

# 50.007 Machine Learning

## Hidden Markov Model

(Continue...)

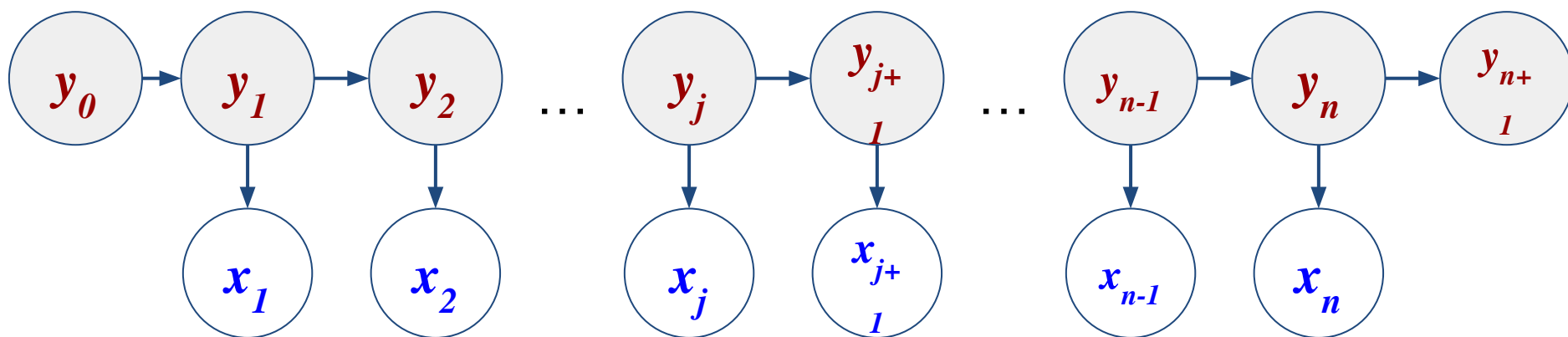
Roy Ka-Wei Lee

Assistant Professor, DAI/ISTD, SUTD



SINGAPORE UNIVERSITY OF  
TECHNOLOGY AND DESIGN

# HMM Parameterization



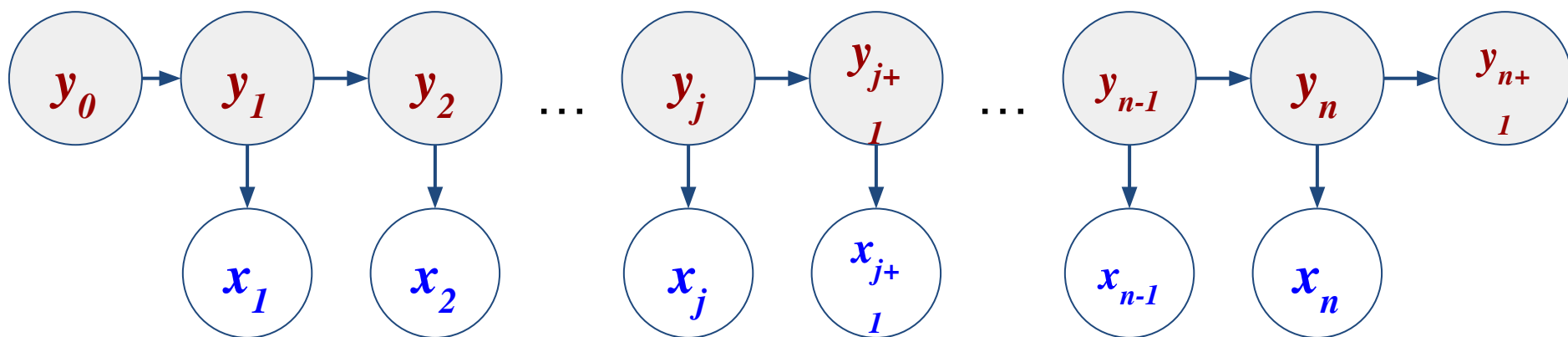
$$p(x_1, x_2, \dots, x_{n-1}, x_n, y_0, y_1, y_2, \dots, y_{n-1}, y_n, y_{n+1})$$

$$\underbrace{\prod_{j=0}^n a_{y_j, y_{j+1}}}_{\text{Transition Probabilities}} \times \underbrace{\prod_{j=1}^n b_{y_j}(x_j)}_{\text{Emission Probabilities}}$$

Transition Probabilities

Emission Probabilities

# HMM Supervised Learning



$$p(x_1, x_2, \dots, x_{n-1}, x_n, y_0, y_1, y_2, \dots, y_{n-1}, y_n, y_{n+1})$$

$$a_{u,v} = \frac{\text{count}(u,v)}{\text{count}(u)}$$

$$b_u(o) = \frac{\text{count}(u \rightarrow o)}{\text{count}(u)}$$

# Hidden Markov Model (Example)

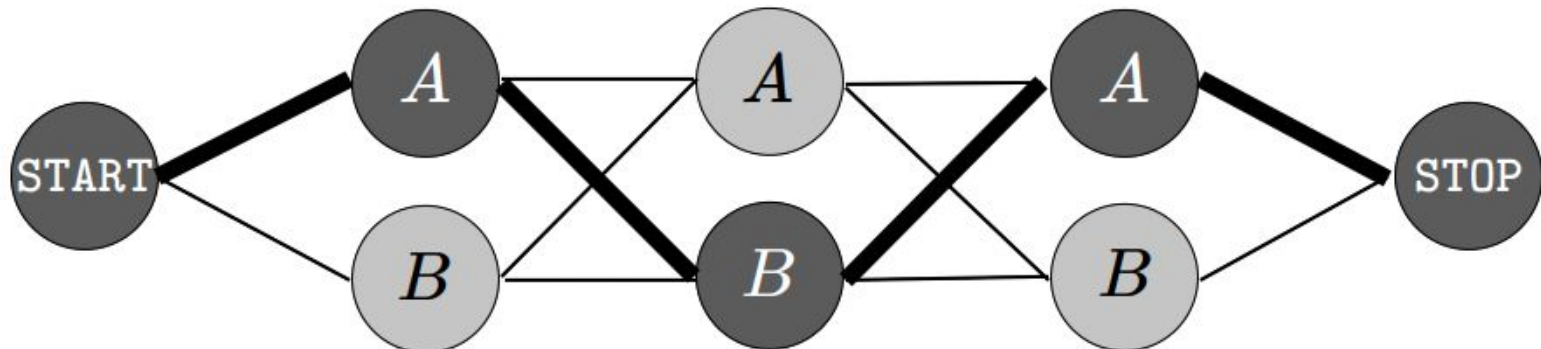
$a_{u,v}$

$u \backslash v$	$A$	$B$	STOP
START	1.0	0.0	0.0
$A$	0.5	0.5	0.0
$B$	0.0	0.8	0.2

$b_u(o)$

$u \backslash o$	"the"	"dog"
$A$	0.9	0.1
$B$	0.1	0.9

$(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$



$$a_{\text{START},A} \times b_A(\text{"the"}) \times a_{A,B} \times b_B(\text{"dog"}) \times a_{B,A} \times b_A(\text{"the"}) \times a_{A,\text{STOP}}$$

# Hidden Markov Model (Example)

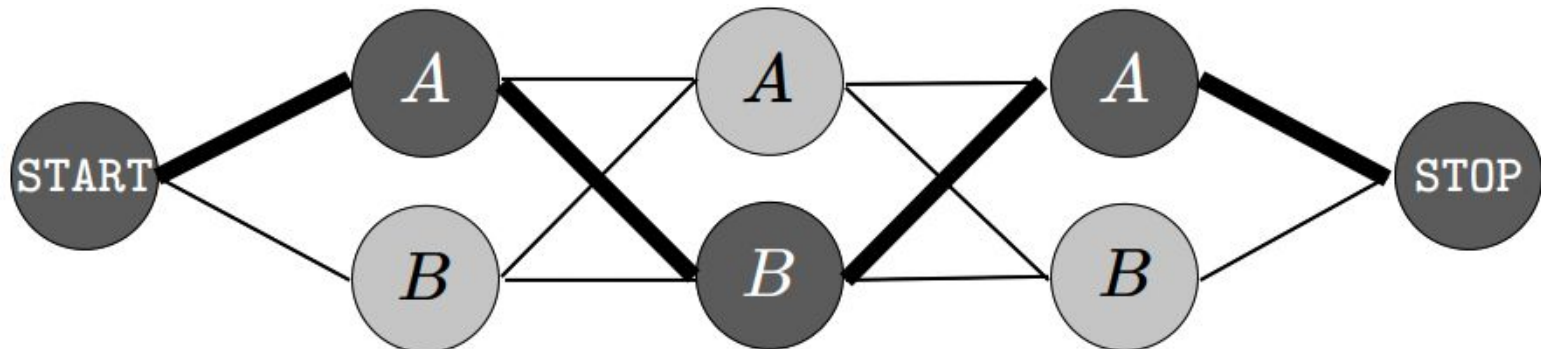
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$(\mathbf{x}, \mathbf{y}) = \text{the}/B, \text{dog}/B, \text{the}/B$



What about this new  $y$  label sequence?

# Hidden Markov Model (Example)

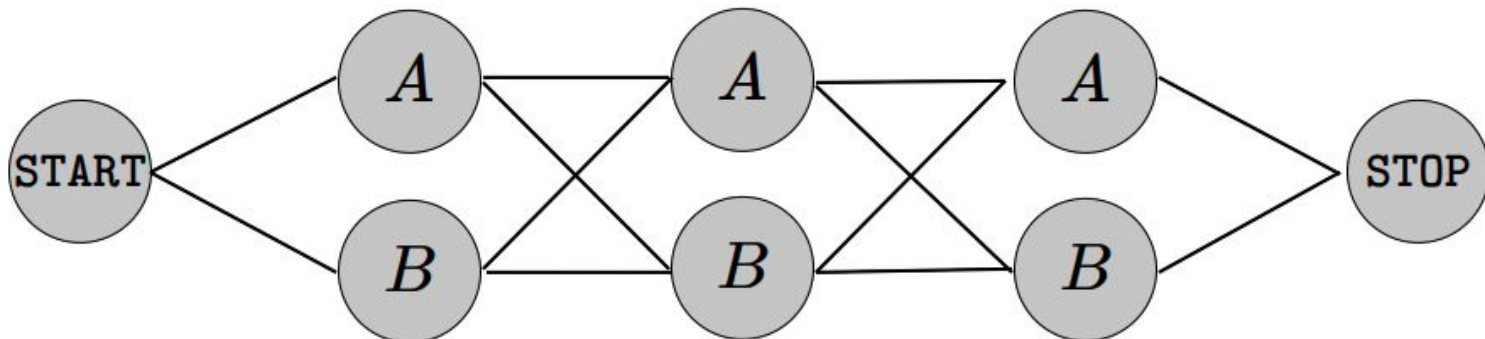
$a_{u,v}$

$u \backslash v$	$A$	$B$	STOP
START	1.0	0.0	0.0
$A$	0.5	0.5	0.0
$B$	0.0	0.8	0.2

$b_u(o)$

$u \backslash o$	"the"	"dog"
$A$	0.9	0.1
$B$	0.1	0.9

$\mathbf{x} = \text{the dog the}$



Which label sequence  $y$  is the most probable given the word sequence  $x$ ?

