

50.007 Machine Learning

Hidden Markov Model

(Adapted from Prof. Lu Wei's slides)

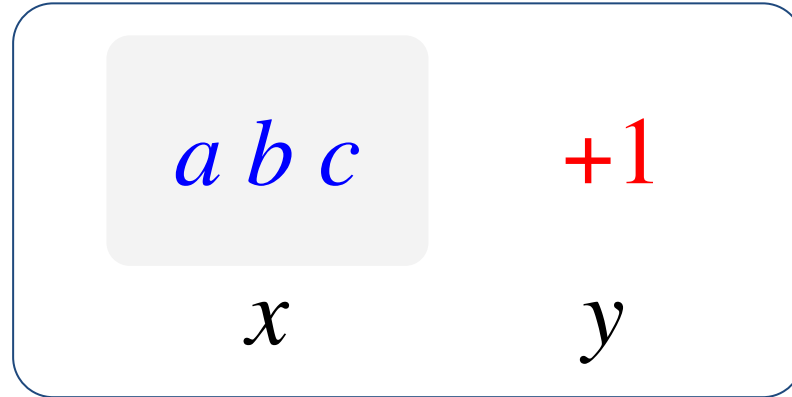
Roy Ka-Wei Lee

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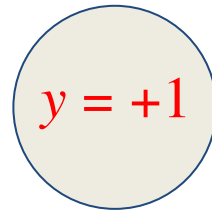
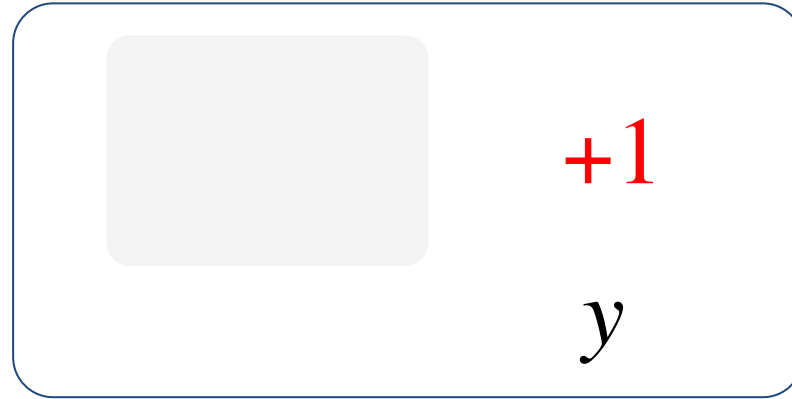


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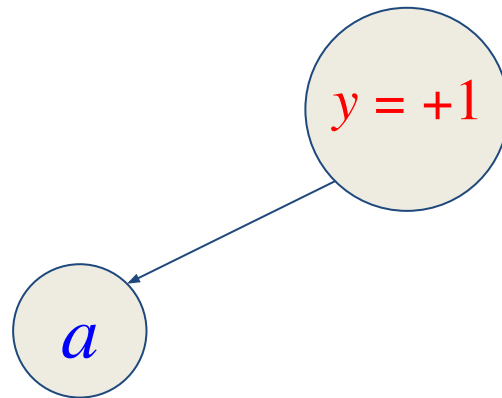
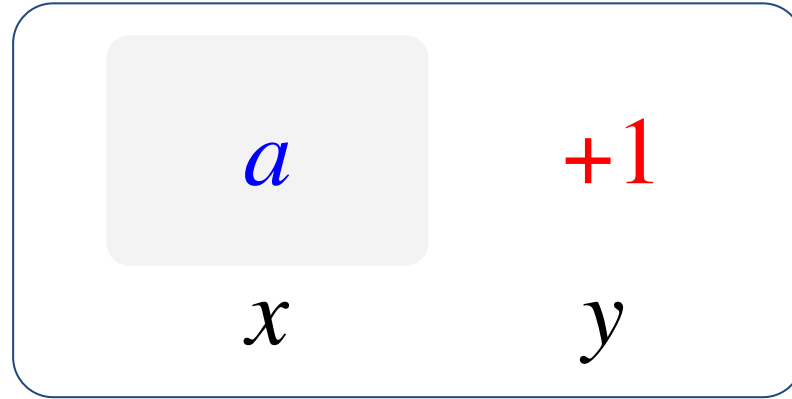
Generative Models



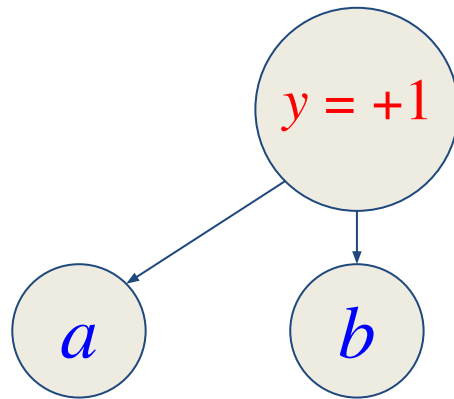
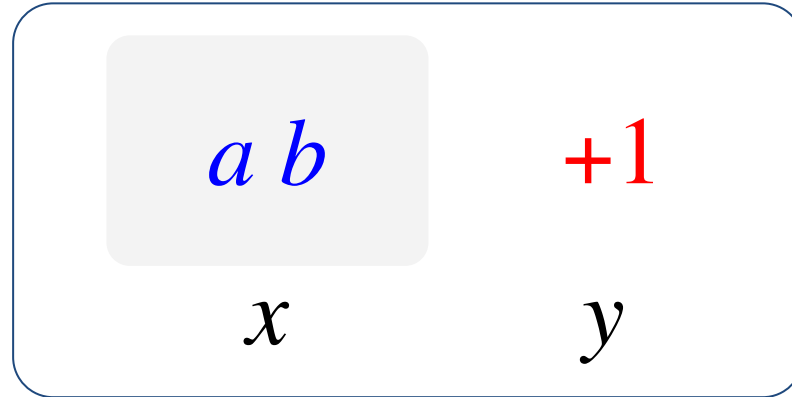
Generative Models



