

# 50.007

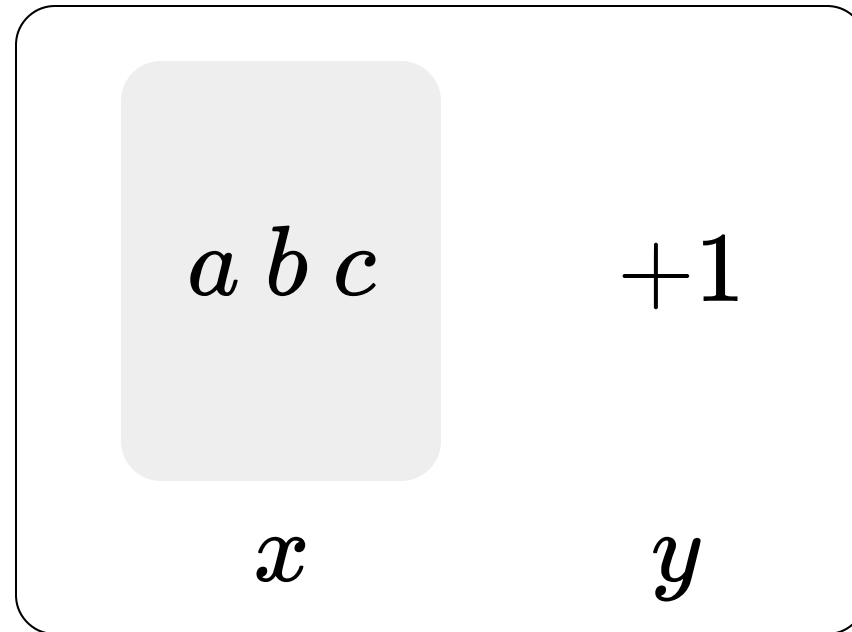
# Machine Learning

Lu, Wei

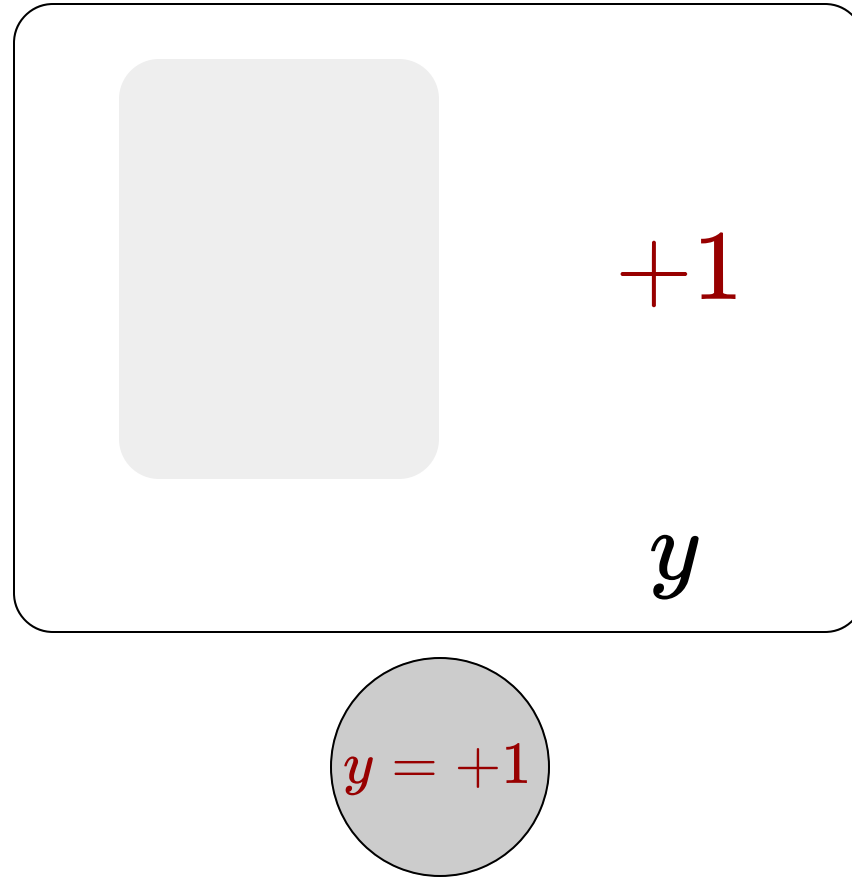


# Hidden Markov Model (I)

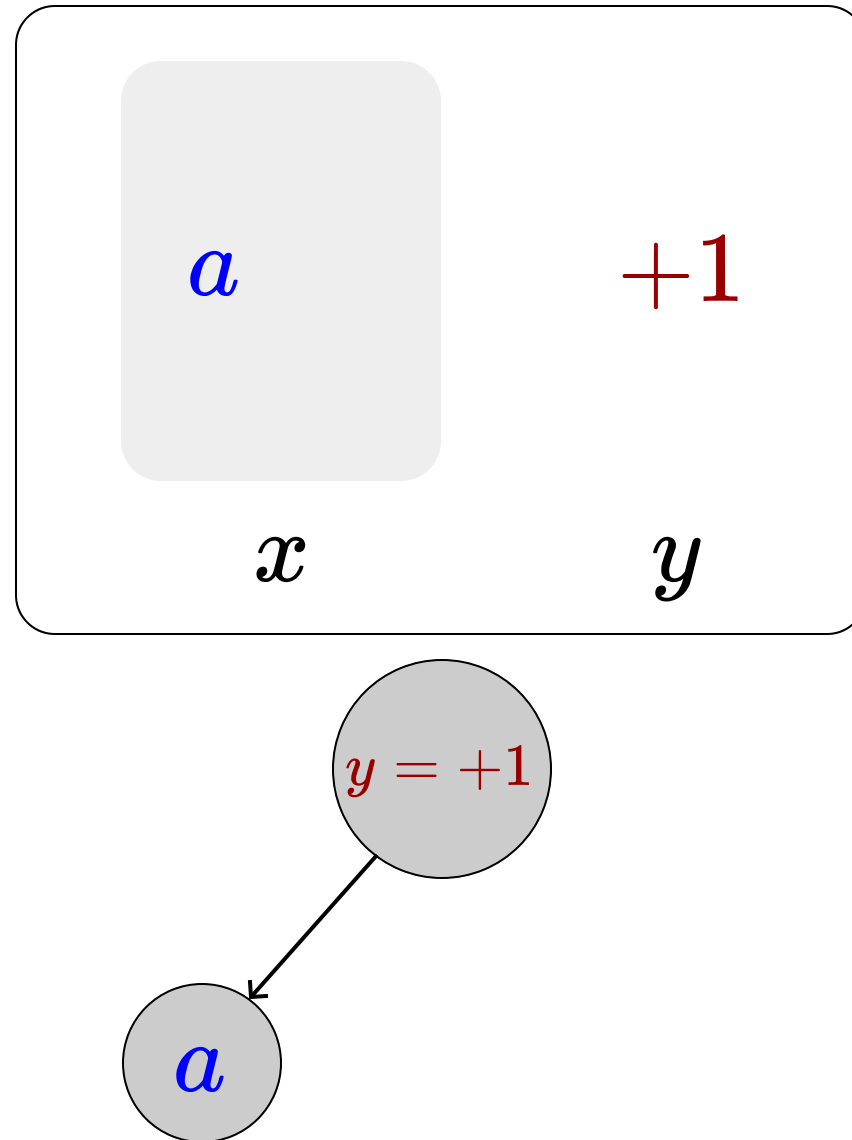
# Generative Models



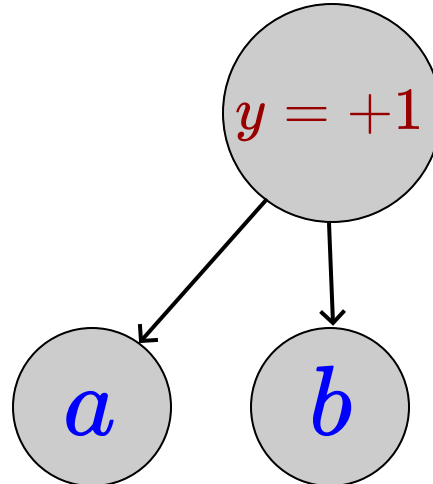
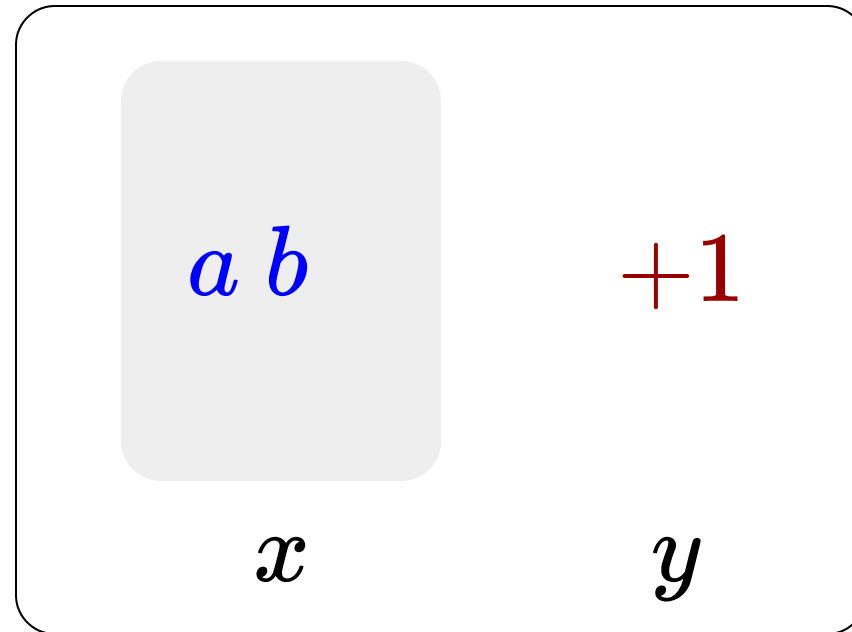
# Generative Models