# Hidden Markov Model (Example)

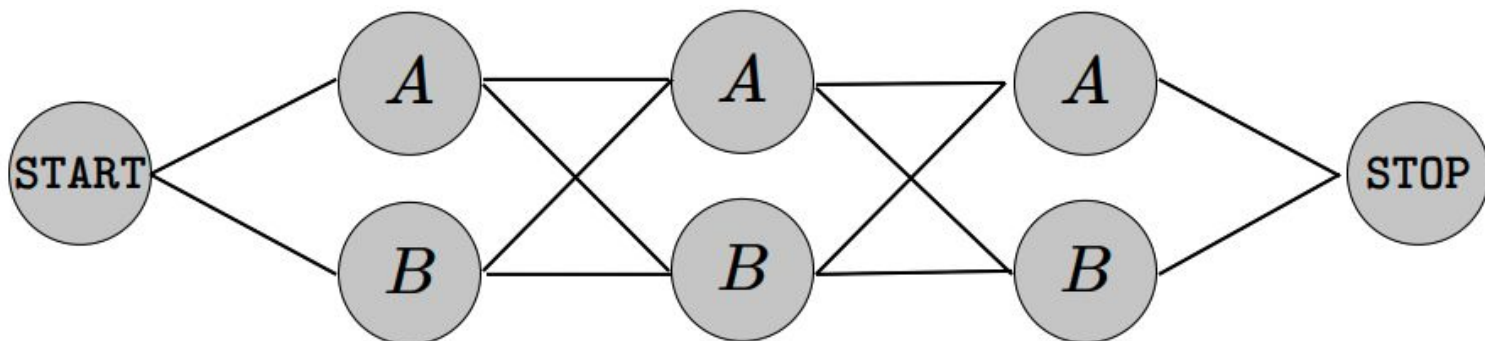
$a_{u,v}$

$u \backslash v$	$A$	$B$	STOP
START	1.0	0.0	0.0
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$A$	0.9	0.1
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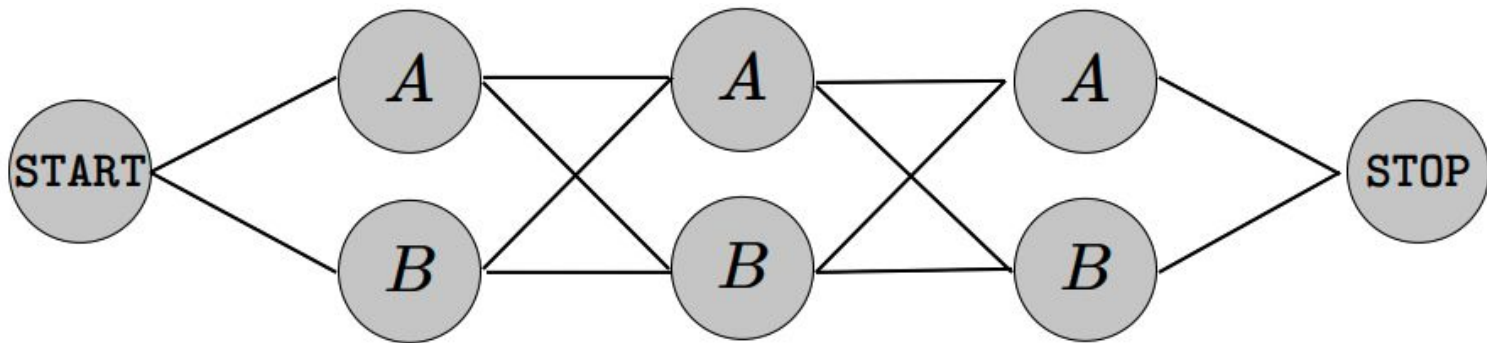
$\mathbf{x} = \text{the dog the}$



$$\mathbf{y}^* = \arg \max_{\mathbf{y}} p(\mathbf{y} | \mathbf{x})$$

# Hidden Markov Model (Example)

**x** = the dog the

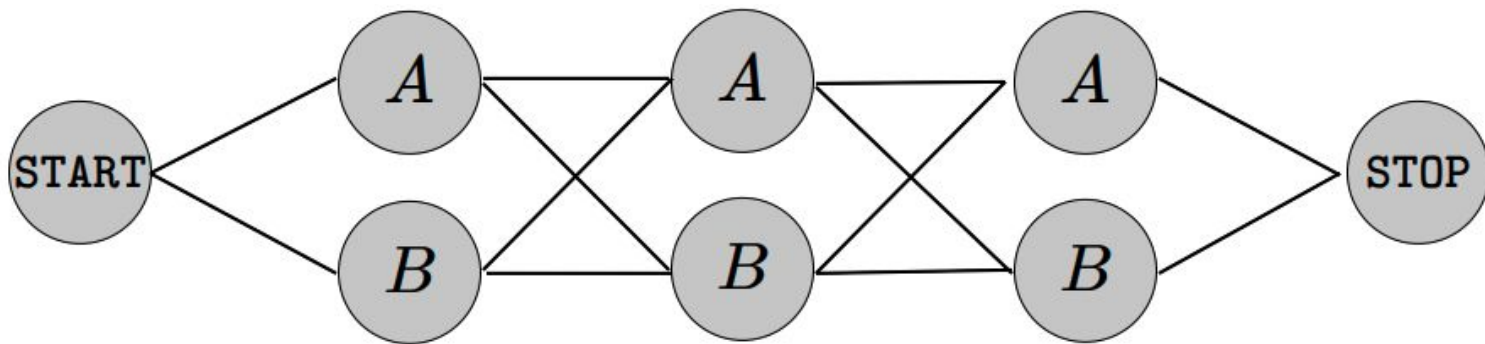


$$\mathbf{y}^* = \arg \max_{\mathbf{y}} p(\mathbf{y}|\mathbf{x})$$



# Hidden Markov Model (Example)

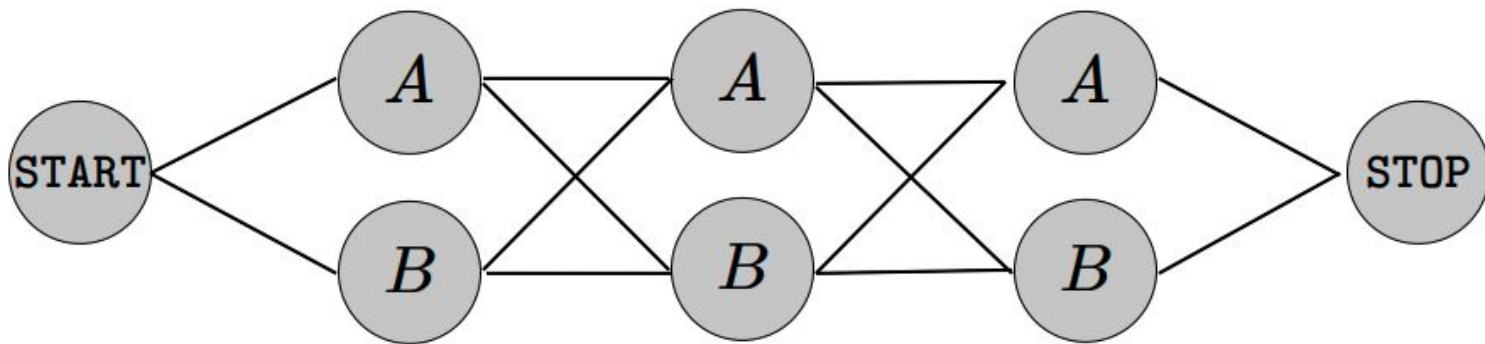
$\mathbf{x} = \text{the dog the}$



$$\begin{aligned} \mathbf{y}^* &= \arg \max_{\mathbf{y}} p(\mathbf{y} | \mathbf{x}) \\ &= \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y}) / p(\mathbf{x}) \end{aligned}$$

# Hidden Markov Model (Example)

$\mathbf{x} = \text{the dog the}$



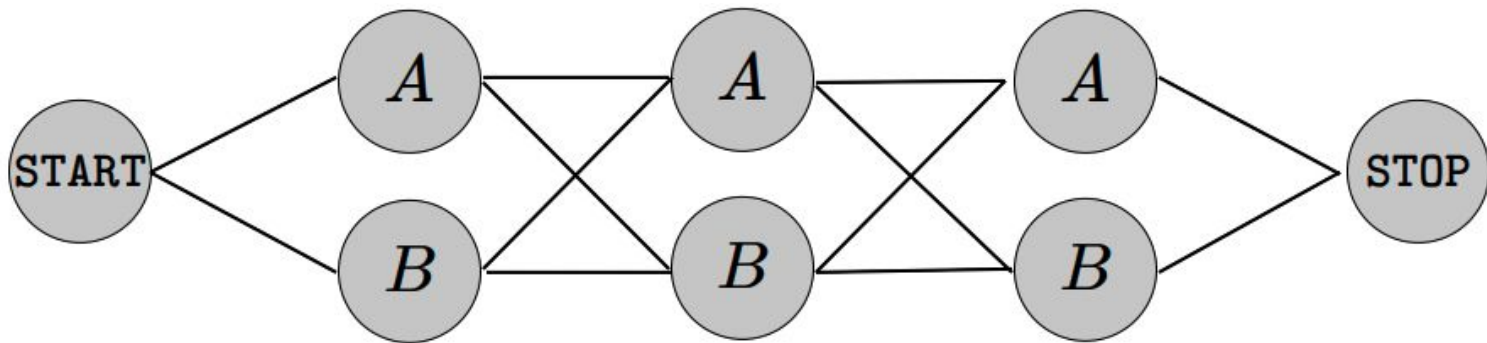
$$\mathbf{y}^* = \arg \max_{\mathbf{y}} p(\mathbf{y}|\mathbf{x})$$

$$= \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y}) / p(\mathbf{x})$$

$$= \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y})$$

# Hidden Markov Model (Example)

$\mathbf{x} = \text{the dog the}$

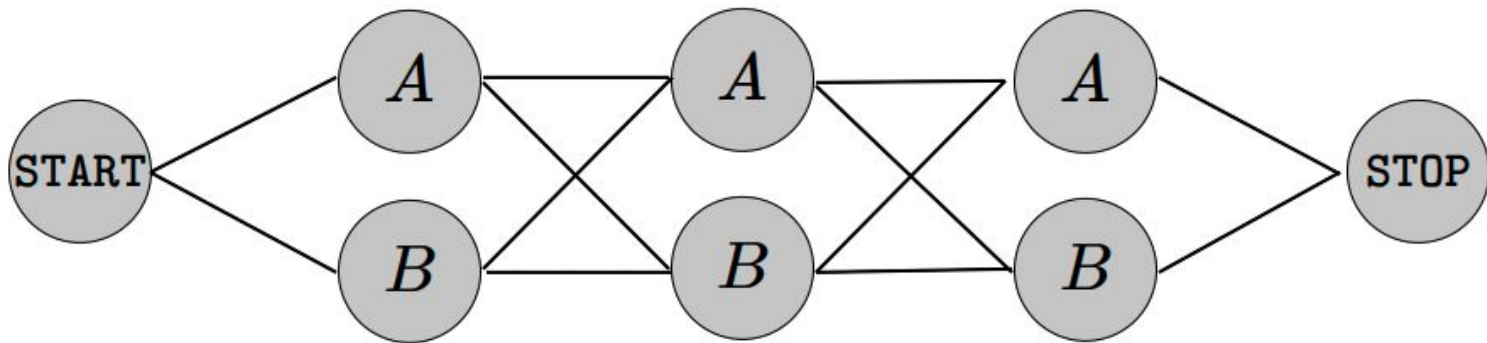


$$\begin{aligned} \mathbf{y}^* &= \arg \max_{\mathbf{y}} p(\mathbf{y} | \mathbf{x}) \\ &= \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y}) / p(\mathbf{x}) \\ &= \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y}) \end{aligned}$$

We can try one  $\mathbf{y}$  at a time, and see which gives the highest score!