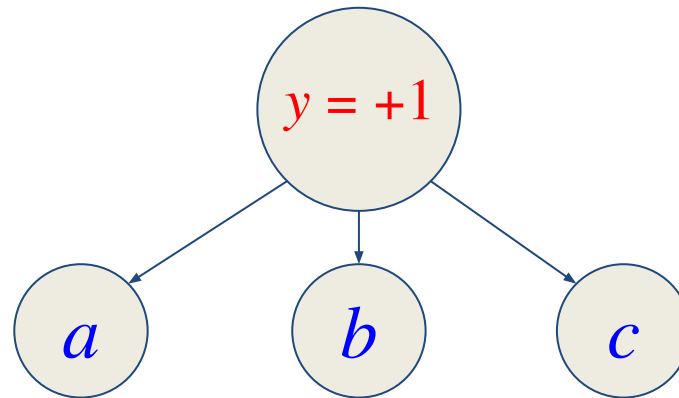
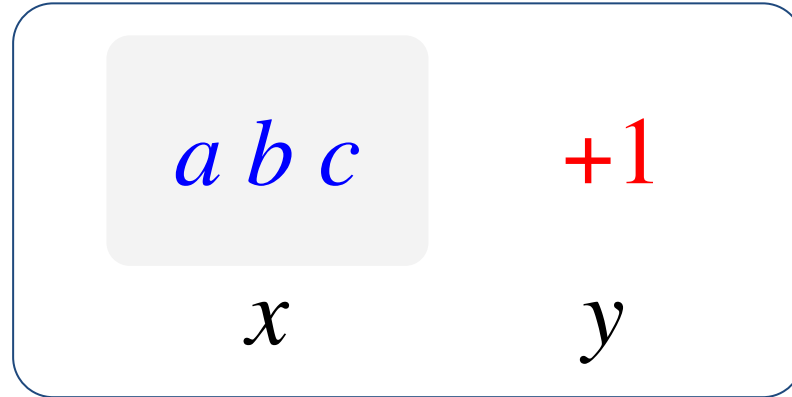
Generative Models



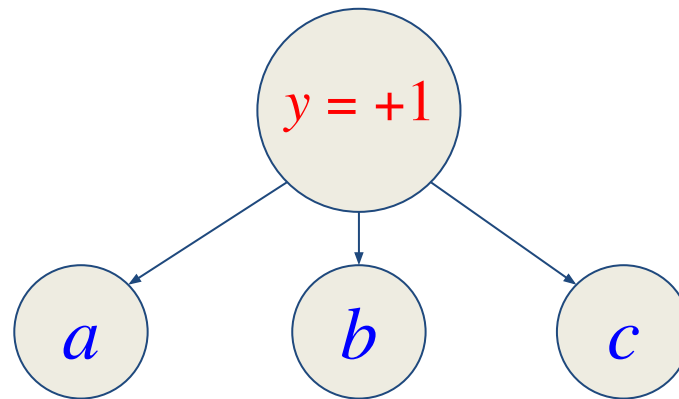
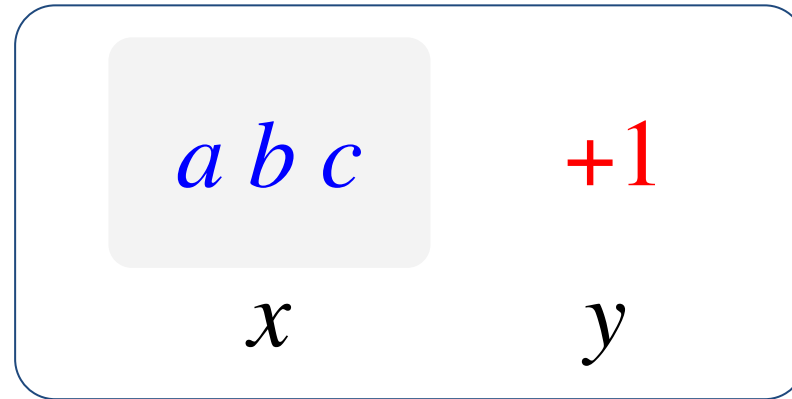
Generative Models



Generative Models

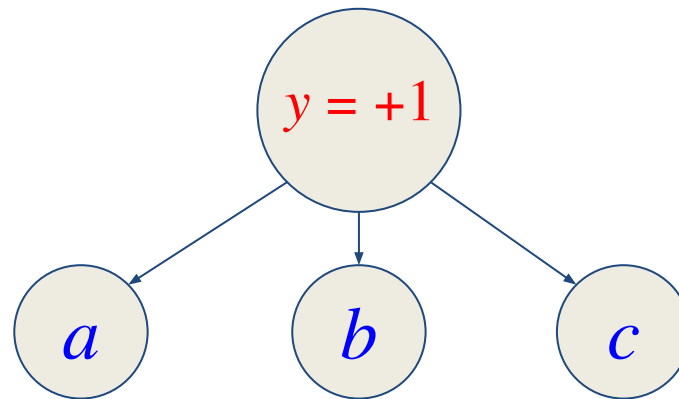
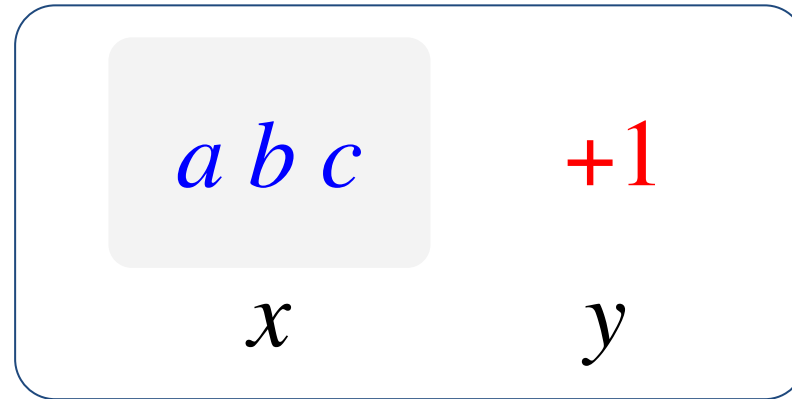