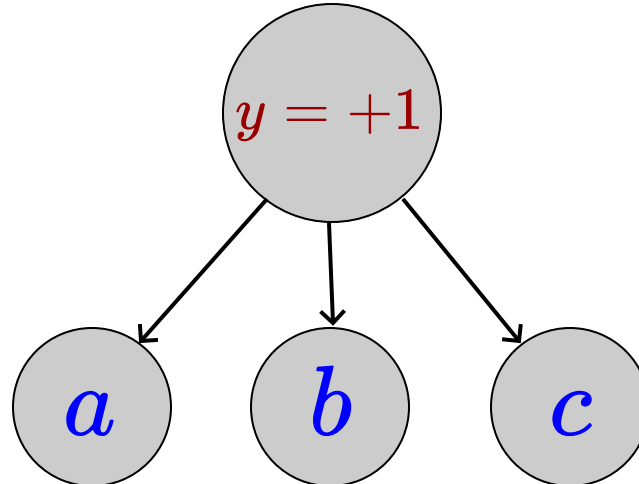
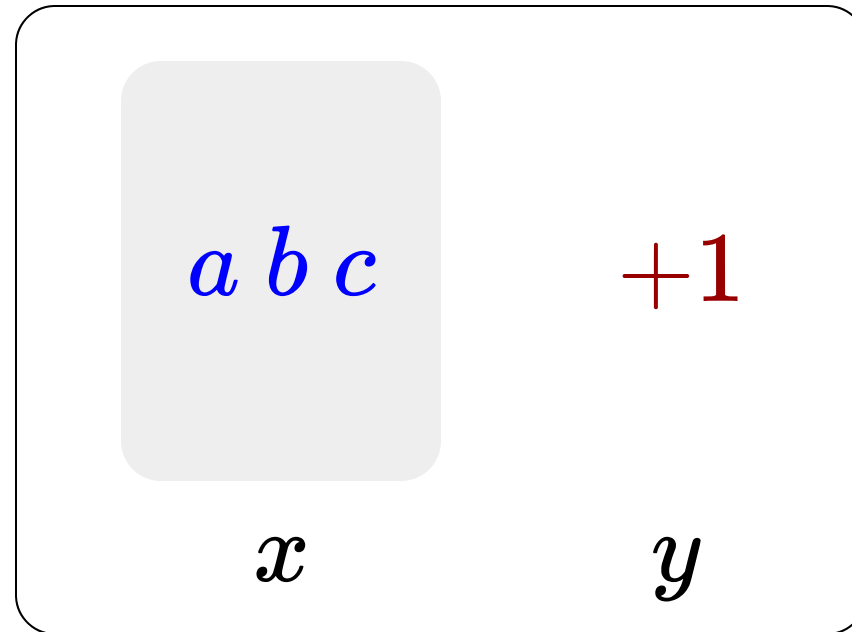
# Generative Models