# Hidden Markov Model (Example)

$\mathbf{x}$  = the dog the



$$\mathbf{y}^* = \arg \max_{\mathbf{y}} p(\mathbf{y}|\mathbf{x})$$

$$= \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y}) / p(\mathbf{x})$$

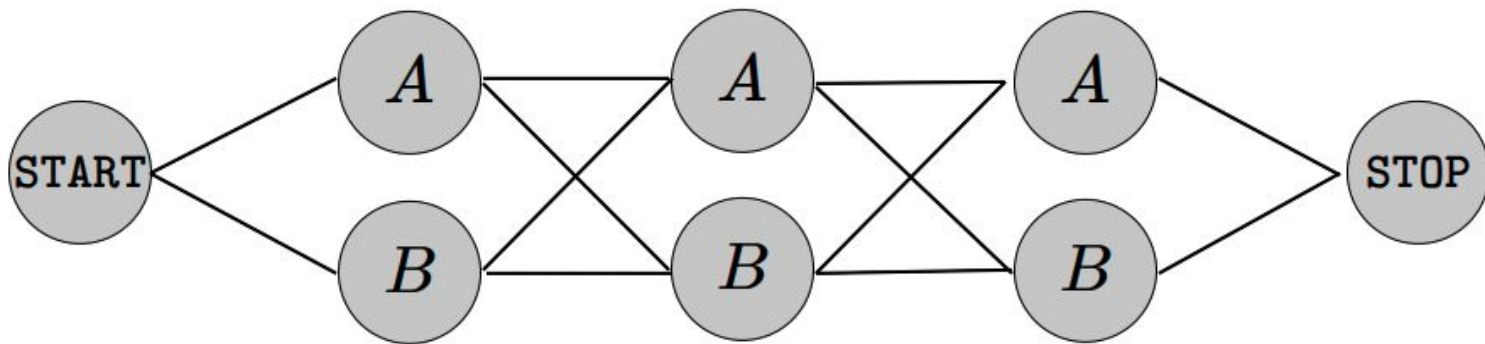
$$= \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y})$$

Is this a  
feasible  
approach?



# Hidden Markov Model (Example)

$\mathbf{x} = \text{the dog the}$



$$\mathbf{y}^* = \arg \max_{\mathbf{y}} p(\mathbf{x}, \mathbf{y})$$

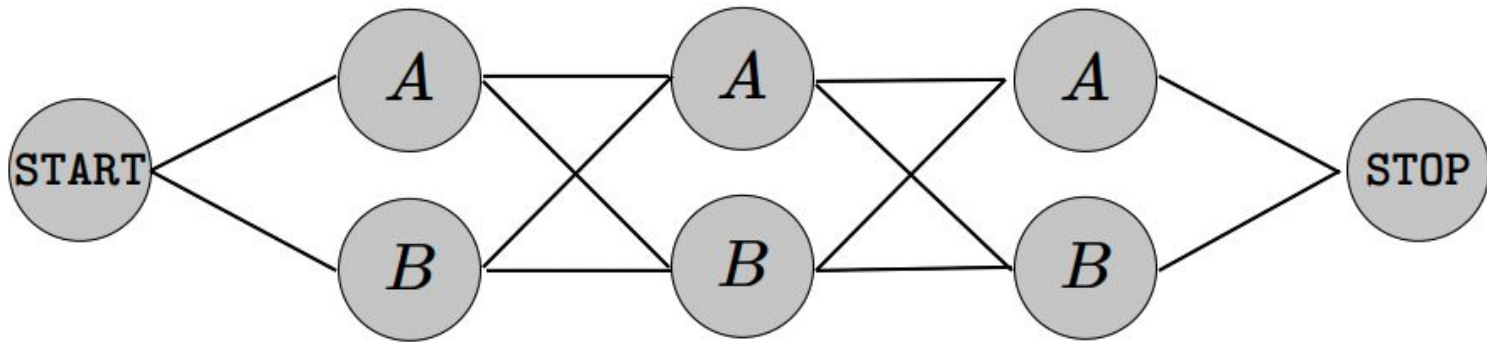
Number of words in the sentence

There are  $O(|\mathcal{T}|^n)$  possible  $\mathbf{y}$ 's!

Number of possible tags at each word/position

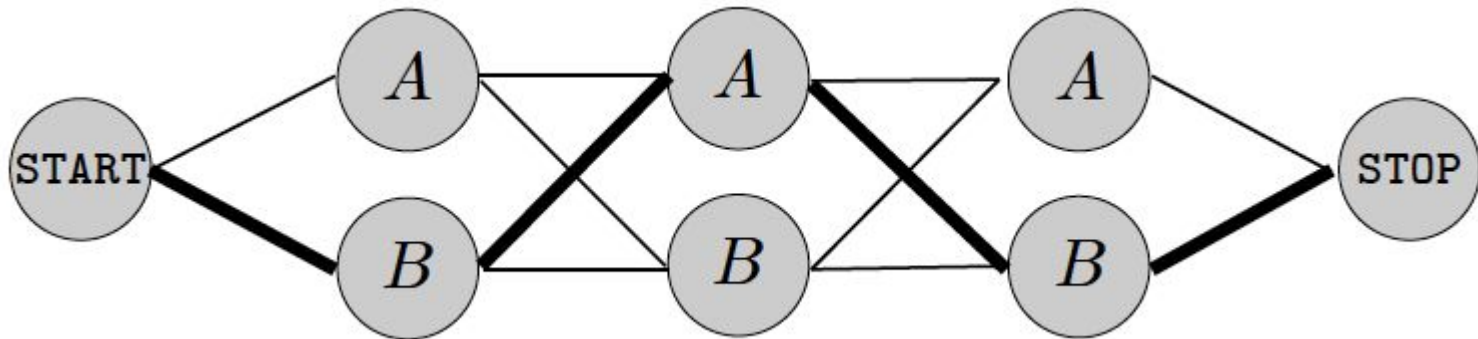
# Finding Highest Scoring Path

We are facing a problem of finding the highest scoring path connecting START and STOP



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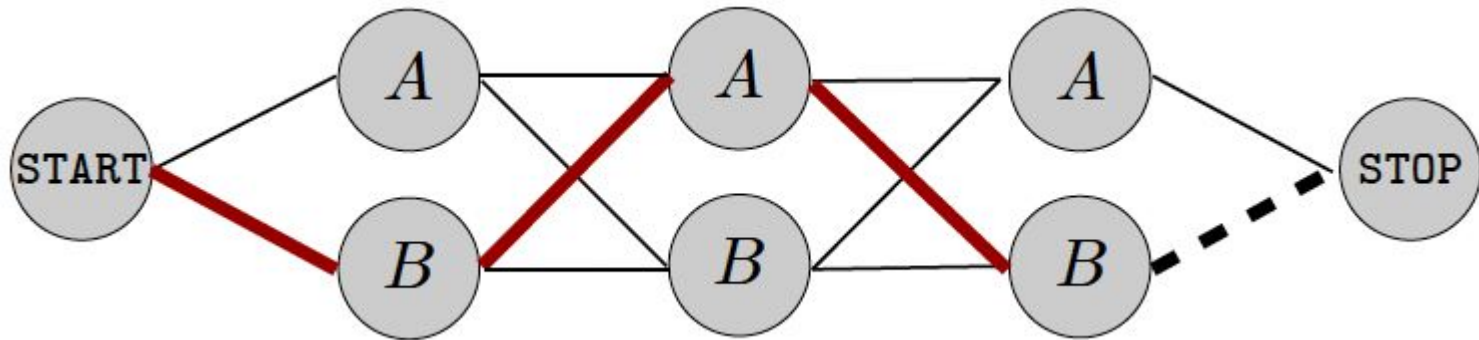


Let's assume this is the highest scoring path



# Finding Highest Scoring Path

We are facing a problem of finding the highest scoring path connecting START and STOP



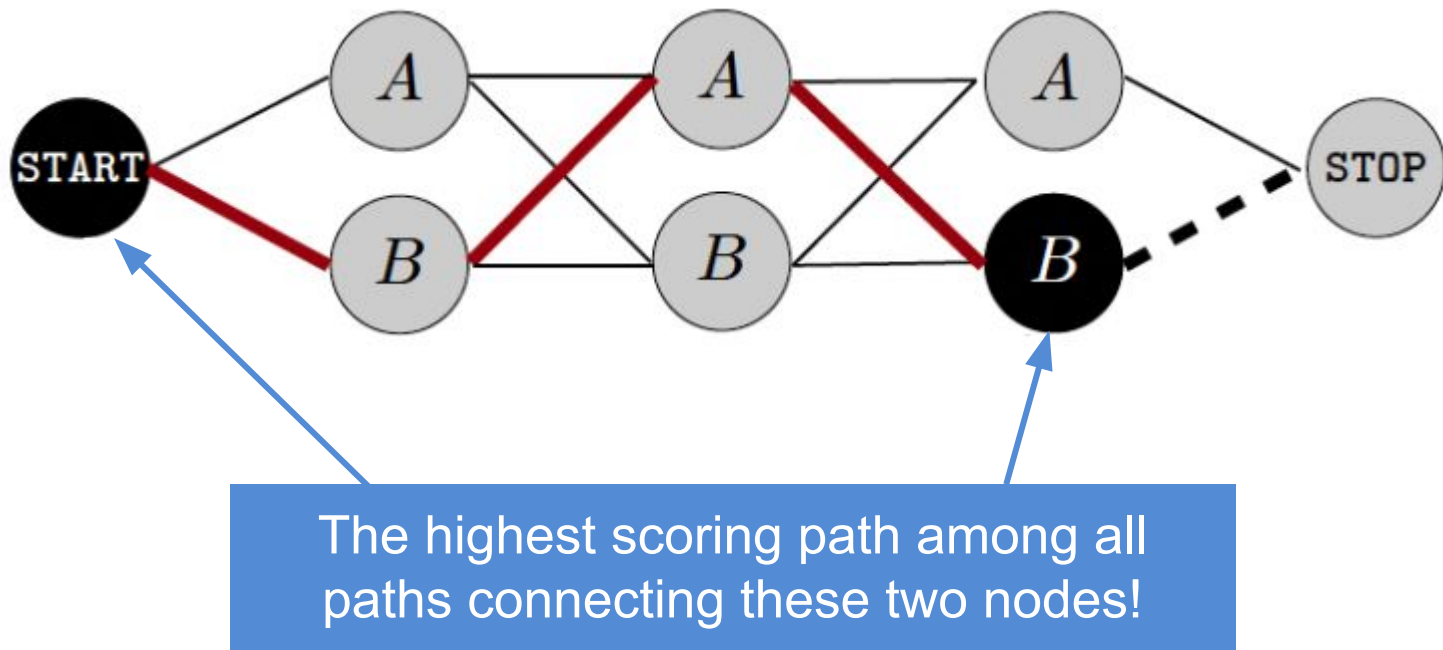
Let's assume this is the highest scoring path

Then, what can we say about this partial path?  
(What types of properties do we know for this path?)