Generative Models



$$p(x = "a, b, c", y = +1)$$

Generative Models



$$p(x = "a, b, c", y = +1) = p(y = +1) p(a | y = +1) p(b | y = +1) p(c | y = +1)$$

Sequence Labeling

Faith is a fine invention

Sequence Labeling

Noun

Verb

Determiner

Adjective

Noun

N

V

D

A

N

Faith

is

a

fine

invention

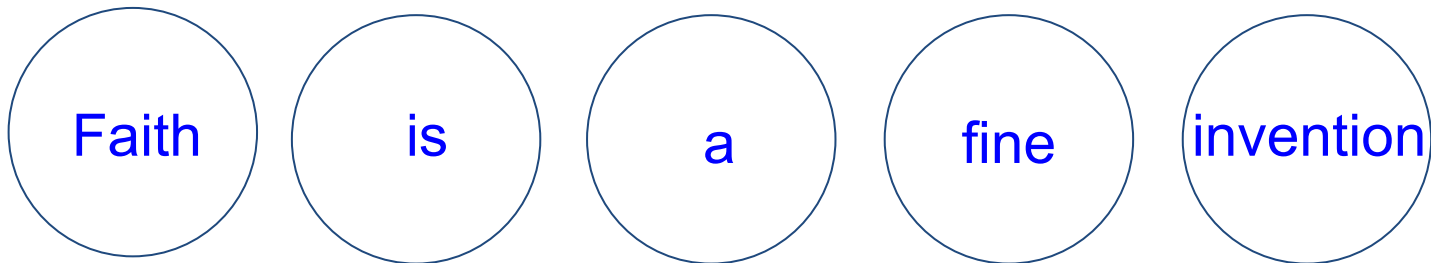
