	0	0
NN	0	0.1	0.3	0.1
VB	0	0.2	0.15	0.3

### Transition Probability

	DT	NN	VB
Start	8.0	0.2	0
DT	0	0.9	0.1
NN	0	0.5	0.5
VB	0.5	0.5	0

### POS Tagging -Viterbi Algorithm



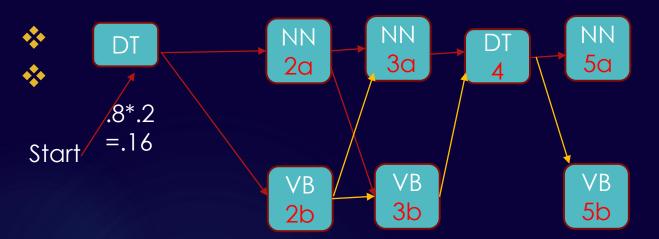
### **Emission Probability**

	The	Fans	Watc h	Race
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### Transition Probability

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# POS Tagging - Viterbi Algorithm Frobability



	The	Fans	Watc h	Race
DT	0.2	0	0	0
NN	0	0.1	0.3	0.1
VB	0	0.2	0.15	0.3

- ◆ 1-2b =.1\*.2\*.16 =.0032
- 2a-3a = .5\*.3\*.0144 = .00126 (Taken)
- ♦ 2b-3a = .5\*.3\*.0032=.00048
- 2a-3b = .5\*.15\*.0144=.00108 (Taken)
- $\diamond$  2b-3b = 0\*...=0
- **♦** 3a-4 =0\*...=0

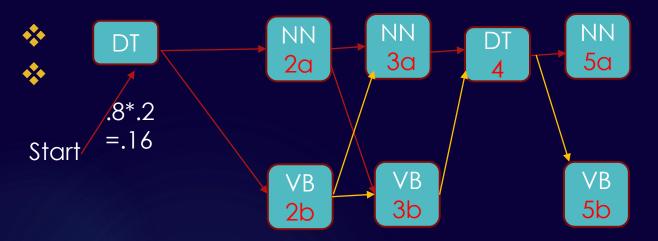
The

**♦** 3b-4 = .5\*.15\*.00108=.000081

#### Transition Probability

	DT	NN	VB
Start	8.0	0.2	0
DT	0	0.9	0.1
NN	0	0.5	0.5
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# POS Tagging - Viterbi Algorithm Frobability



	The	Fans	Watc h	Race
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NN	0	0.1	0.3	0.1
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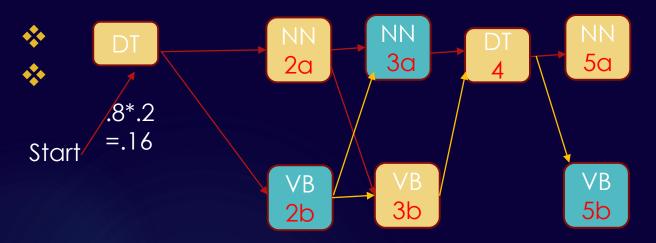
**♦** 3a-4 =0\*...=0

The

- $\Rightarrow$  3b-4 = .5\*.2\*.00108=.000108(Taken)
- **♦** 4-5a = .9\*.1\*.000108 = 9.72 \* 10^-6
- $4-5b = .1*.3*.000108 = 3.24*10^-6$

	DT	NN	VB
Start	8.0	0.2	0
DT	0	0.9	0.1
NN	0	0.5	0.5
VB	0.5	0.5	0

# POS Tagging - Viterbi Algorithm Frobability



	The	Fans	Watc h	Race
DT	0.2	0	0	0
NN	0	0.1	0.3	0.1
VB	0	0.2	0.15	0.3

**♦** 3a-4 =0\*...=0

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- $\Rightarrow$  3b-4 = .5\*.2\*.00108 = .000108 (Taken)
- **♦** 4-5a = .9\*.1\*.000108 = 9.72 \* 10^-6
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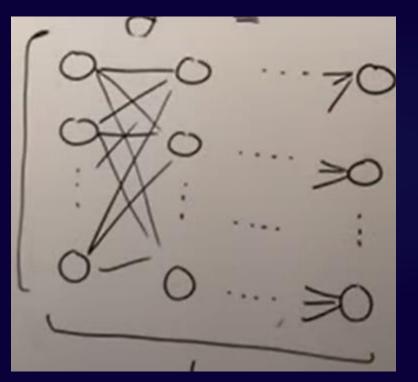
	DT	NN	VB
Start	8.0	0.2	0
DT	0	0.9	0.1
NN	0	0.5	0.5
VB	0.5	0.5	0

# Why Viterbi Algorithm is better?

Imagine sentence of length L and each word can have one

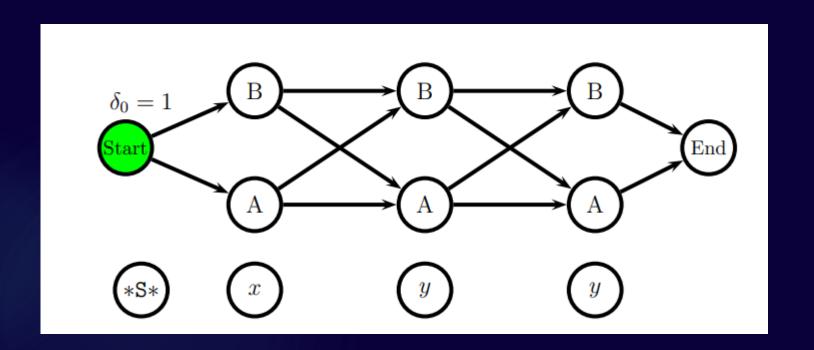
of P POS

- ♦ O(P^L) in Brute force
- ❖In Viterbi
- **♦**O(P^2 \* L)
- ❖So Viterbi is better



# Example 3

# Use Viterbi Algorithm



	Next			
Current		В	End	
Start	0.7	0.3	0	
A	1	0.7	0.1	
В	0.7	0.2	0.1	

	$\operatorname{Word}$				
State	*S*	x	y		
Start	1	0	0		
A	0	0.4	0.6		
В	0	0.3	0.7		

# Why Viterbi Algorithm is better?

- Imagine sentence of length L and each word can have one of P POS
- ♦ O(P^L) in Brute force
- ❖In Viterbi
- **❖**O(P^2 \* L)
- ❖So Viterbi is better