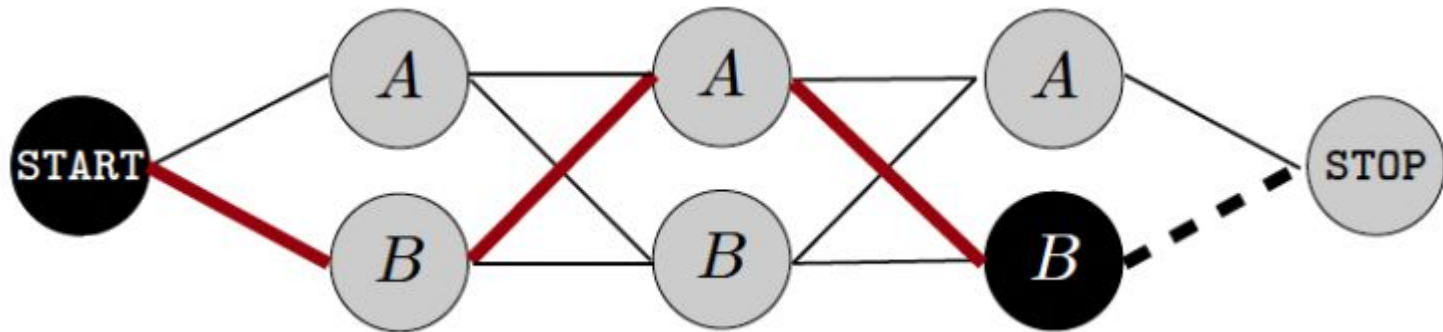
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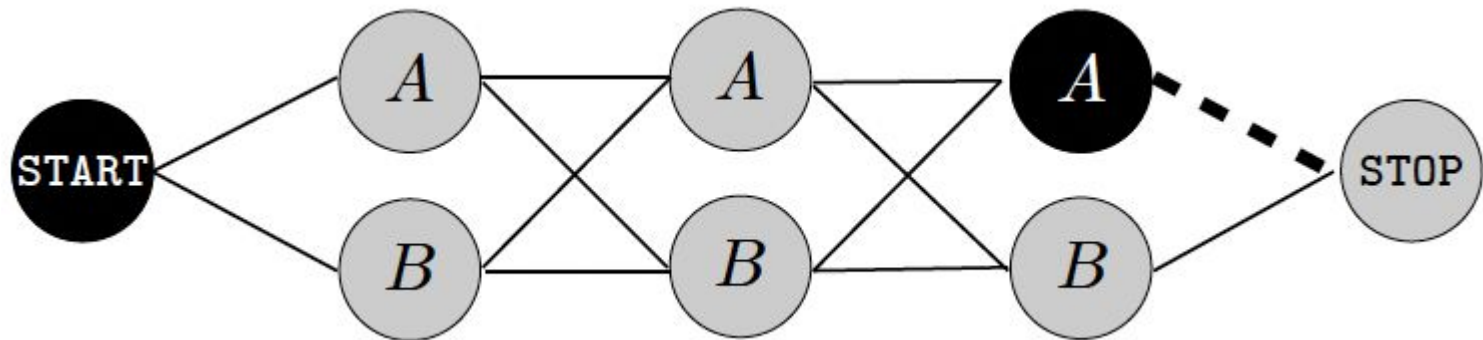


Is it possible to solve the original problem, if we already know the solutions to such sub-problems?

# Finding Highest Scoring Path

## Case A

The second last node in the highest scoring path is A.



Find the highest scoring path from START to A at position n

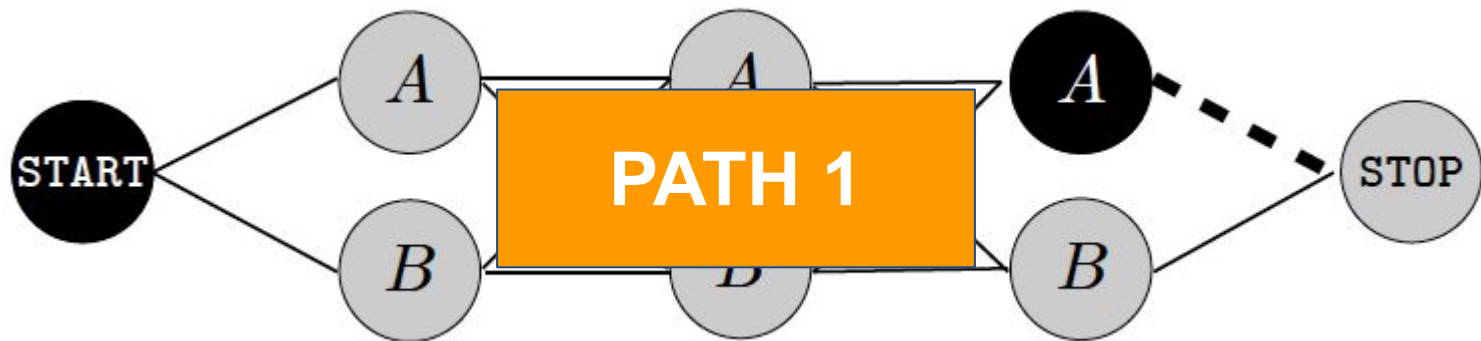


A single edge from node A to STOP

# Finding Highest Scoring Path

## Case A

The second last node in the highest scoring path is A.



Find the highest scoring path from START to A at position n

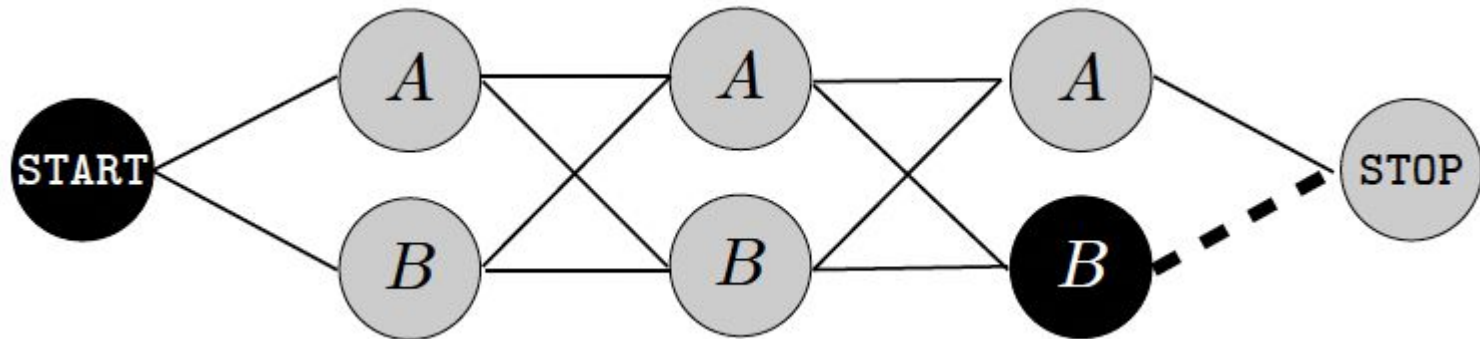


A single edge from node A to STOP

# Finding Highest Scoring Path

## Case B

The second last node in the highest scoring path is B.



Find the highest scoring path from START to B at position n

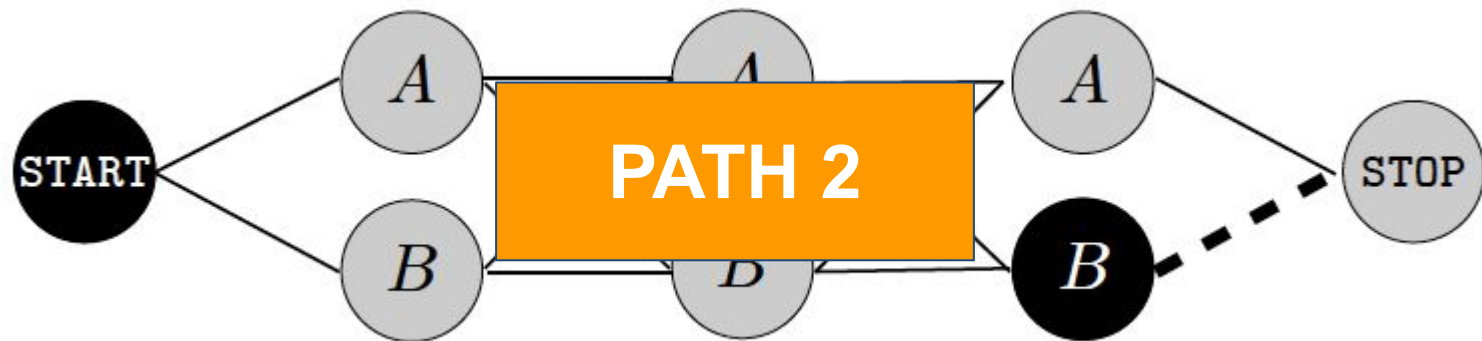


A single edge from node B to STOP

# Finding Highest Scoring Path

## Case B

The second last node in the highest scoring path is B.



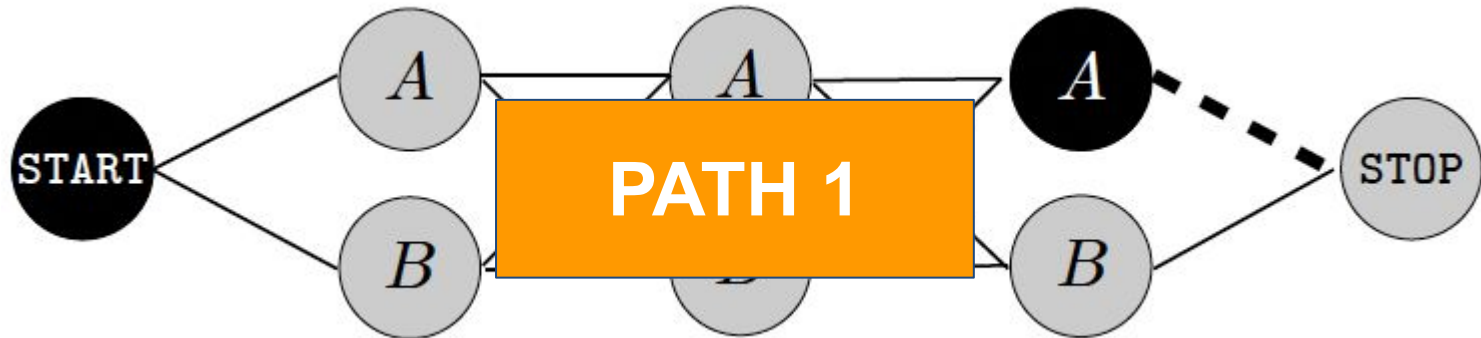
Find the highest scoring path from START to B at position n