Sequence Labeling



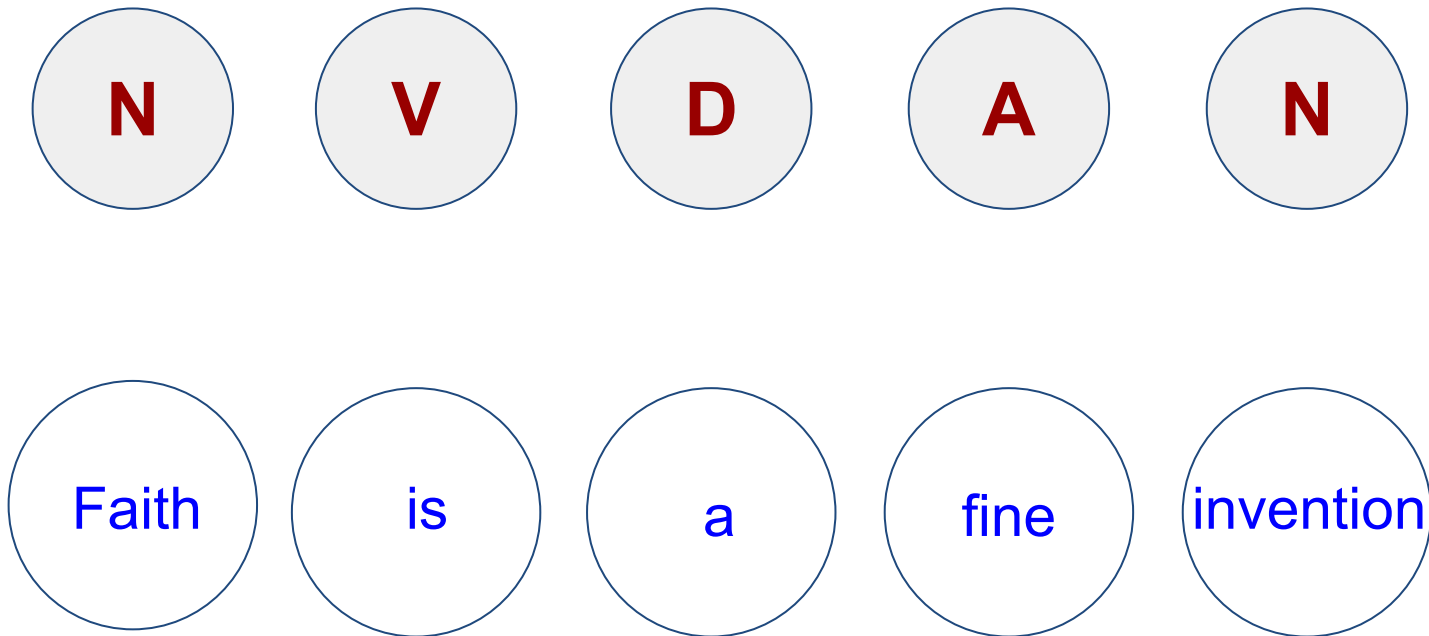
Sequence Labeling



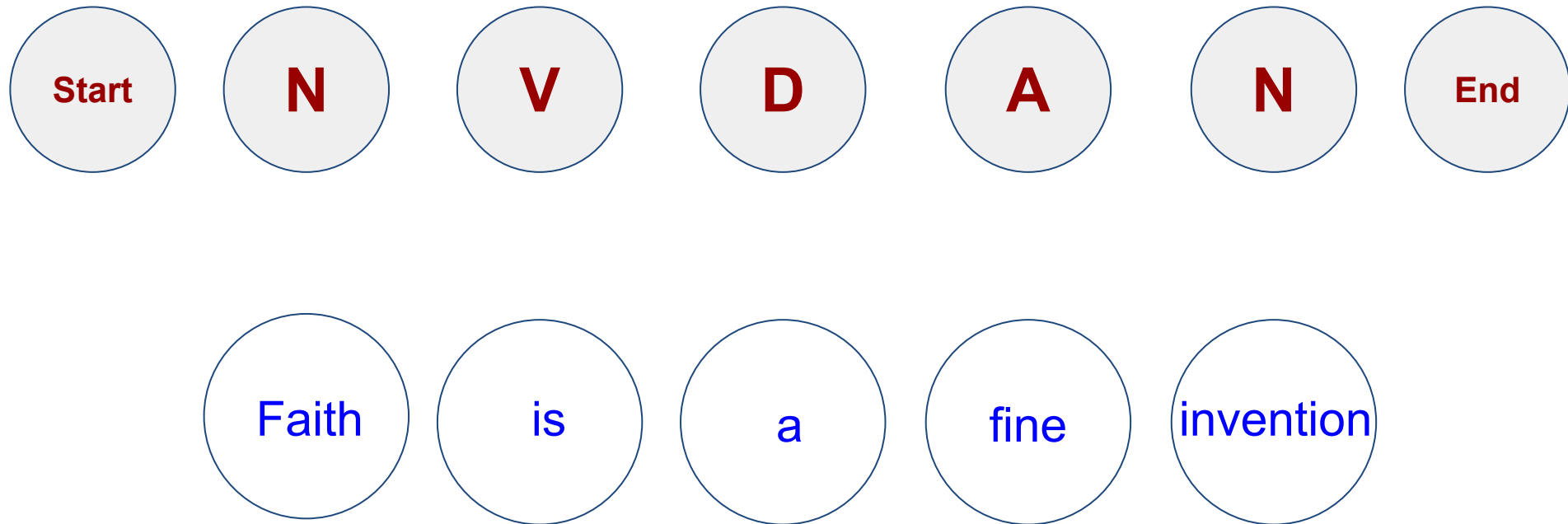
Sequence Labeling



Sequence Labeling



Sequence Labeling

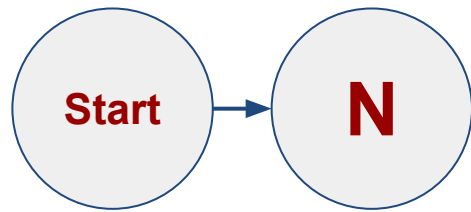


Sequence Labeling

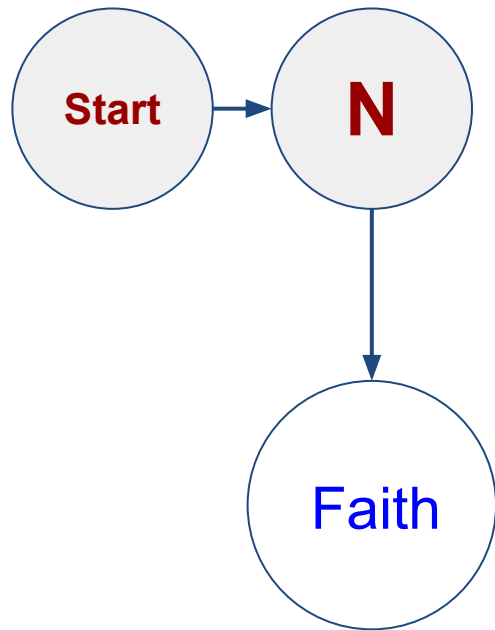


Start