# Generative Models



# Generative Models



# Sequence Labeling

Faith is a fine invention



# Sequence Labeling

Noun

Verb

Determiner

Adjective

Noun

**N**

**V**

**D**

**A**

**N**

Faith

is

a

fine

invention

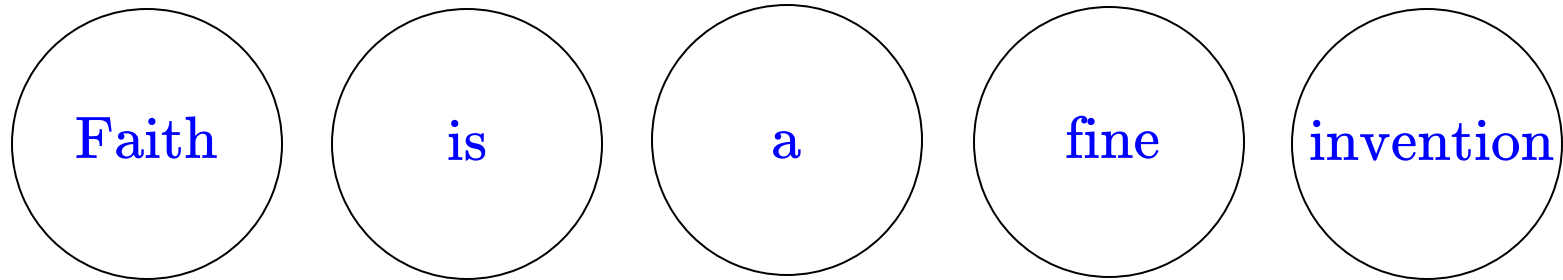
# Sequence Labeling



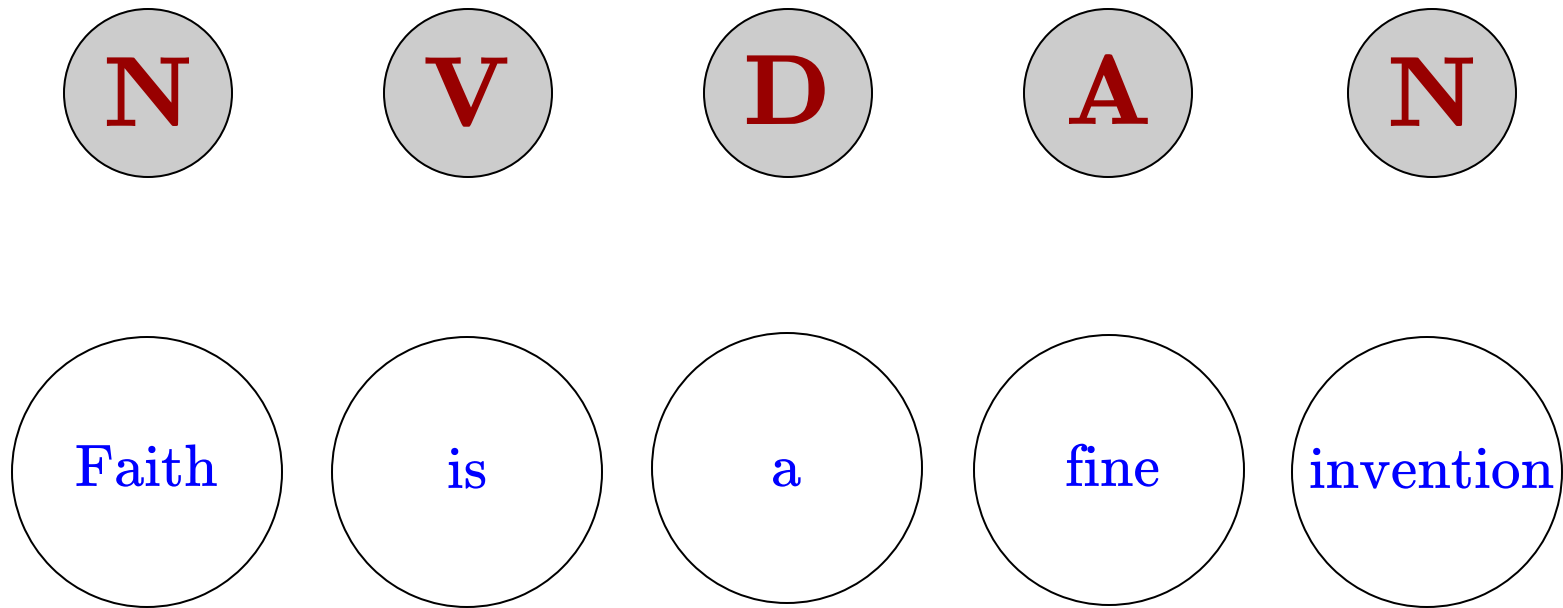
# Sequence Labeling



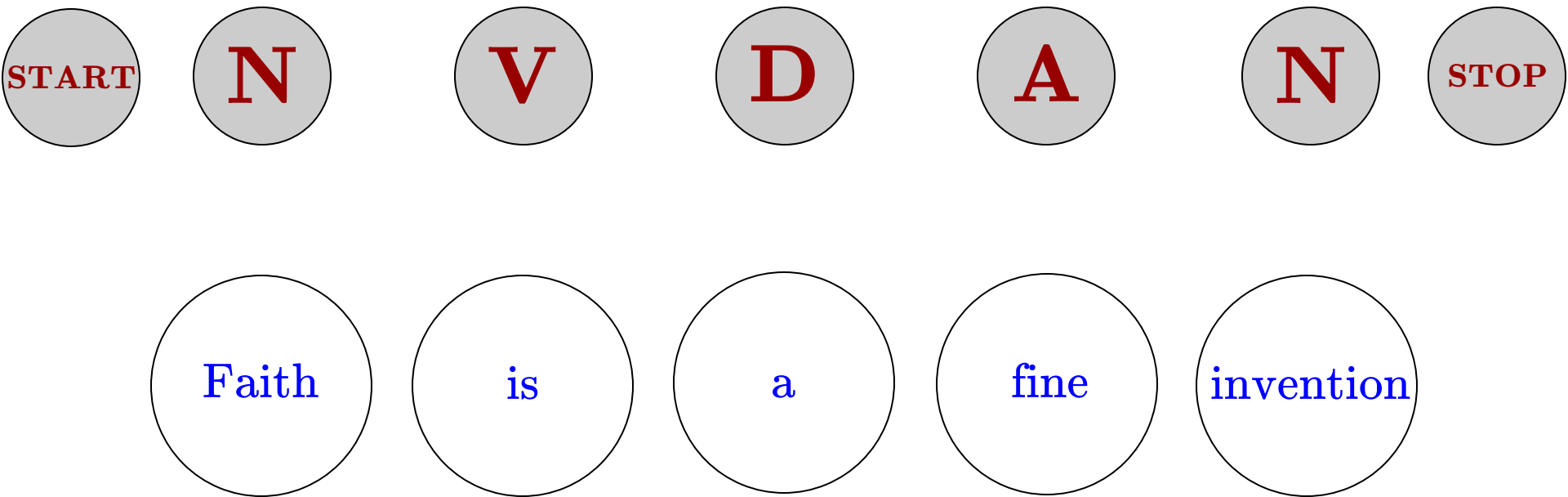
# Sequence Labeling



# Sequence Labeling



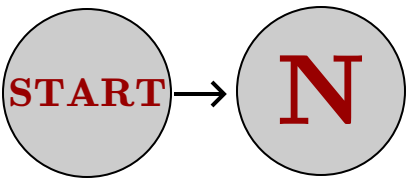
# Sequence Labeling



# Sequence Labeling

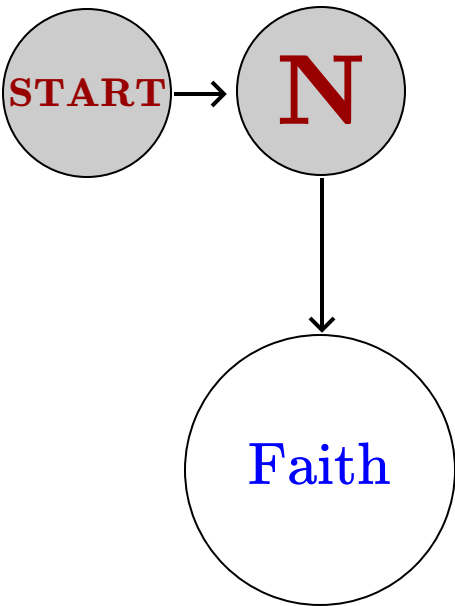


# Sequence Labeling

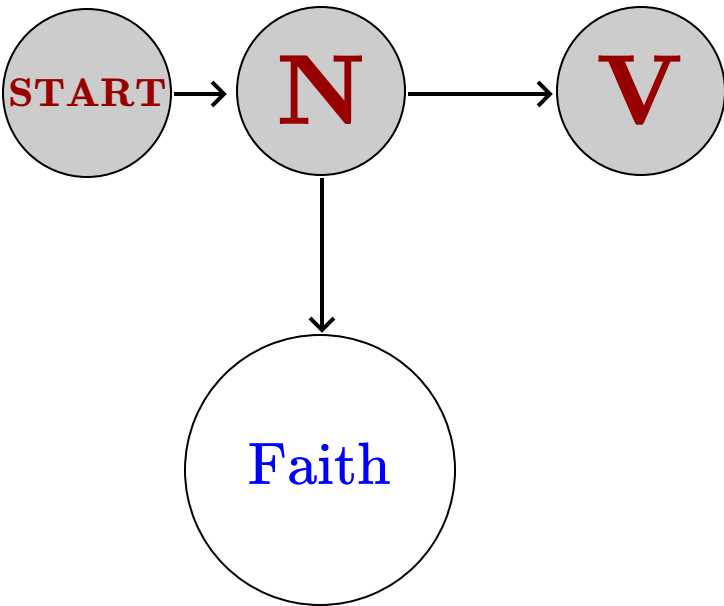




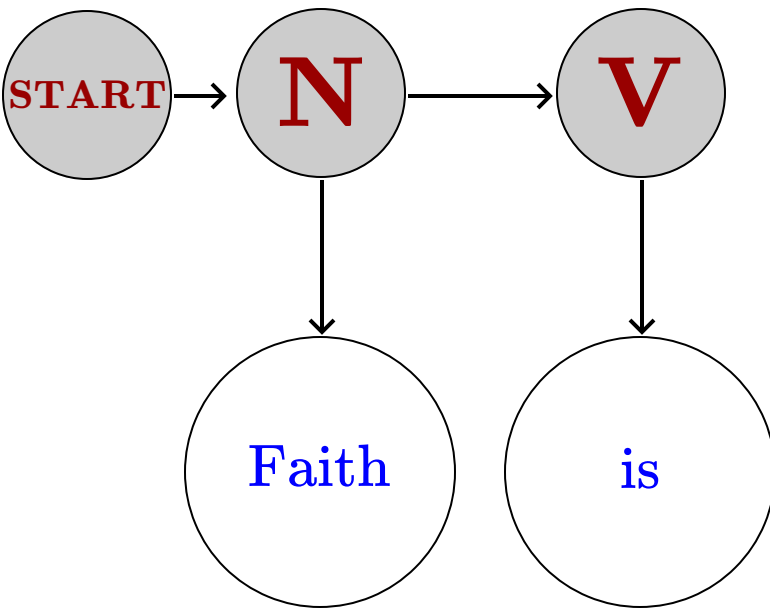