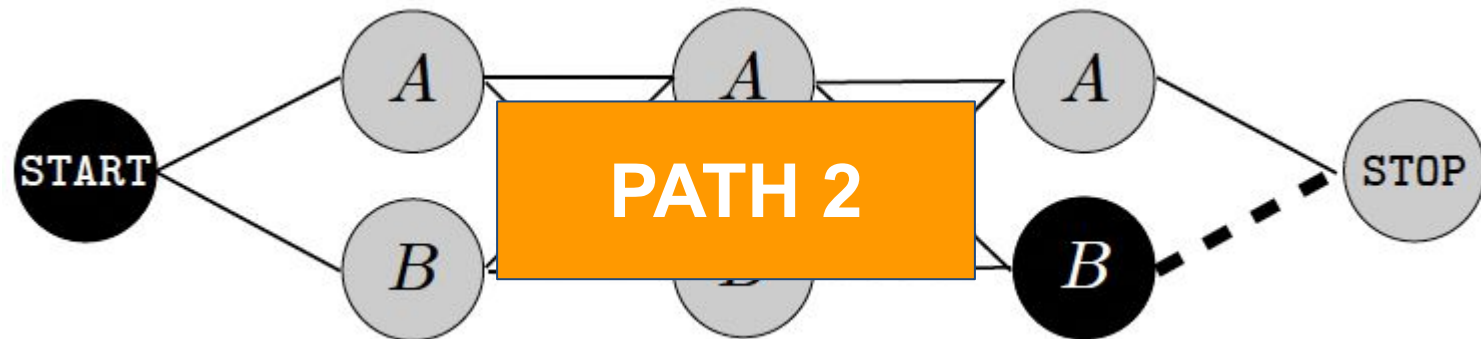
A single edge from node B to STOP

# Finding Highest Scoring Path

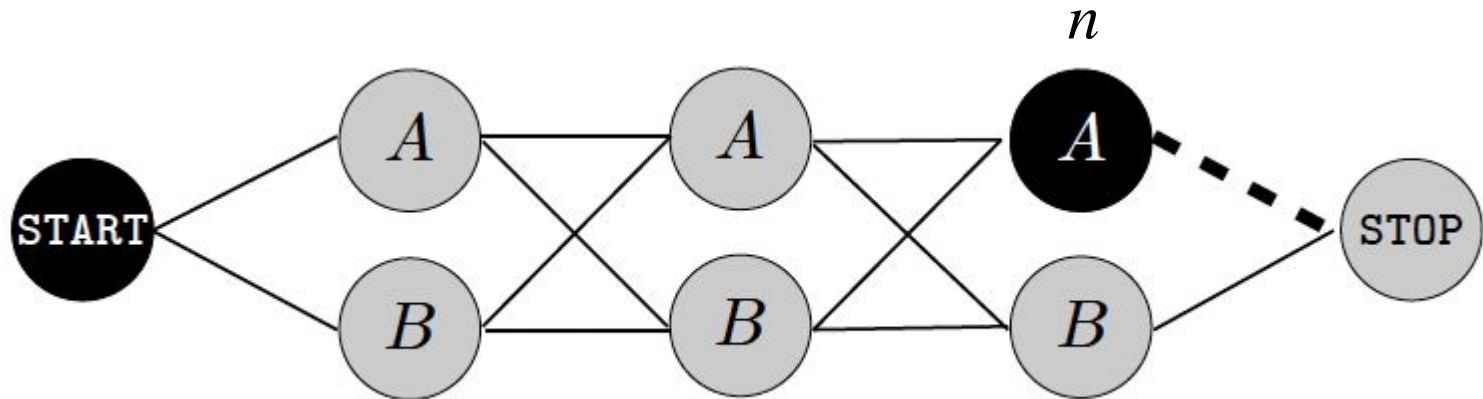
The highest scoring path from START to STOP



Or



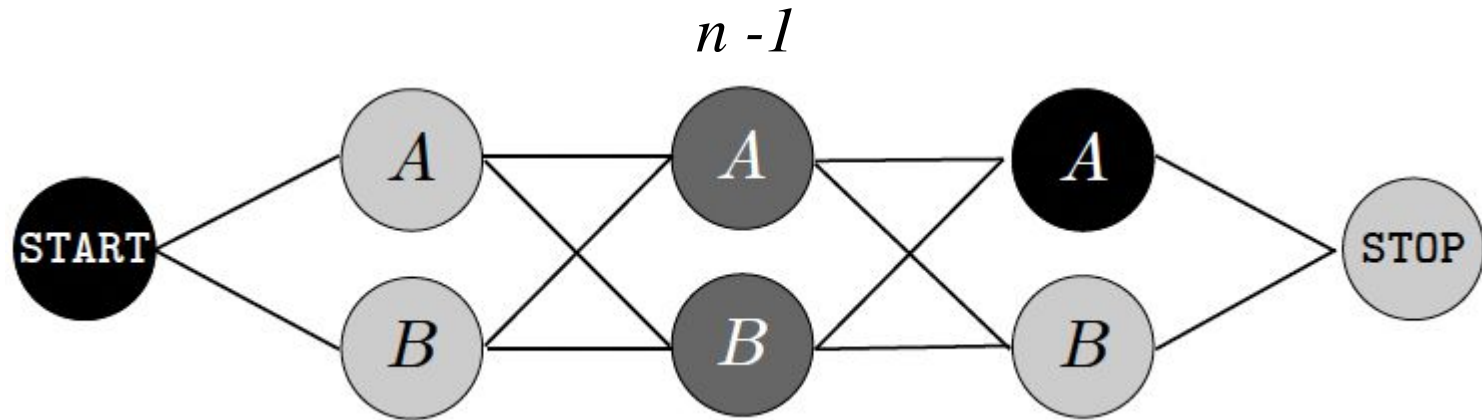
# Finding Highest Scoring Path



How do you find the highest scoring path from START to node  $A$  at position  $n$ ?



# Finding Highest Scoring Path



How do you find the highest scoring path from START to node  $A$  at position  $n$ ?

We shall again rely on the partial paths from START to the two nodes at position  $(n - 1)$

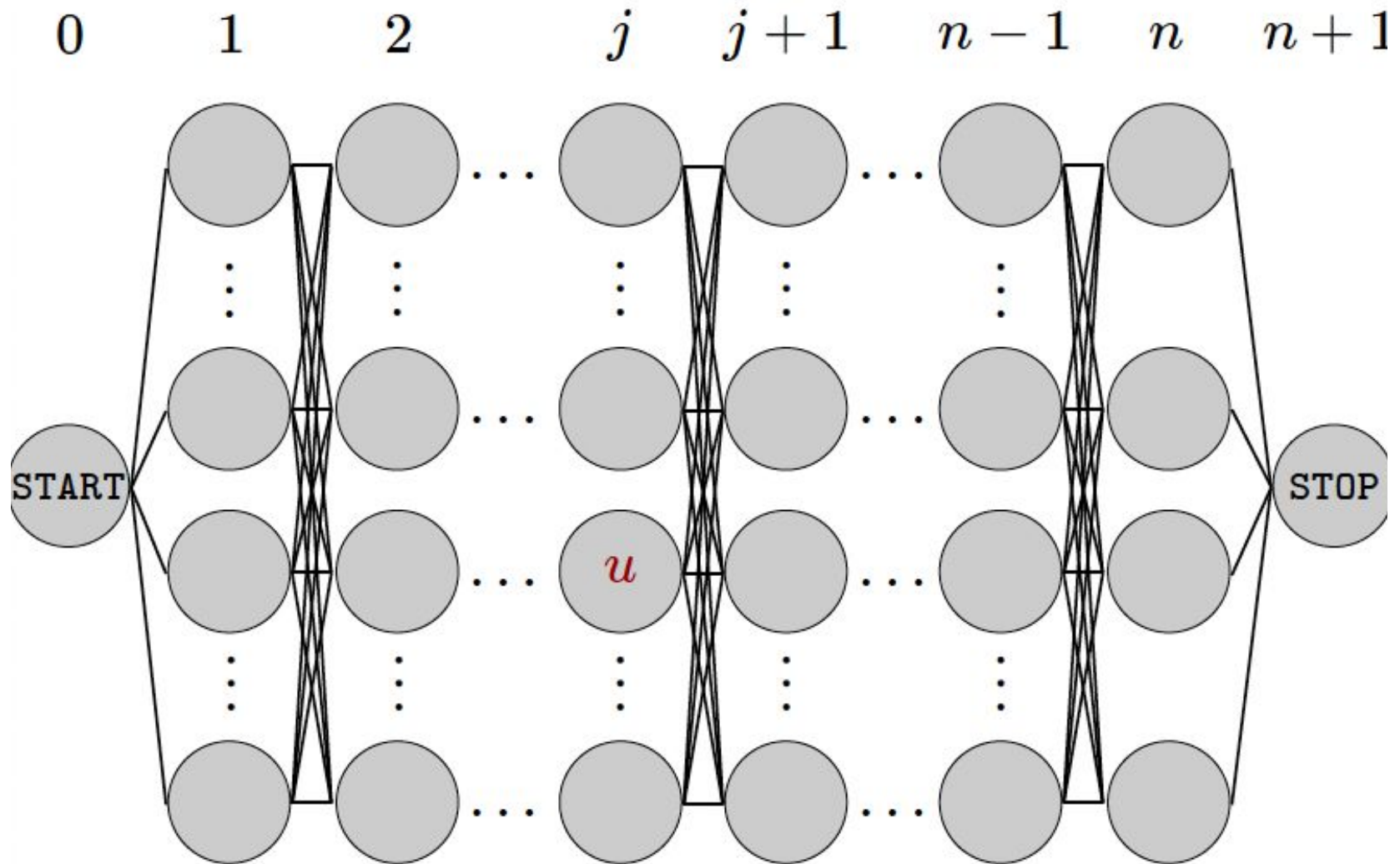
# Question

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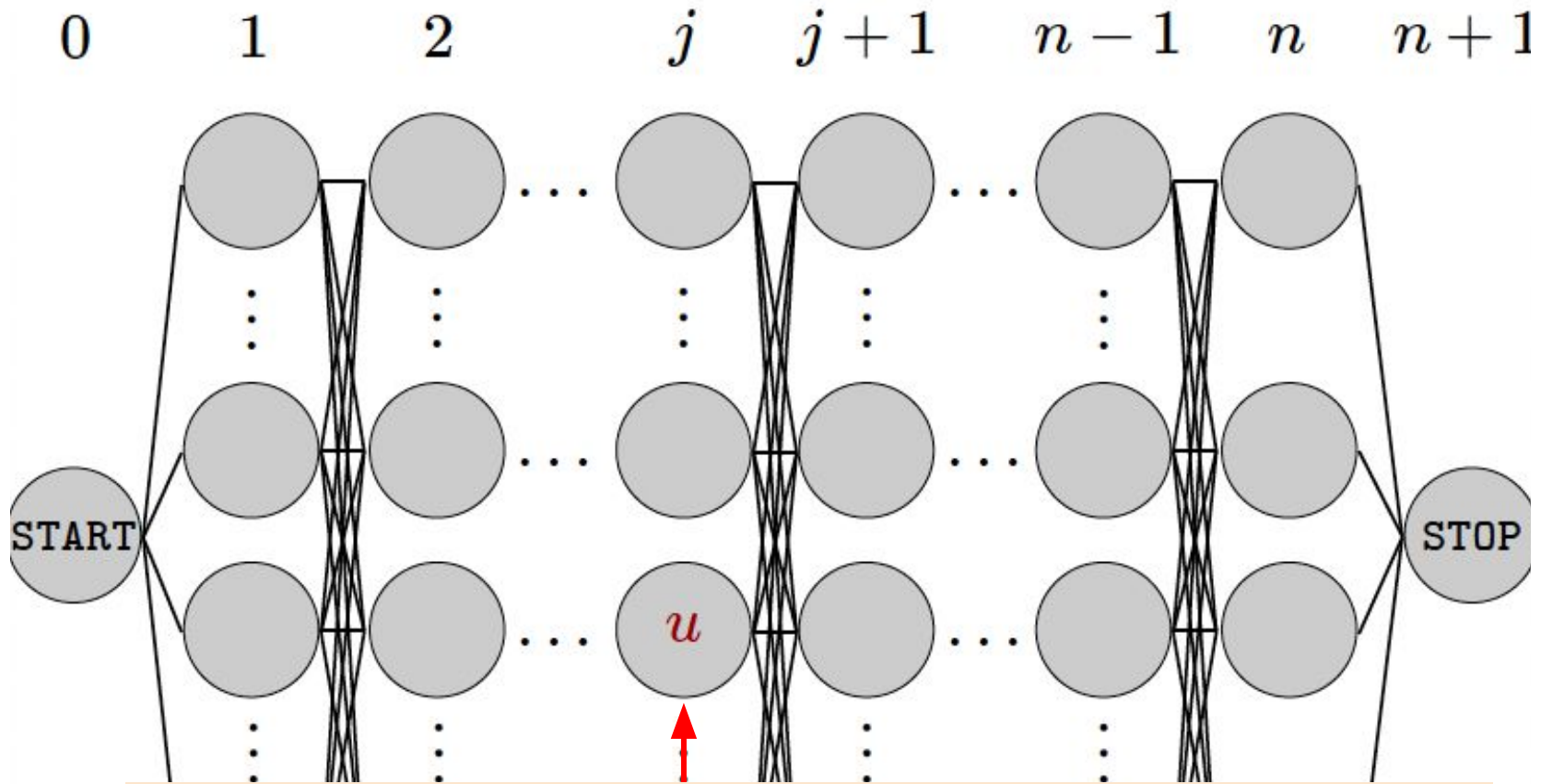
Now, can we develop an efficient algorithm based on such observations?