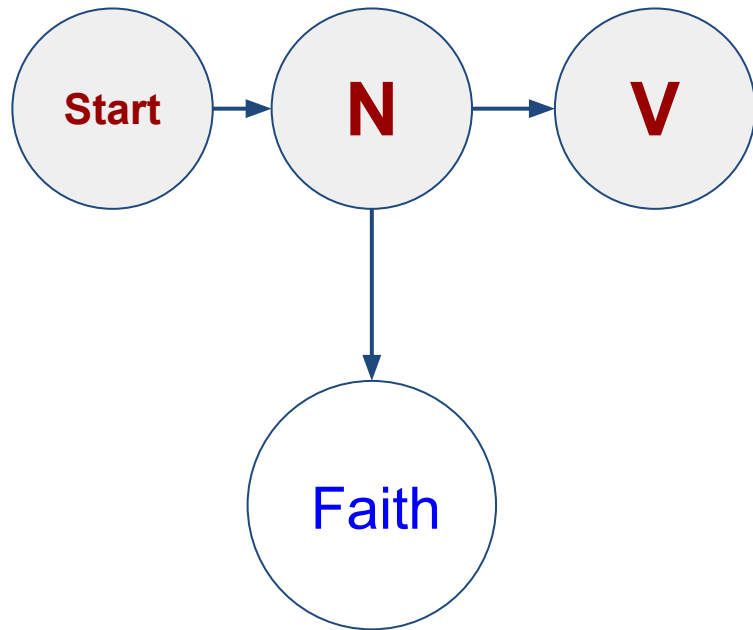
Sequence Labeling



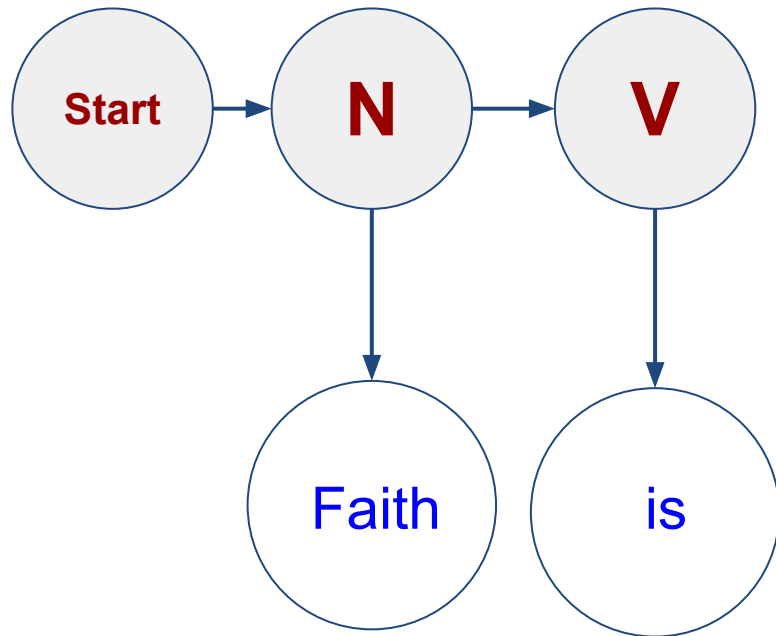
Sequence Labeling



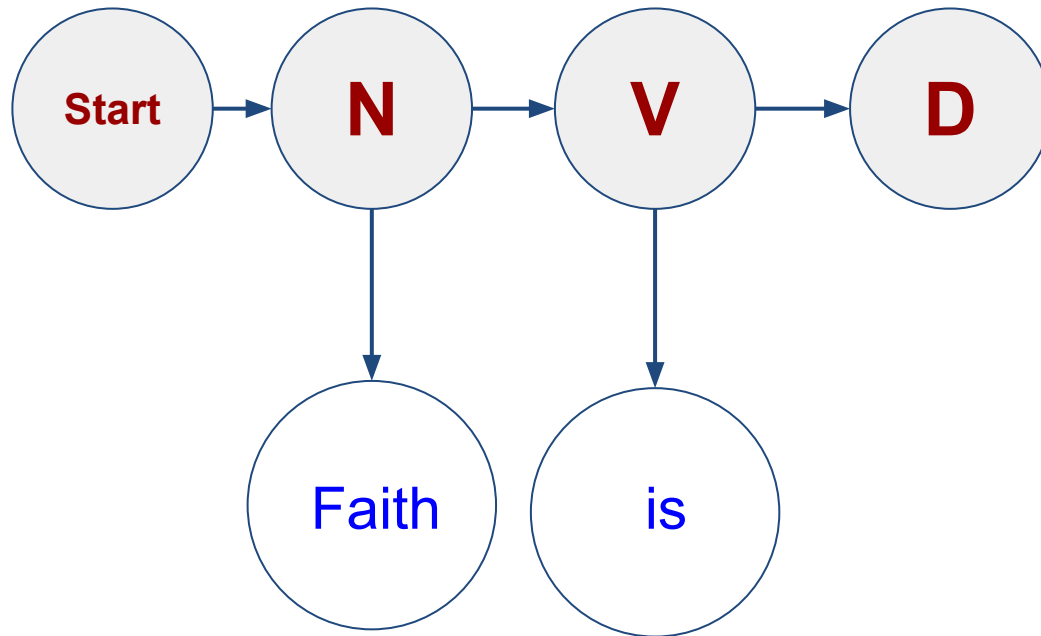
Sequence Labeling



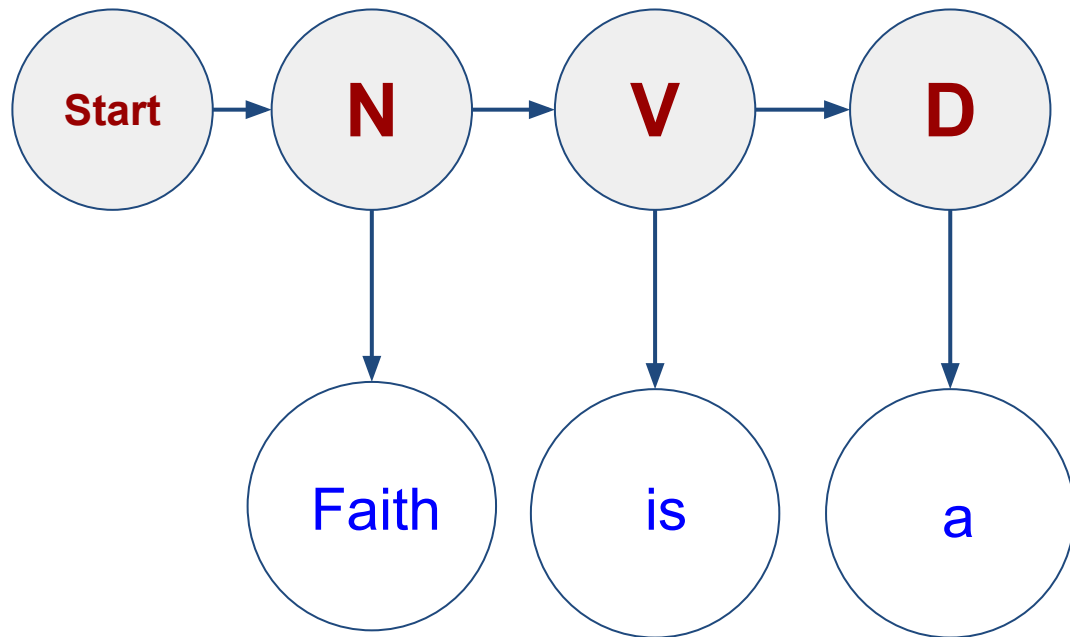
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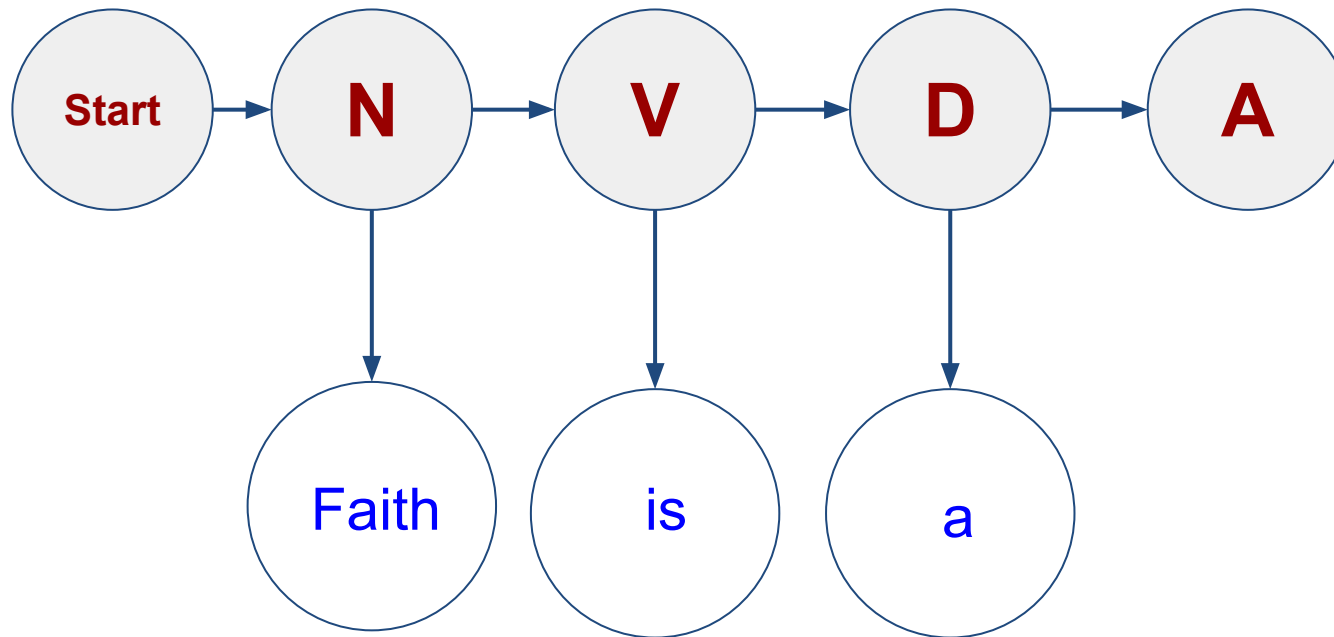
Sequence Labeling