# Sequence Labeling



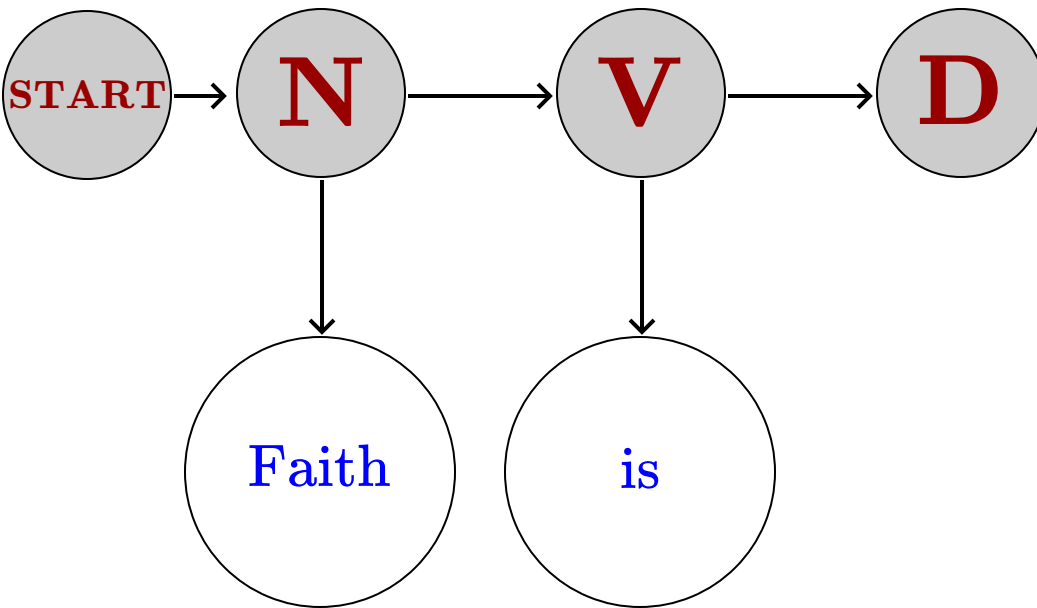
# Sequence Labeling



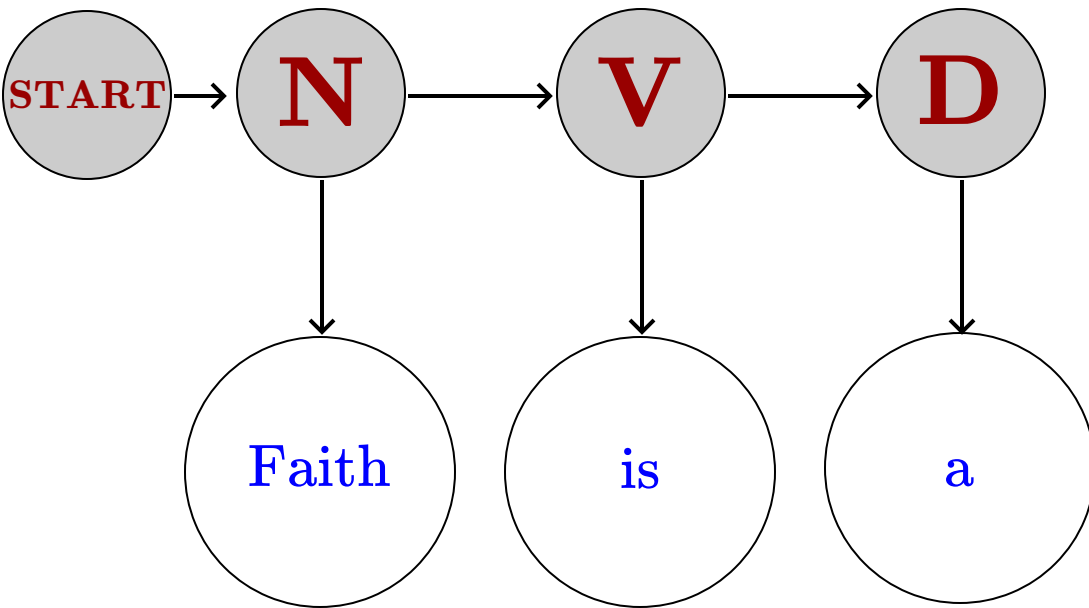
# Sequence Labeling



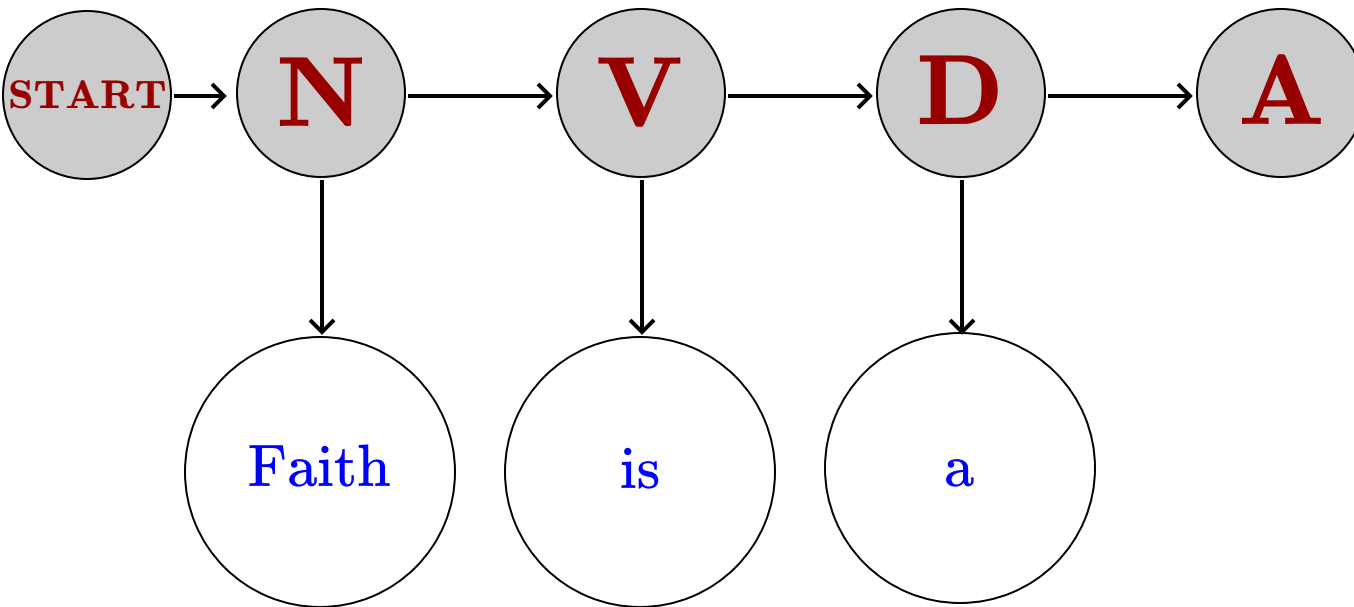
# Sequence Labeling



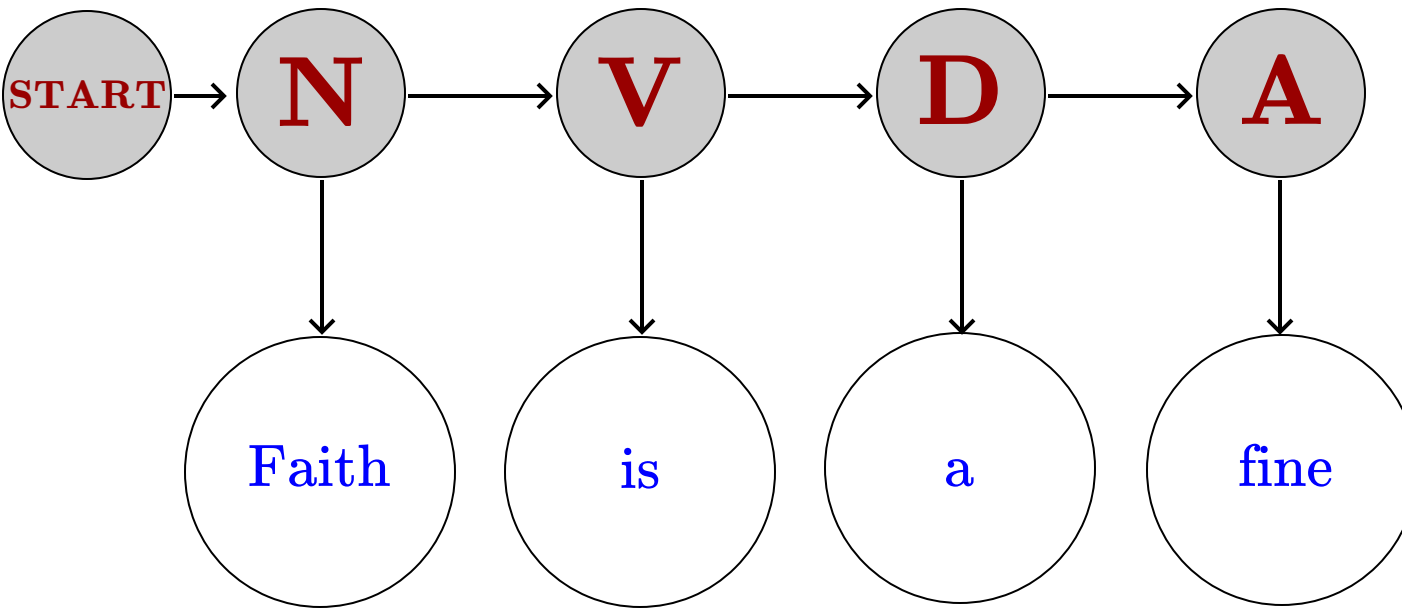
# Sequence Labeling



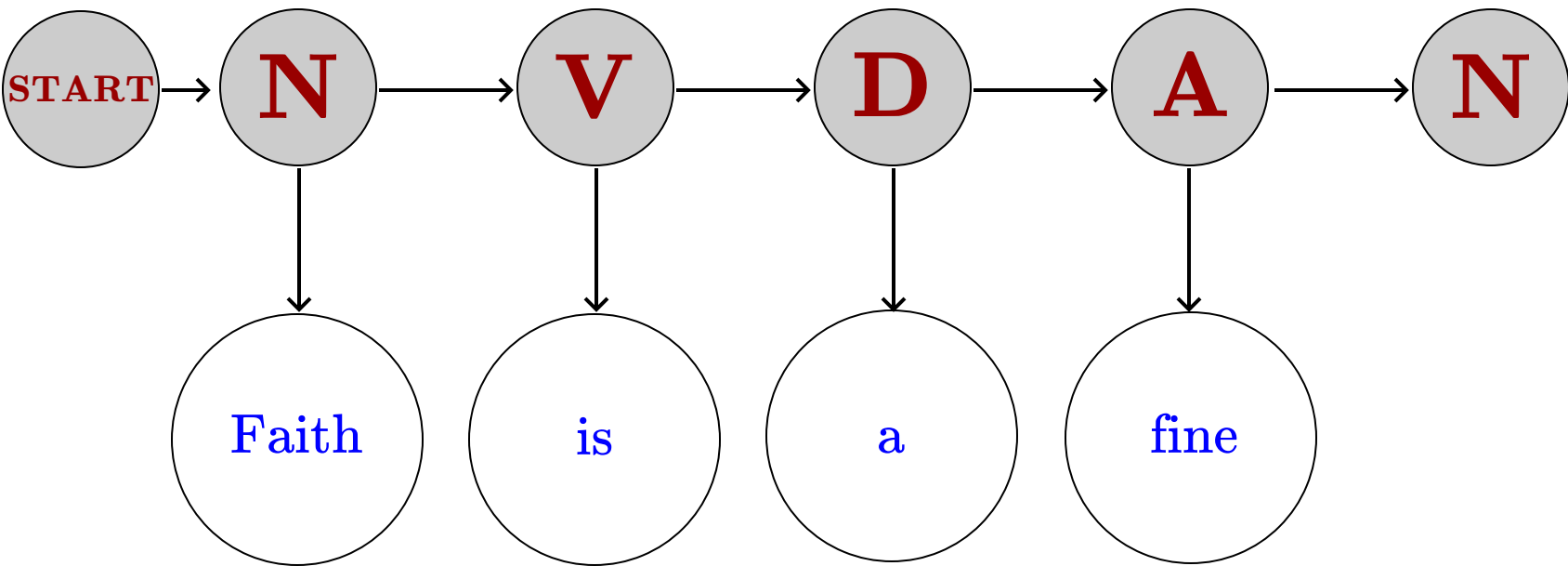
# Sequence Labeling



# Sequence Labeling

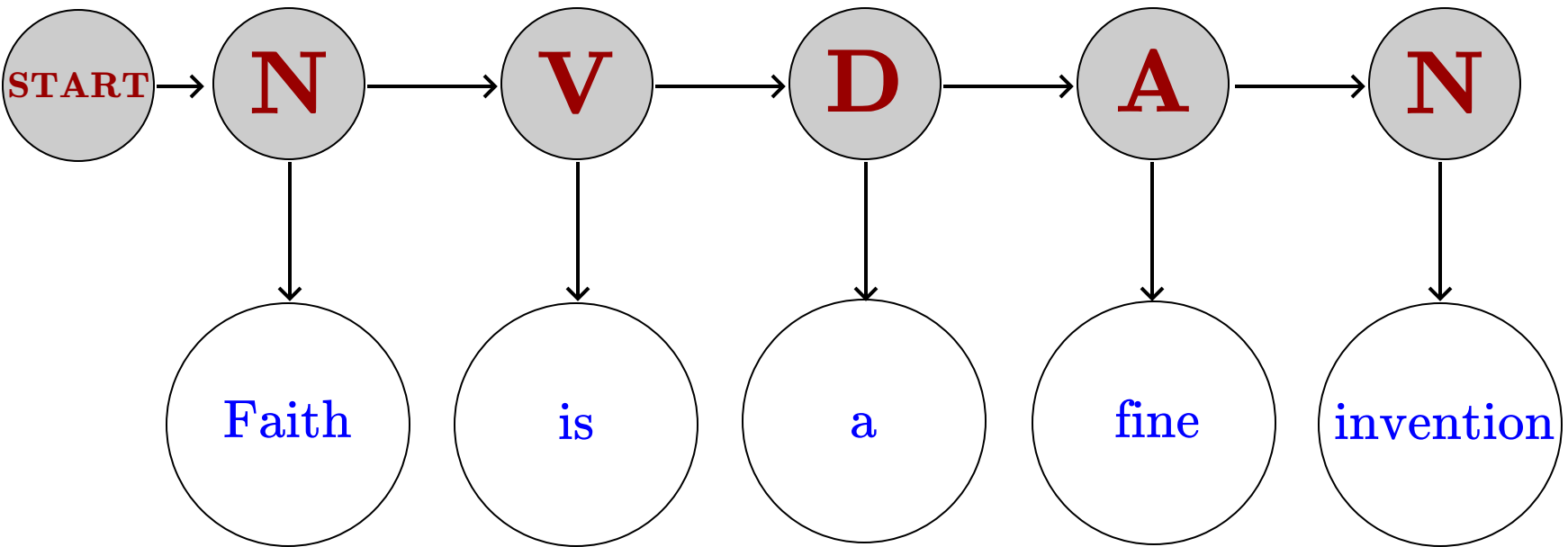


# Sequence Labeling

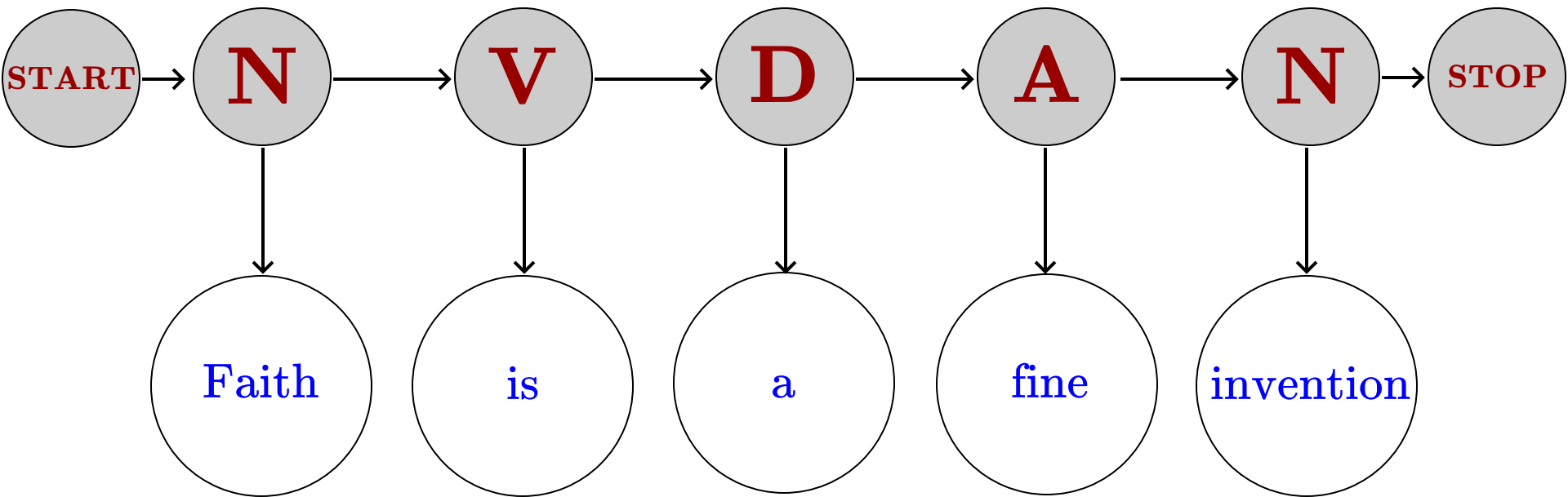




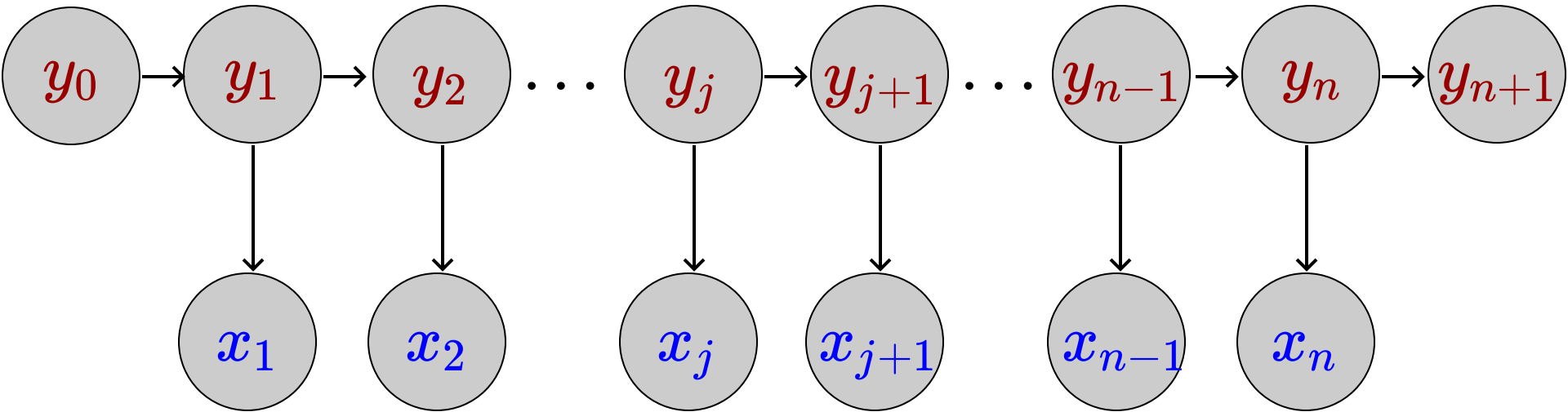
# Sequence Labeling



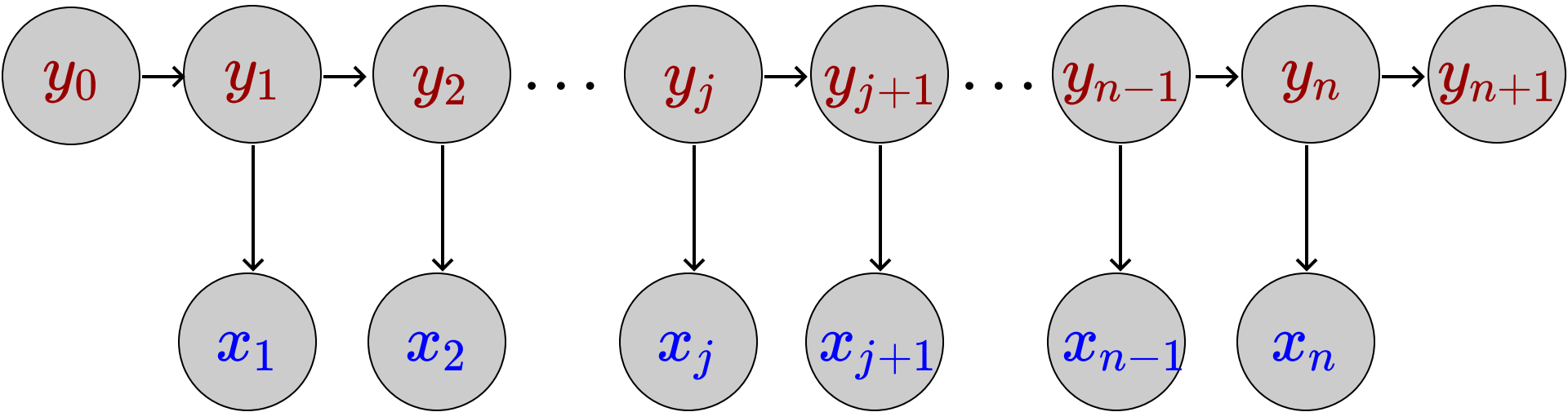
# Sequence Labeling



# Sequence Labeling



# Sequence Labeling

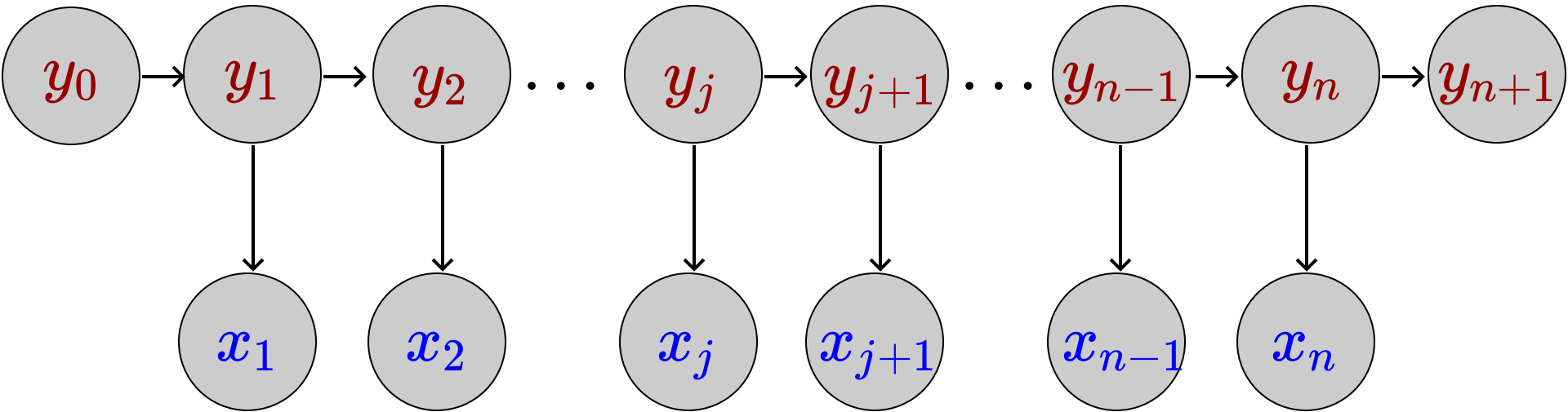