# Viterbi Algorithm

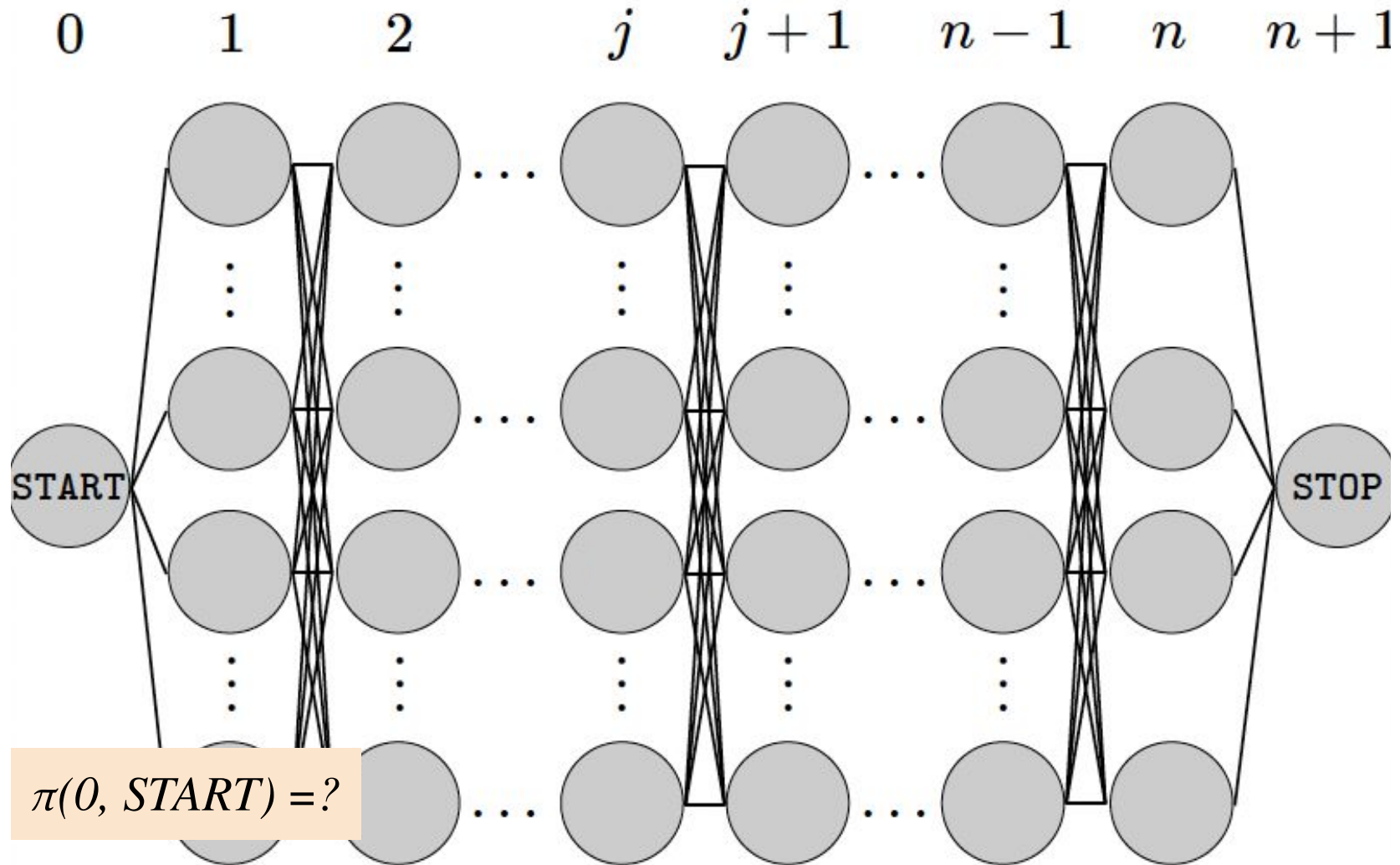


# Viterbi Algorithm

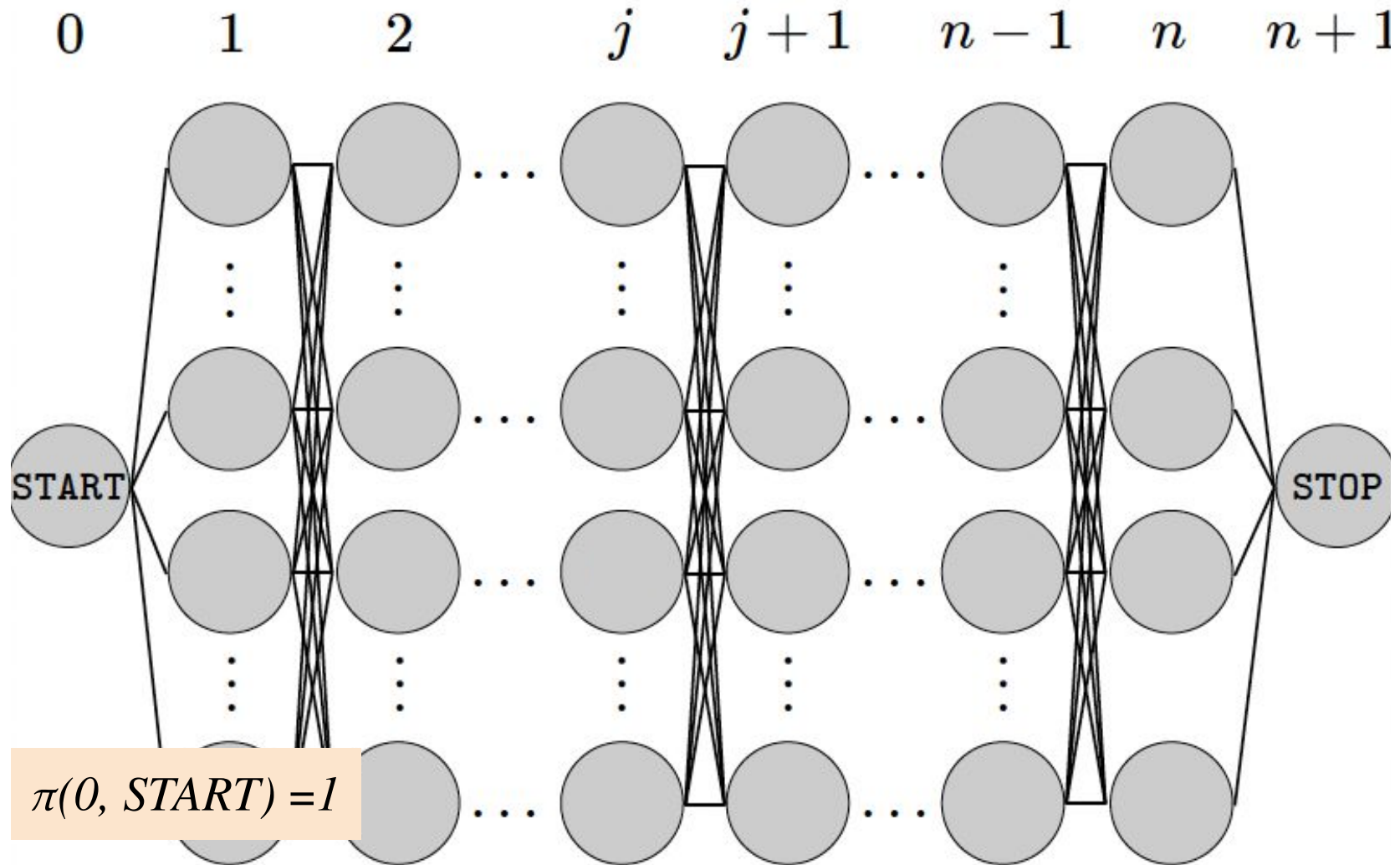


Store inside it  $\pi(j, u)$  – the score of the highest scoring path from START to this node  $(j, u)$