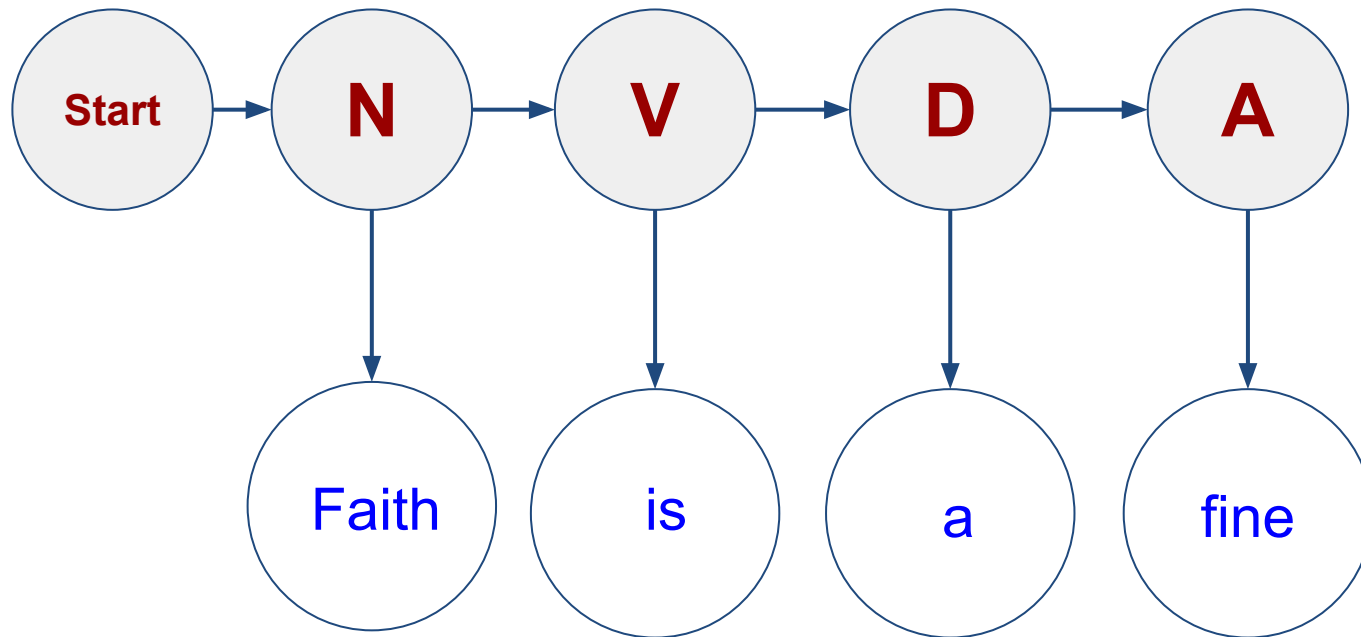
Sequence Labeling



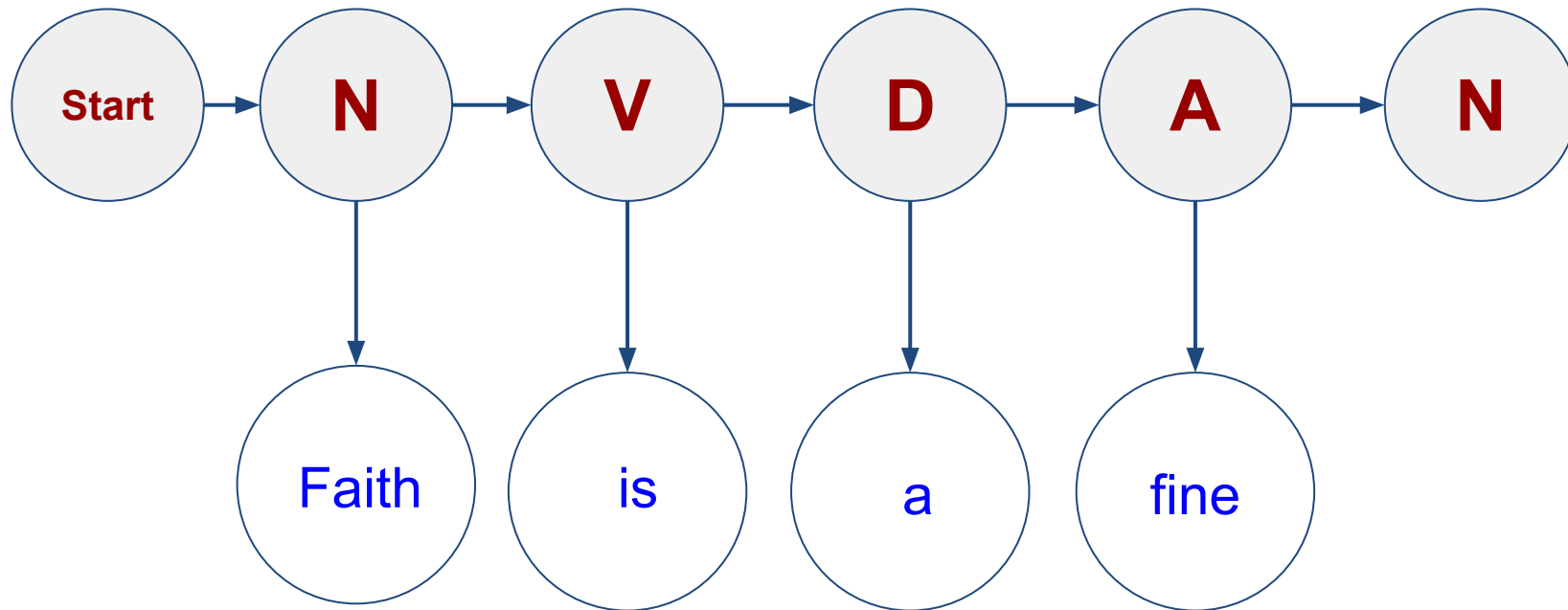
Sequence Labeling



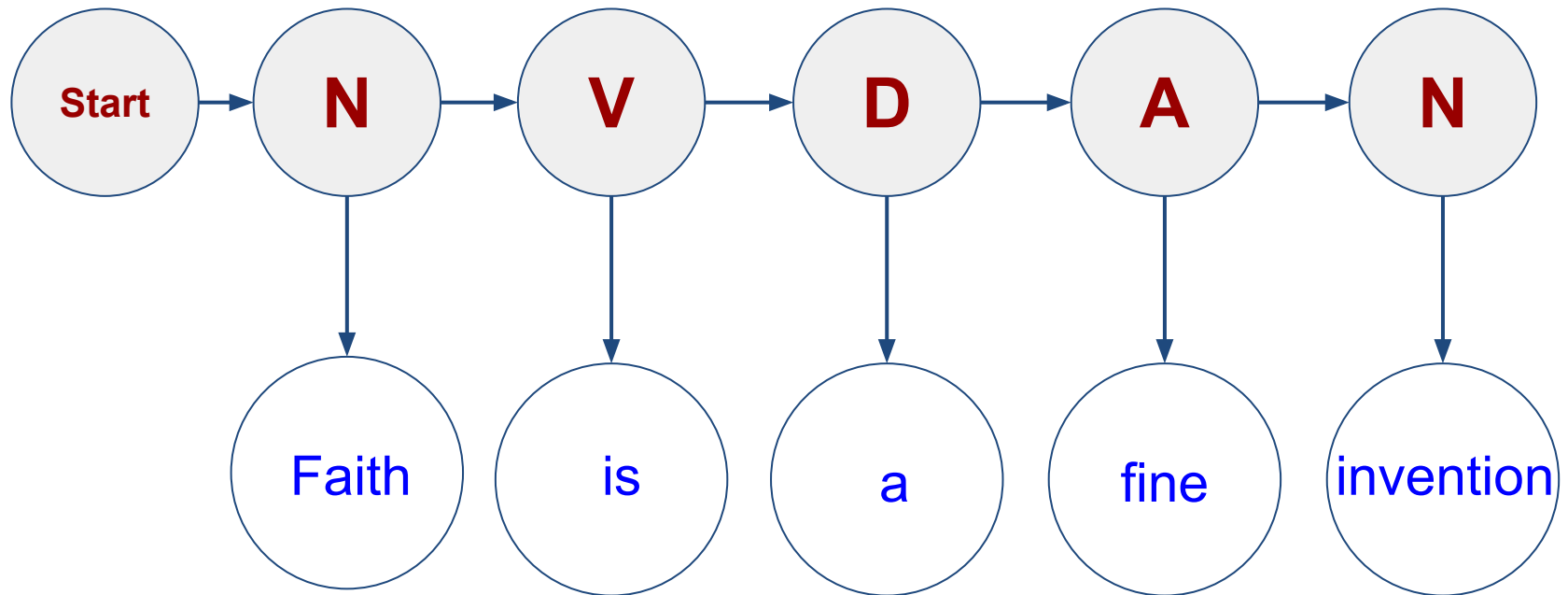