$$p(x_1, x_2, \dots, x_{n-1}, x_n, y_0, y_1, y_2, \dots, y_{n-1}, y_n, y_{n+1})$$

↑  
START

↑  
STOP

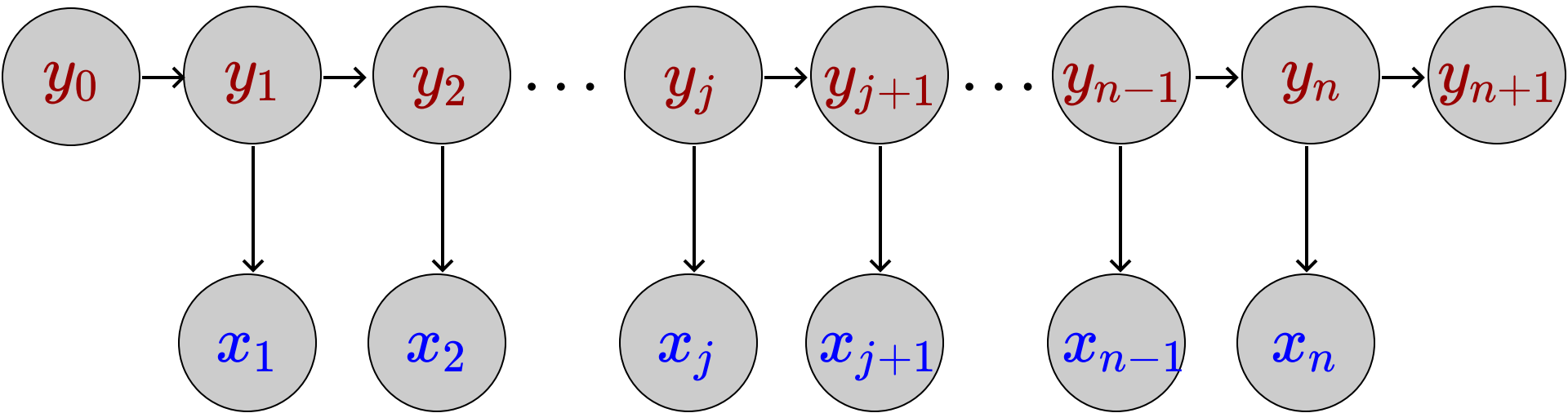
# Sequence Labeling



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

$$\prod_{j=0}^n p(y_{j+1}|y_j) \times \prod_{j=1}^n p(x_j|y_j)$$

# Hidden Markov Model



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

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

Transition probabilities

Emission probabilities

# Hidden Markov Model

An HMM is defined by a tuple  $\langle \mathcal{T}, \mathcal{O}, \theta \rangle$ , where

$\mathcal{T}$

a set of states including START and STOP states.