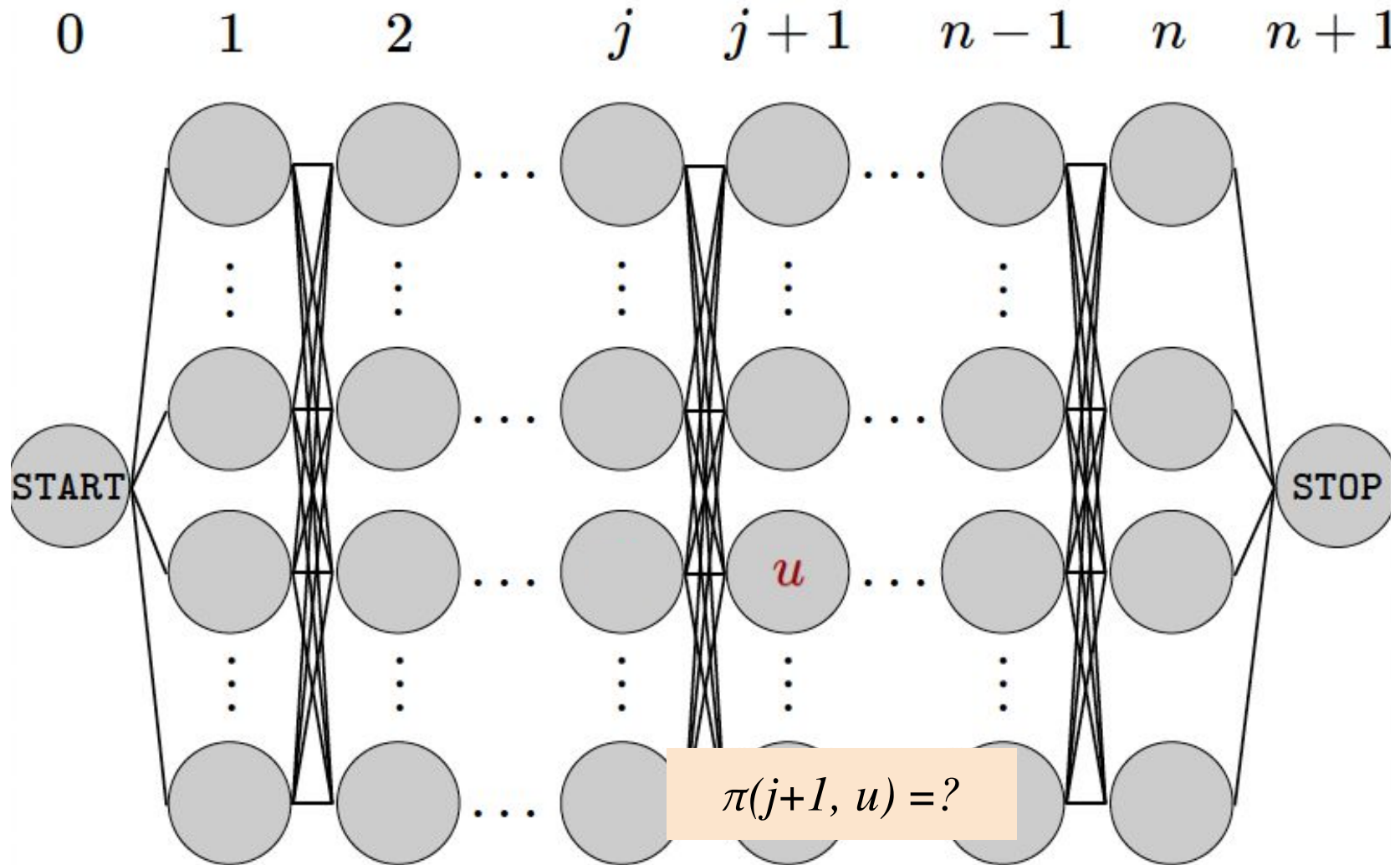
# Viterbi Algorithm



# Viterbi Algorithm

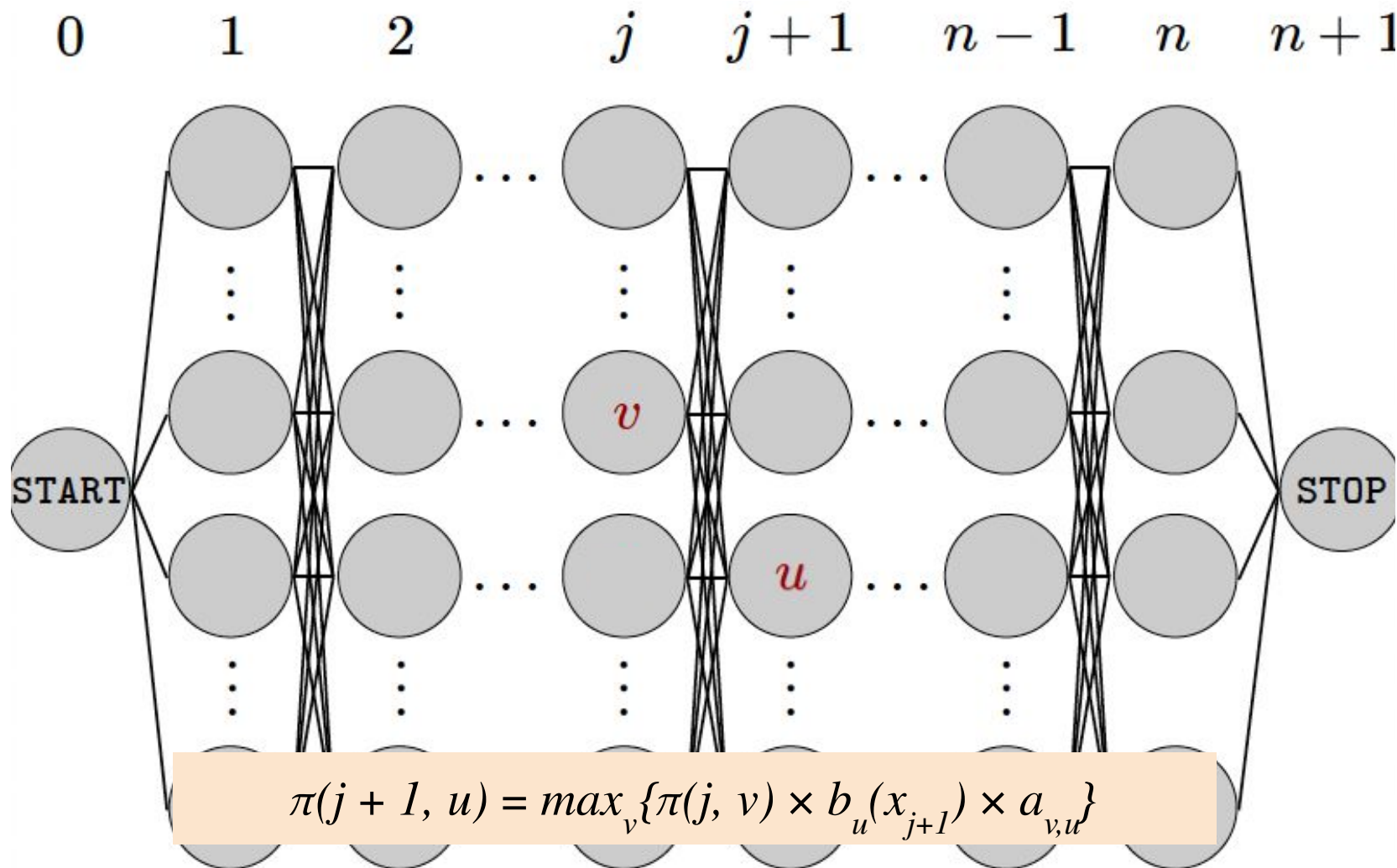


# Viterbi Algorithm



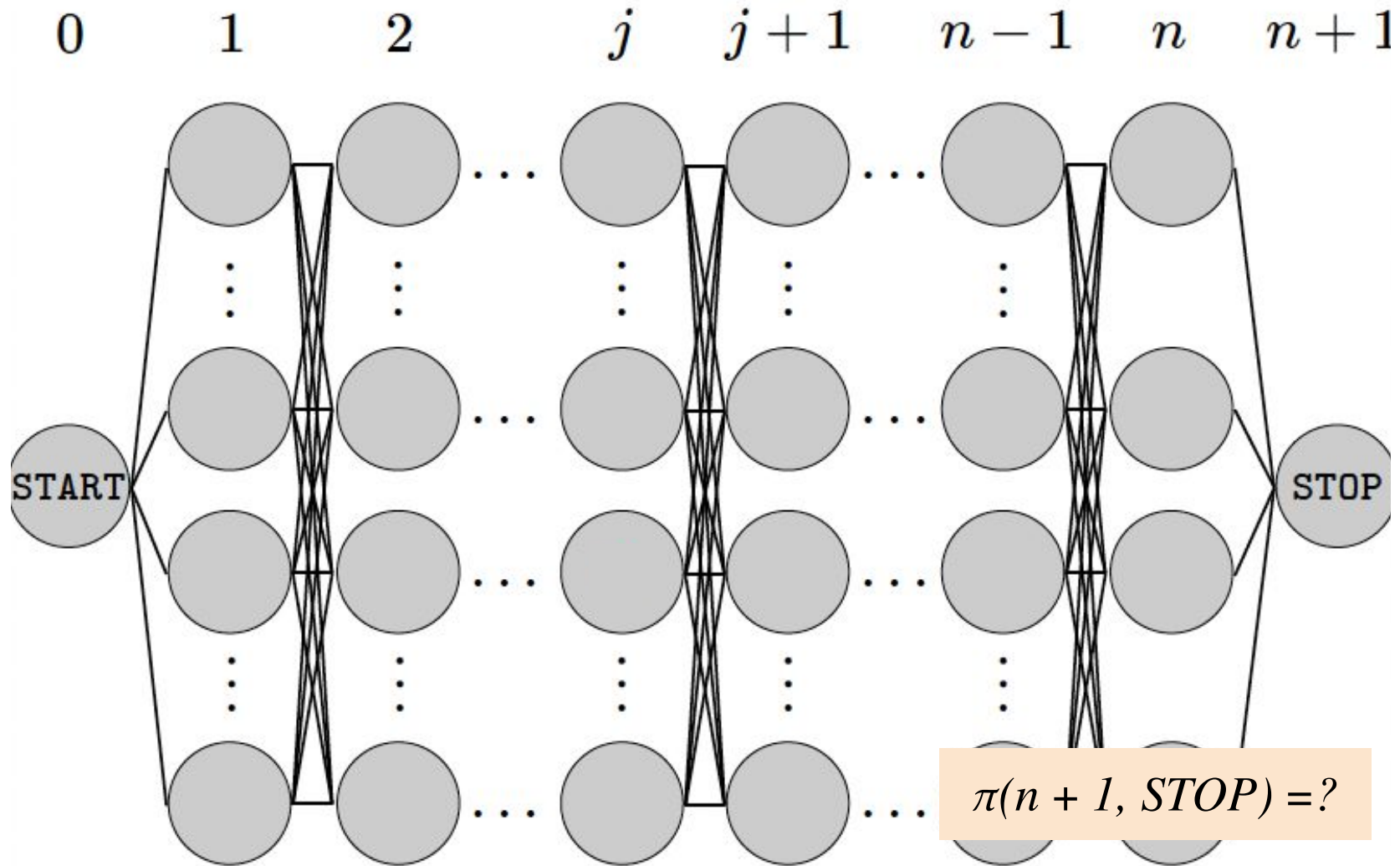


# Viterbi Algorithm





# Viterbi Algorithm



# Viterbi Algorithm

0      1      2                   $j$     $j + 1$        $n - 1$        $n$        $n + 1$

## 1. Initialization

$$\pi(0, u) = \begin{cases} 1 & \text{if } u = \text{START} \\ 0 & \text{otherwise} \end{cases}$$

## 2. For $j = 0 \dots n - 1$ , for each $u \in \mathcal{T}$


$$\pi(j + 1, u) = \max_v \{ \pi(j, v) \times b_u(x_{j+1}) \times a_{v,u} \}$$

## 3. Final Step

$$\pi(n + 1, \text{STOP}) = \max_v \{ \pi(n, v) \times a_{v, \text{STOP}} \}$$

# Viterbi Algorithm

0      1      2                   $j$     $j+1$        $n-1$        $n$        $n+1$

## 1. Initialization

$$\pi(0, u) = \begin{cases} 1 & \text{if } u = \text{START} \\ 0 & \text{otherwise} \end{cases}$$

How do we figure out  
the highest scoring  
path from such scores?