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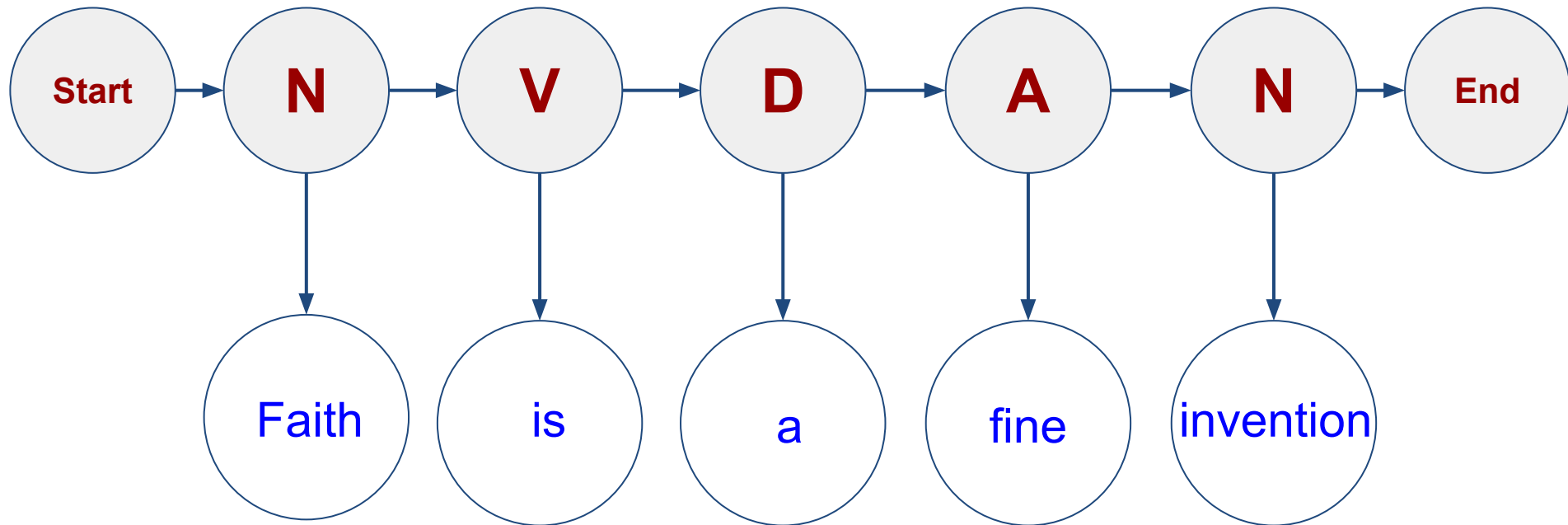
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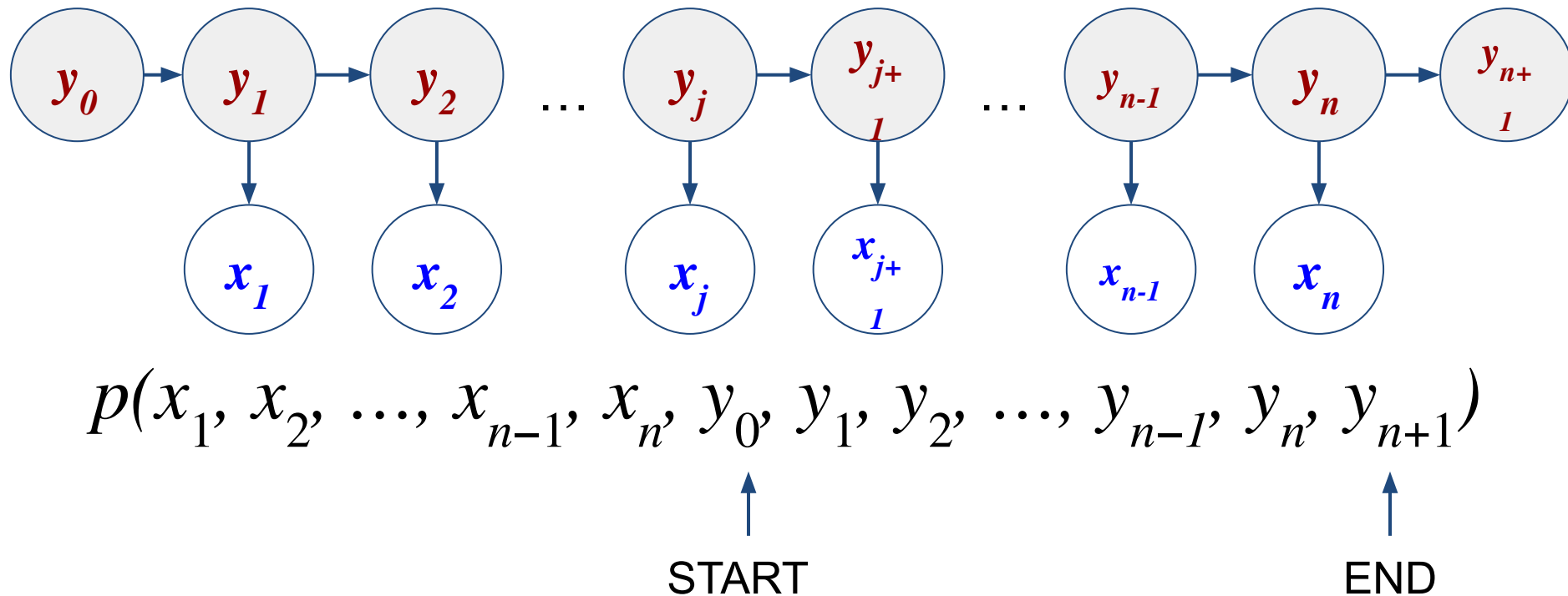
Sequence Labeling