$\mathcal{O}$

a set of observation symbols

$\theta$

Transition and emission parameters  $a_{u,v}$  and  $b_u(o)$ .

# Hidden Markov Model

## An Example

$$\mathcal{T} = \{\text{START}, A, B, \text{STOP}\}$$

$$\mathcal{O} = \{\text{“the”}, \text{“dog”}\}$$

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

$$a_{u,v}$$

$u \backslash o$	“the”	“dog”
$A$	0.9	0.1
$B$	0.1	0.9

$$b_u(o)$$



# Hidden Markov Model

## An 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”
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$B$	0.1	0.9

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



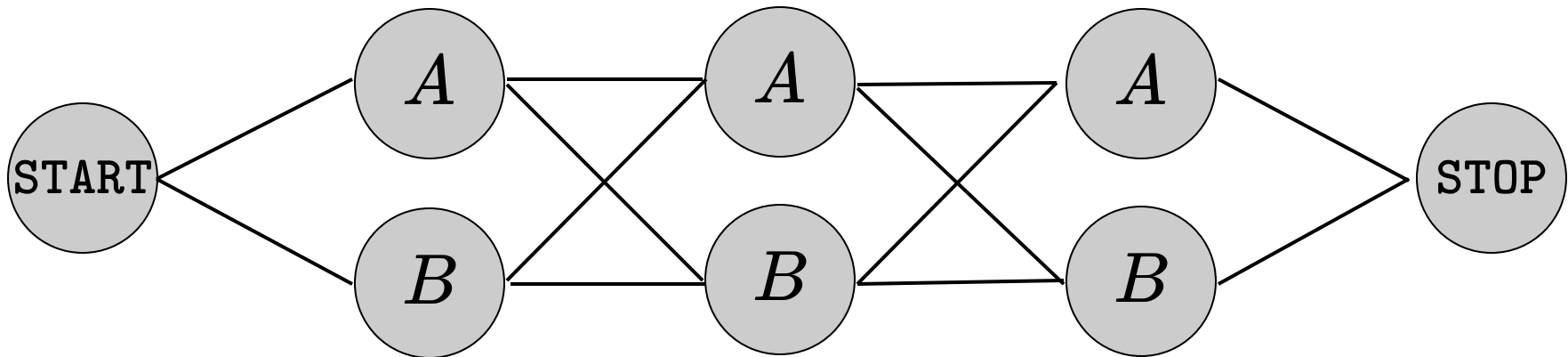
What is  $p(\mathbf{x}, \mathbf{y})$ ?

# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

$u \setminus v$	$A$	$B$	STOP
START	1.0	0.0	0.0
$A$	0.5	0.5	0.0
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$u \setminus o$	“the”	“dog”
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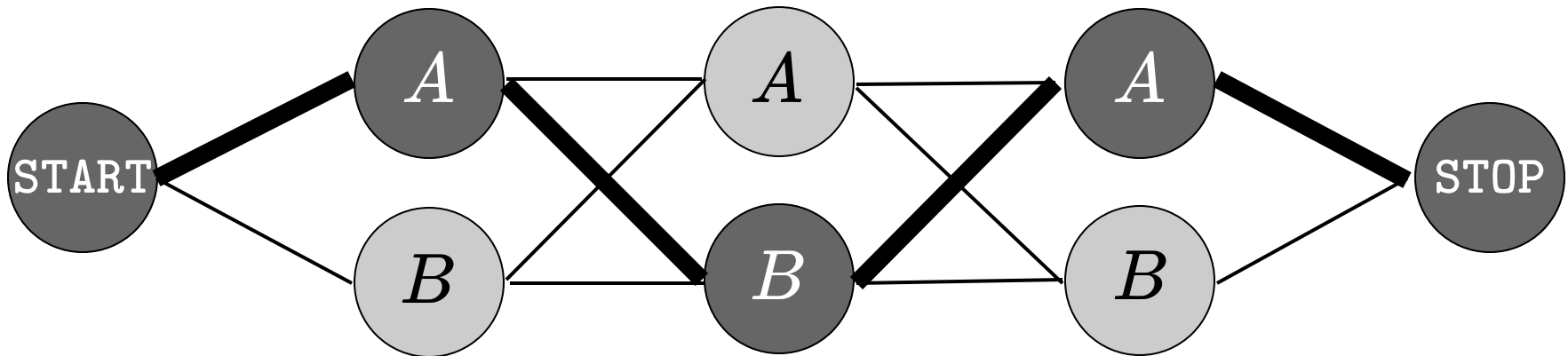
One path corresponds to one label sequence.

# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

$u \backslash v$	$A$	$B$	STOP
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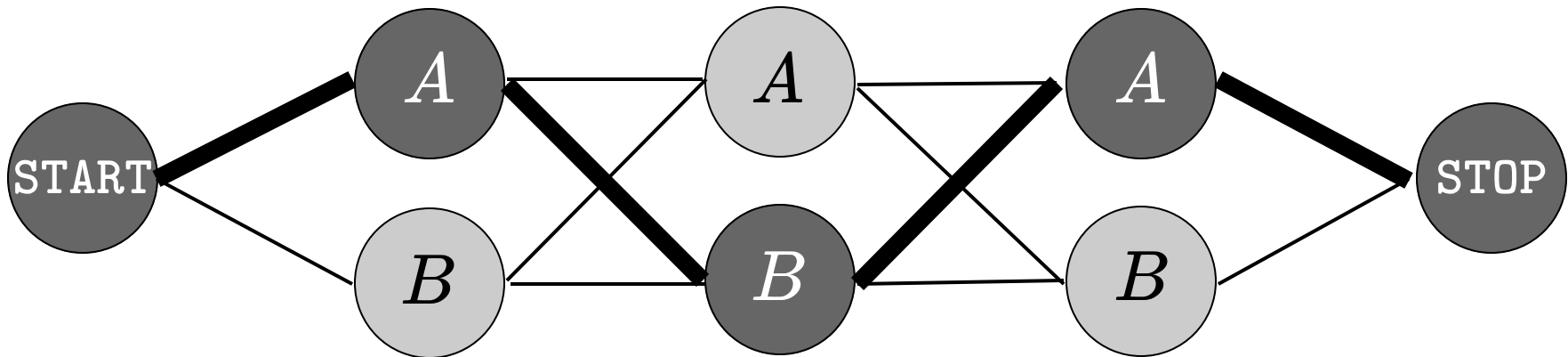
$a_{\text{START},A}$

# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

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

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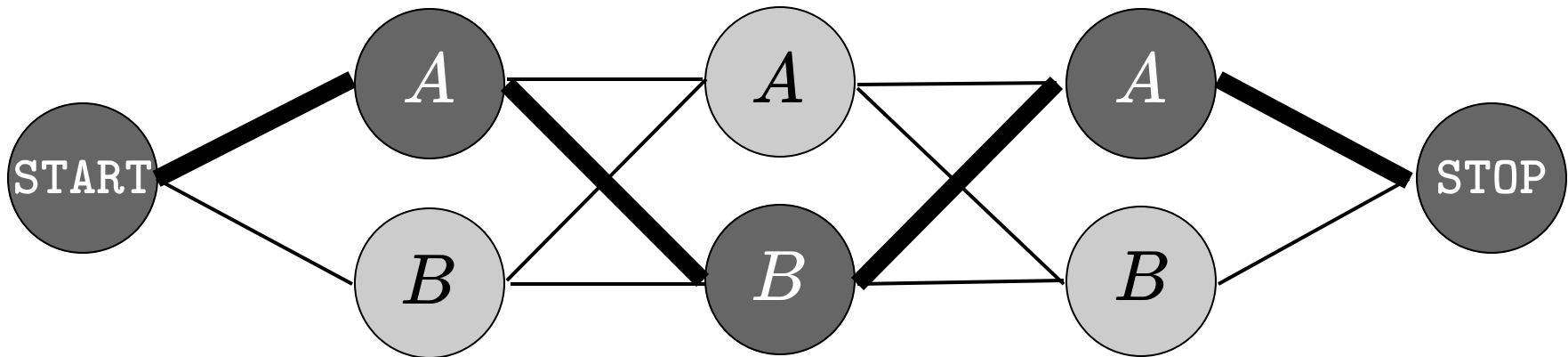
$$a_{\text{START},A} \times b_A(\text{“The”})$$

# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

$u \backslash v$	$A$	$B$	STOP
START	1.0	0.0	0.0
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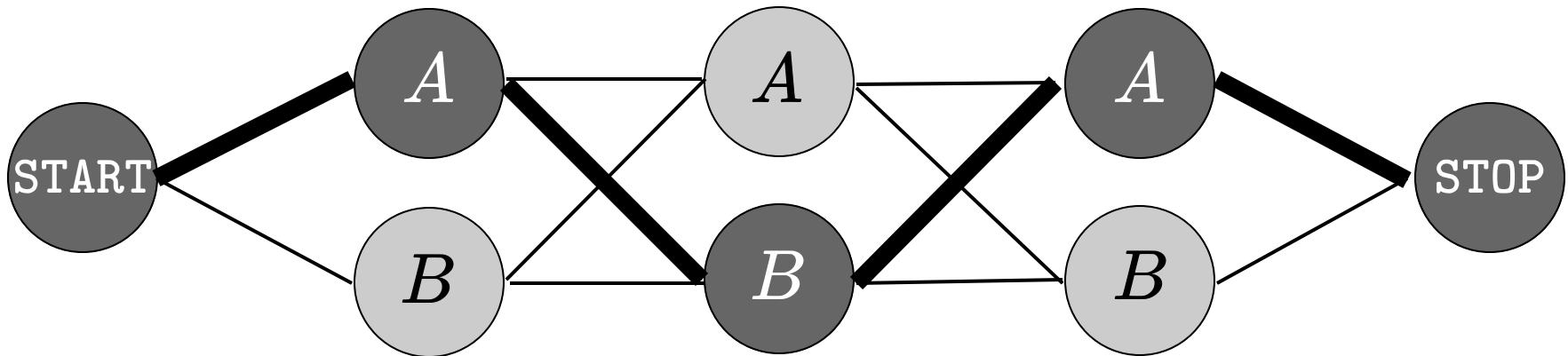
$$a_{\text{START},A} \times b_A(\text{“The”}) \times a_{A,B}$$

# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

$u \backslash v$	$A$	$B$	STOP
START	1.0	0.0	0.0
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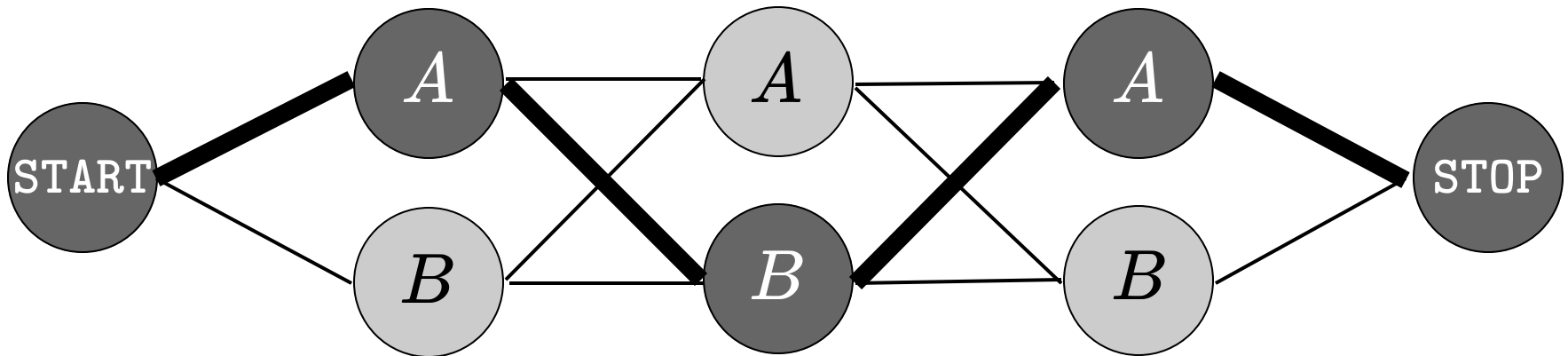
$$a_{\text{START},A} \times b_A(\text{“The”}) \times a_{A,B} \times b_B(\text{“dog”})$$

# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

$u \backslash v$	$A$	$B$	STOP
START	1.0	0.0	0.0
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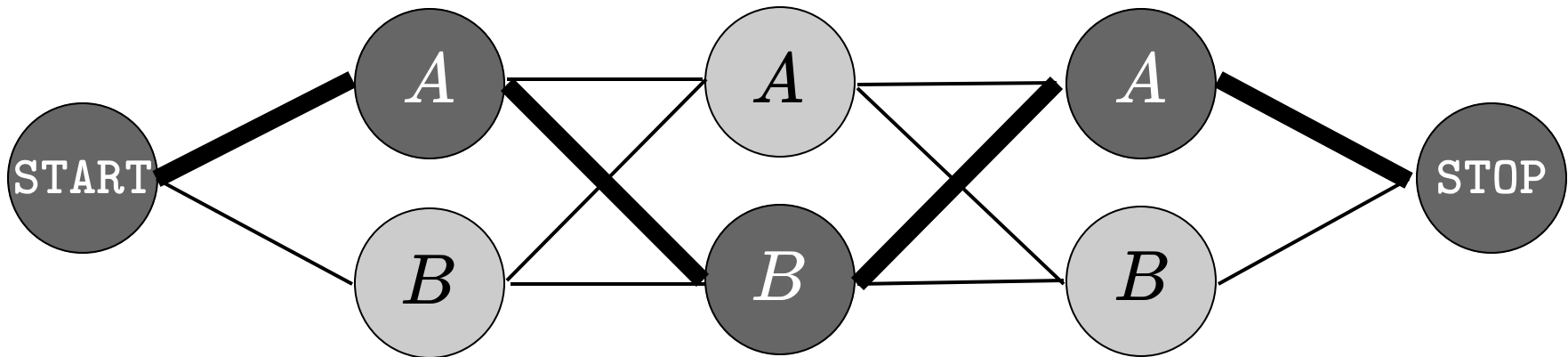
$$a_{\text{START},A} \times b_A(\text{“The”}) \times a_{A,B} \times b_B(\text{“dog”}) \times a_{B,A}$$

# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

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

$u \backslash o$	“the”	“dog”
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$$a_{\text{START},A} \times b_A(\text{“The”}) \times a_{A,B} \times b_B(\text{“dog”}) \times a_{B,A} \times b_A(\text{“the”})$$

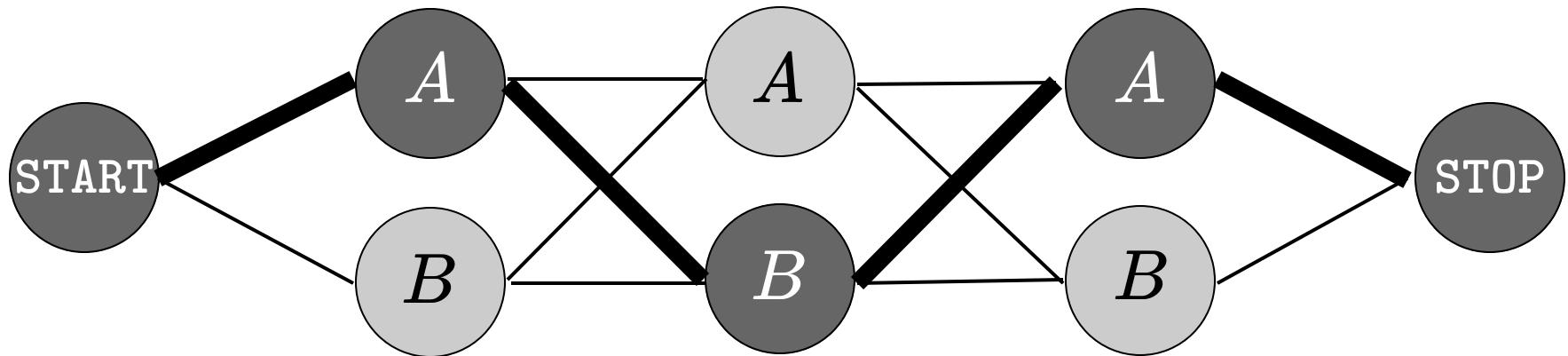


# Hidden Markov Model

$a_{u,v}$        $(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$        $b_u(o)$

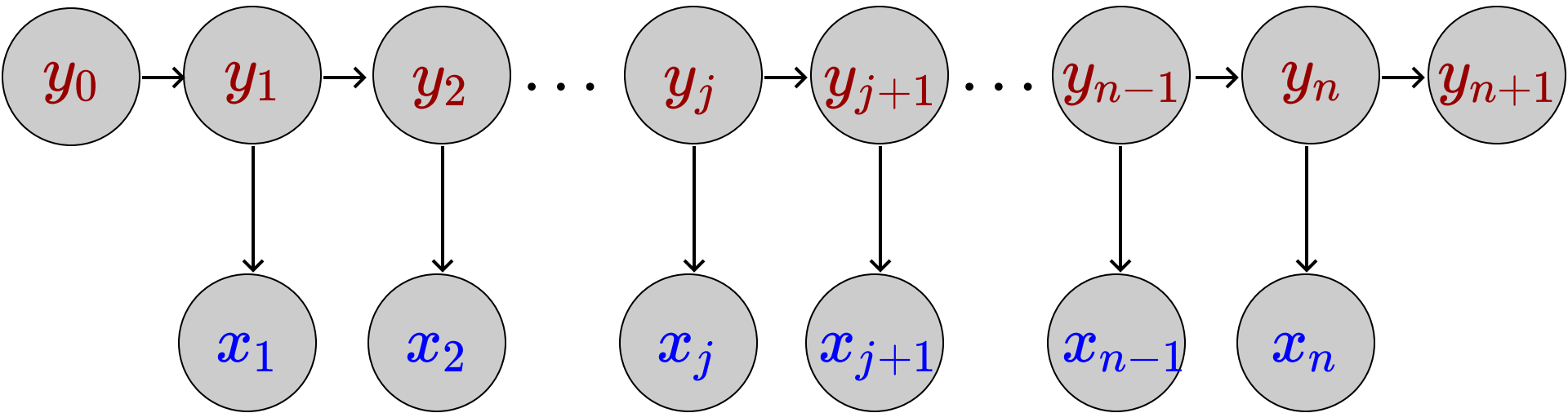
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$$a_{\text{START},A} \times b_A(\text{“The”}) \times a_{A,B} \times b_B(\text{“dog”}) \times a_{B,A} \times b_A(\text{“the”}) \times a_{A,\text{STOP}}$$