for all  $u \in \mathcal{T}$

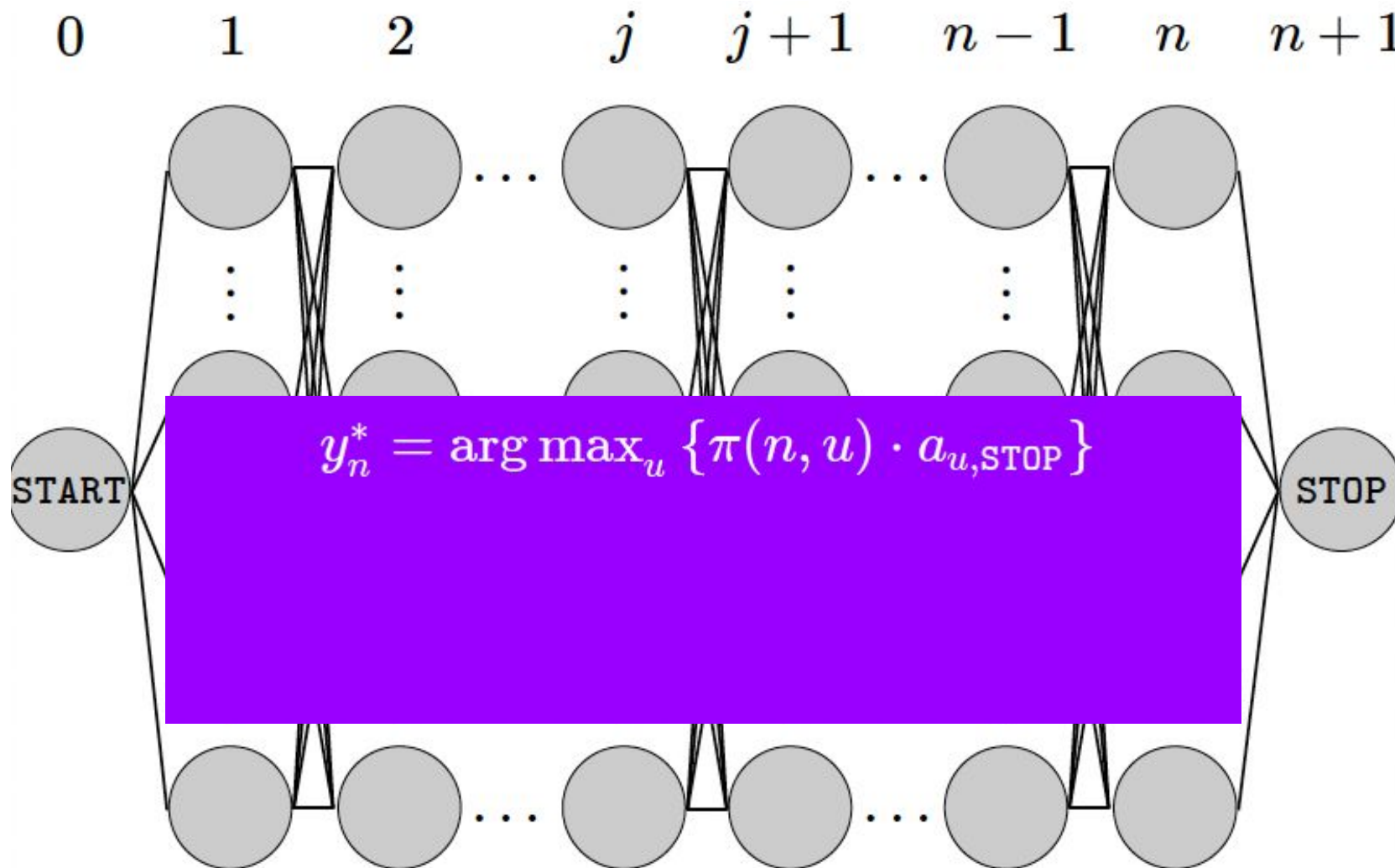
$$\pi(j+1, v) = \max_u \{ \pi(j, u) \times a_{v,u} \}$$

## 3. Final Step

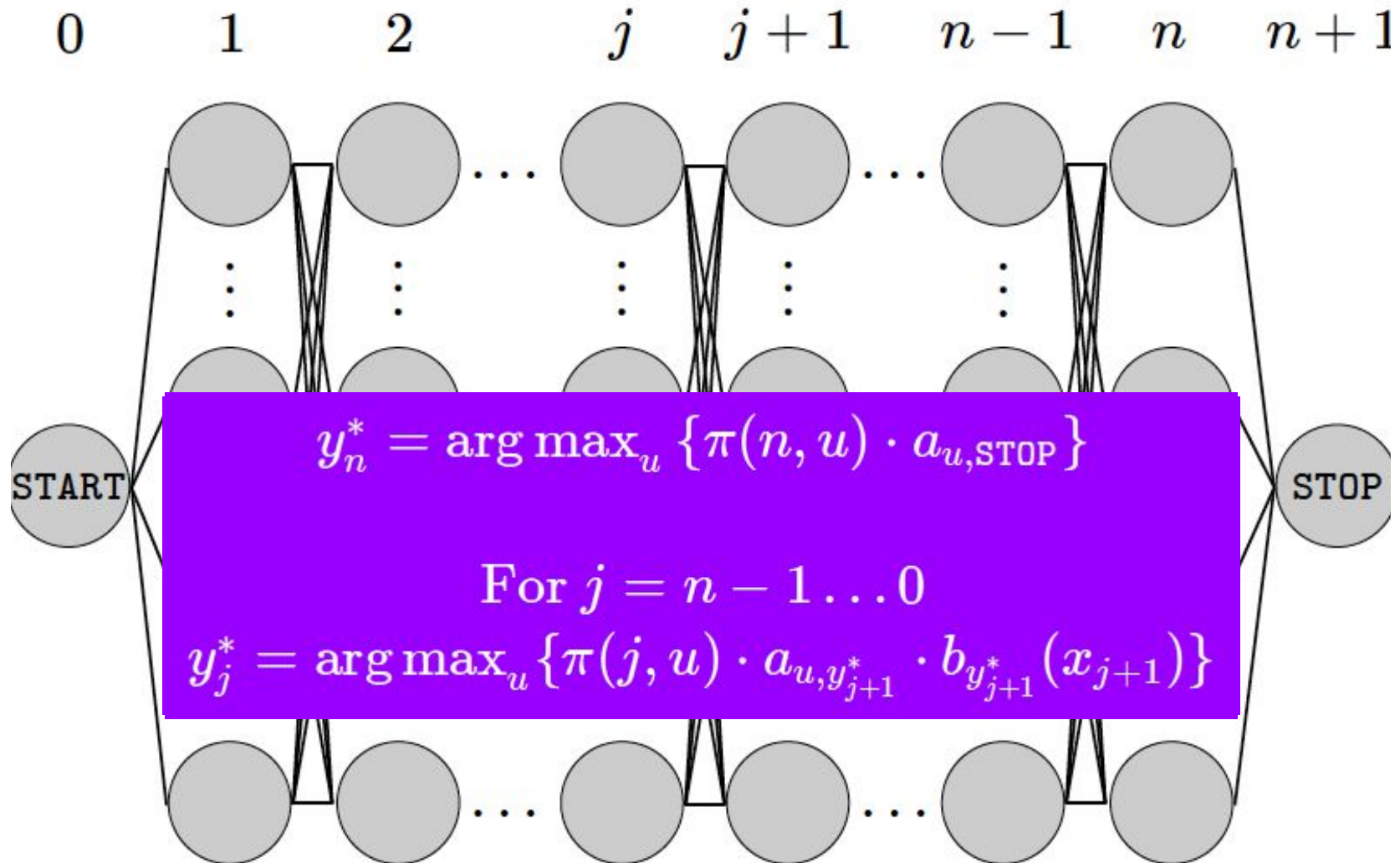
$$\pi(n+1, \text{STOP}) = \max_v \{ \pi(n, v) \times a_{v, \text{STOP}} \}$$



# Viterbi Algorithm

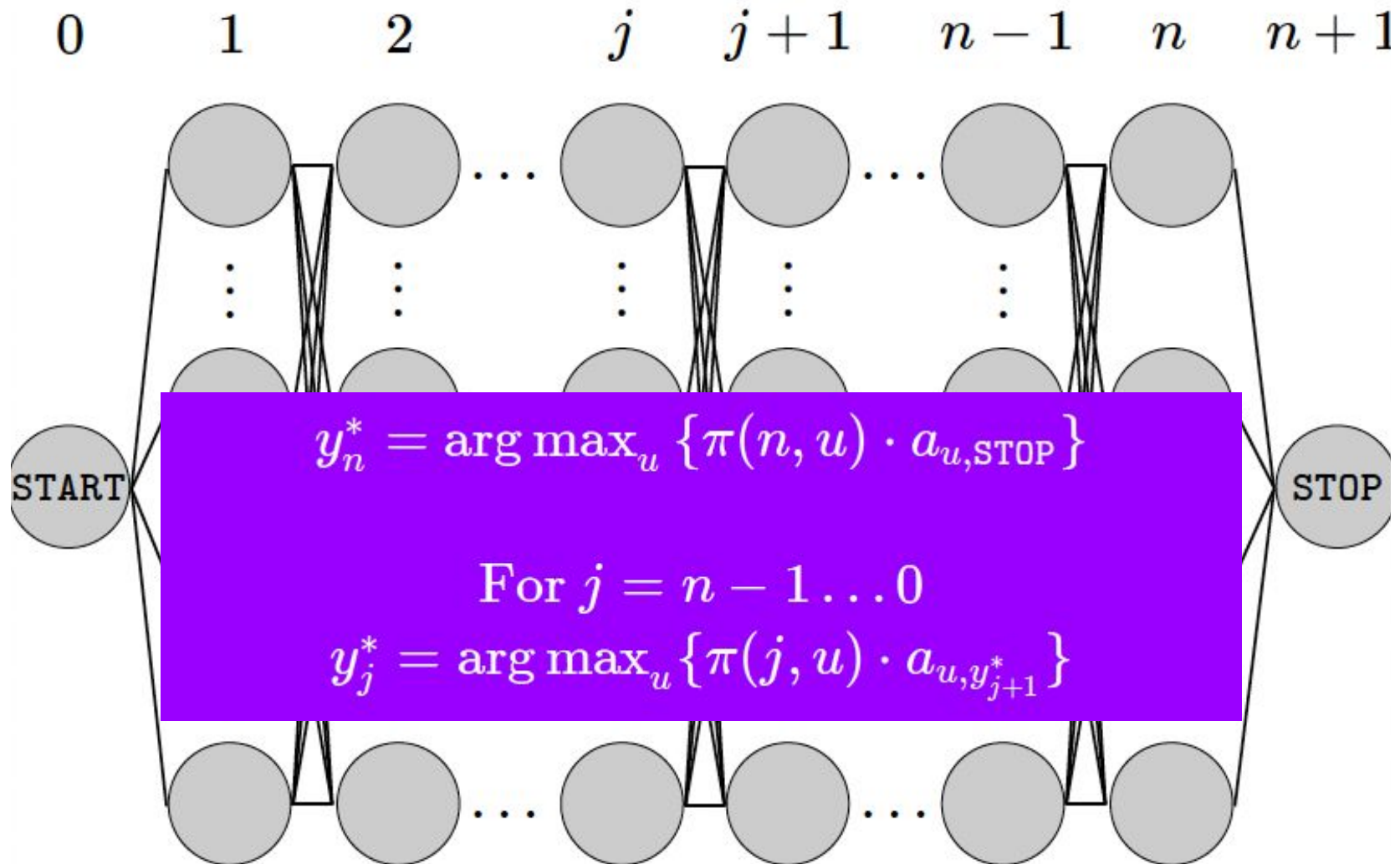


# Viterbi Algorithm





# Viterbi Algorithm



# Question

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What is the time complexity of the Viterbi algorithm?