# Hidden Markov Model

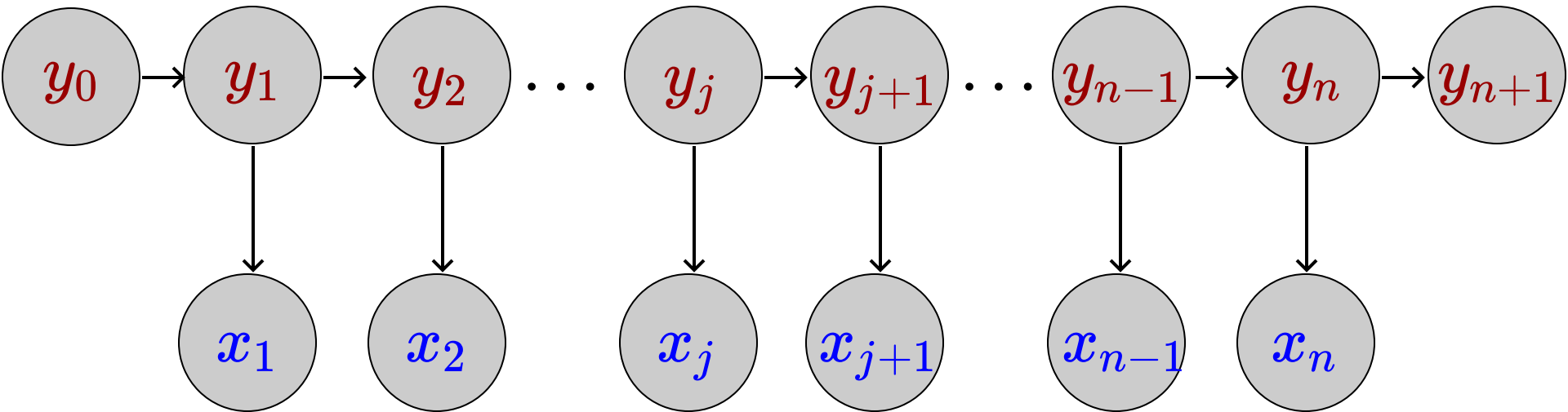


$$p(\mathbf{x}, \mathbf{y}) = \underbrace{\prod_{j=0}^n a_{y_j, y_{j+1}}}_{\text{Transition probabilities}} \times \underbrace{\prod_{j=1}^n b_{y_j}(x_j)}_{\text{Emission probabilities}}$$



Now that we know what are the model parameters, how do we estimate them? In other words, how to do learning?

# Hidden Markov Model



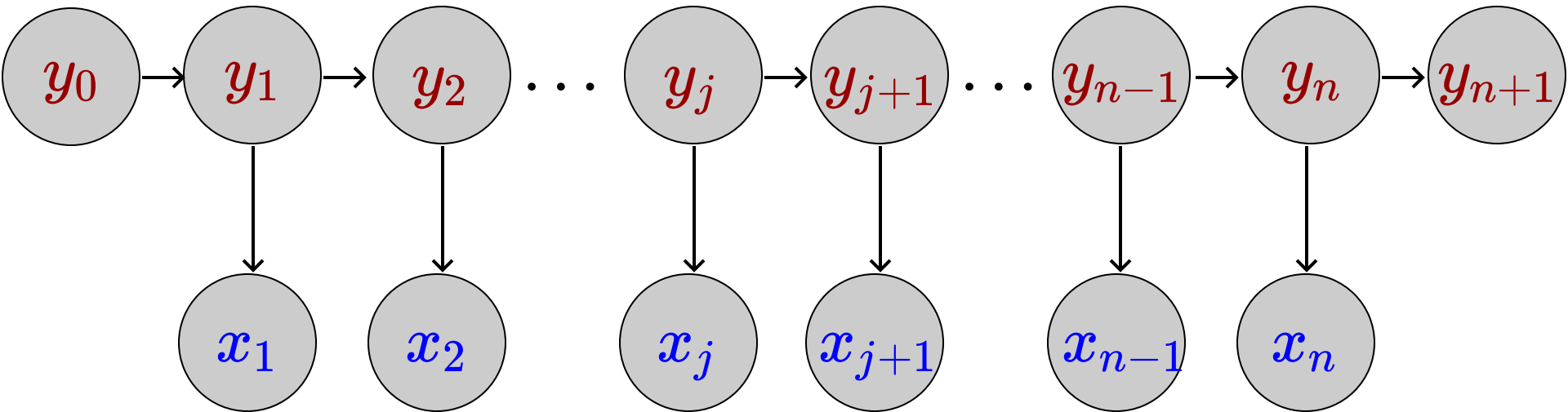
Number of times we see a transition from  $u$  to  $v$

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

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

Number of times we see the state  $u$  in the training set

# Hidden Markov Model



Number of times we see observation  $o$  generated from  $u$



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

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



Number of times we see the state  $u$  in the training set

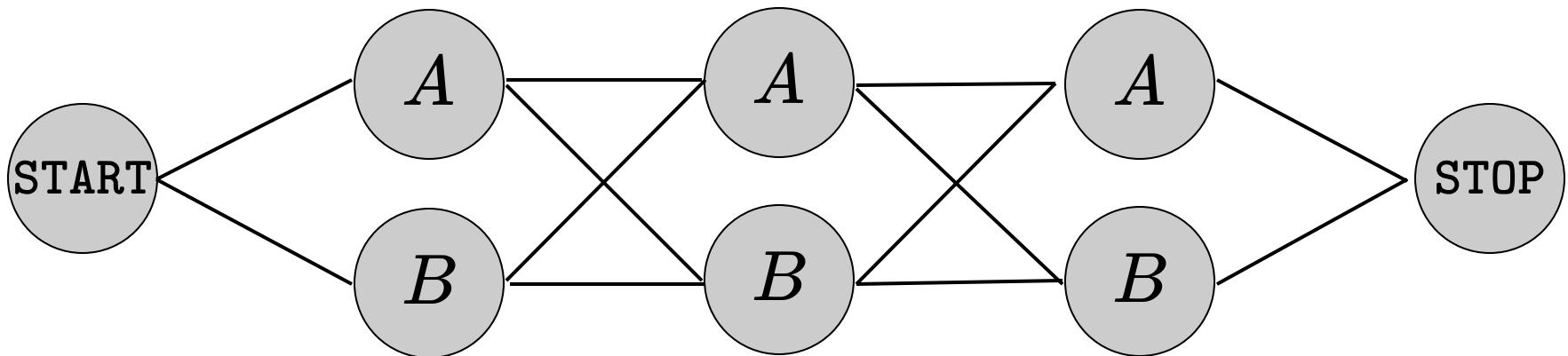
# Hidden Markov Model

$$a_{u,v} \qquad b_u(o)$$

$u \backslash v$	$A$	$B$	STOP
START	1.0	0.0	0.0
$A$	0.5	0.5	0.0
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$u \backslash o$	“the”	“dog”
$A$	0.9	0.1
$B$	0.1	0.9

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



Which label sequence  $\mathbf{y}$  is the most probable given the word sequence  $\mathbf{x}$ ? <sup>45</sup>

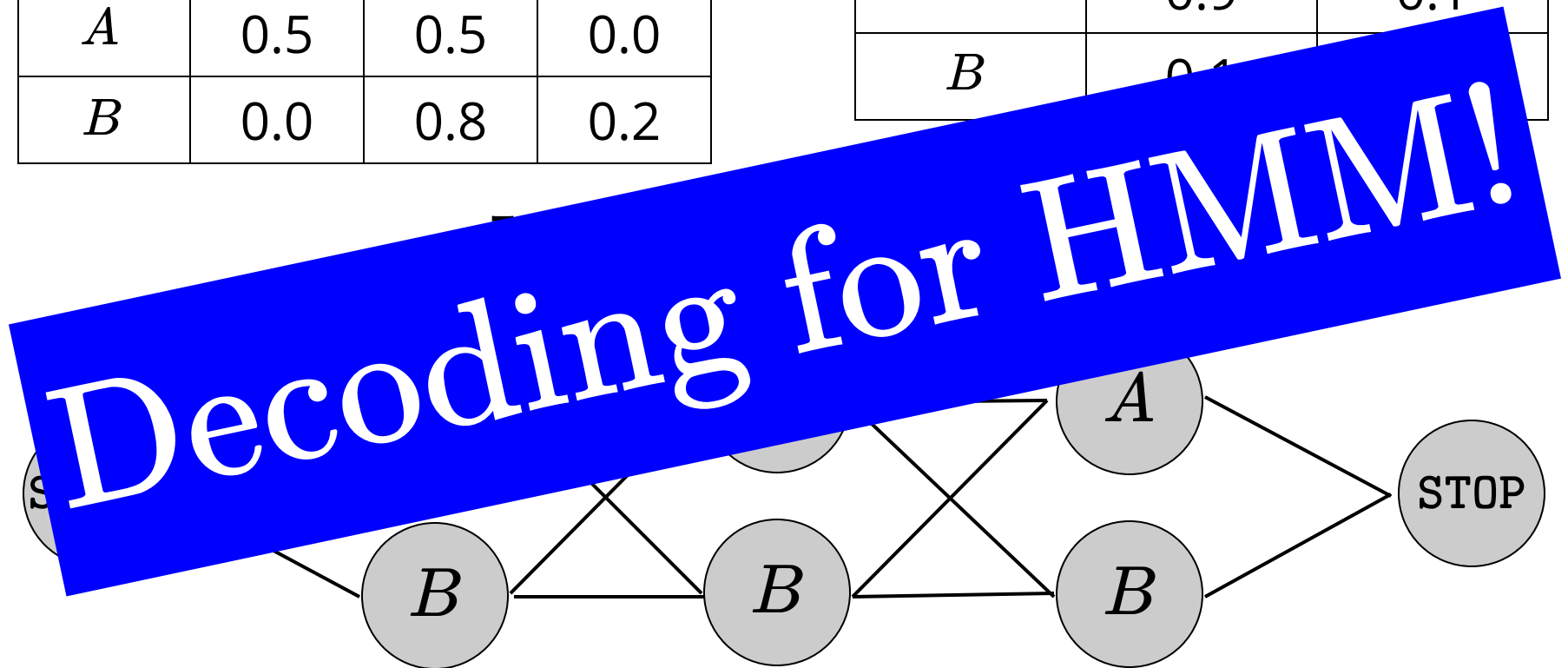
# Hidden Markov Model

$a_{u,v}$

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$b_u(o)$

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