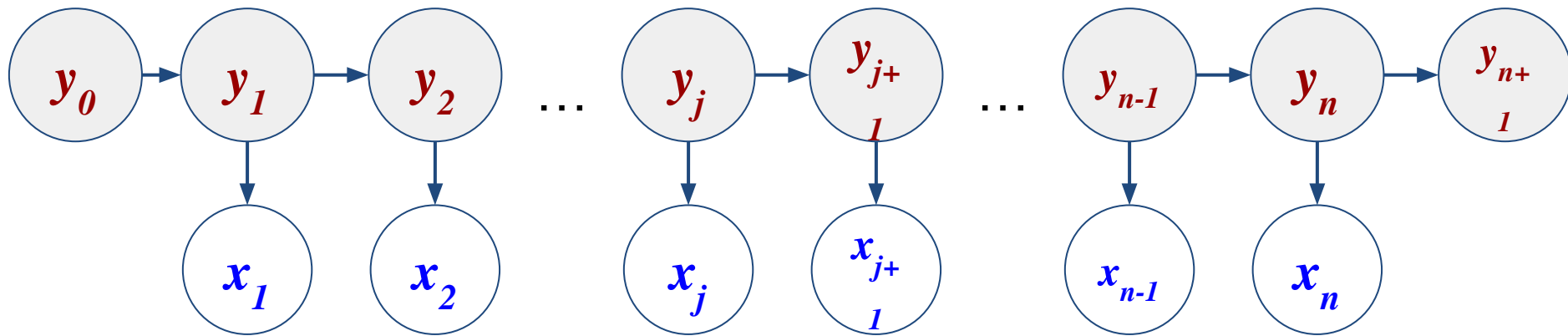
Sequence Labeling



Sequence Labeling



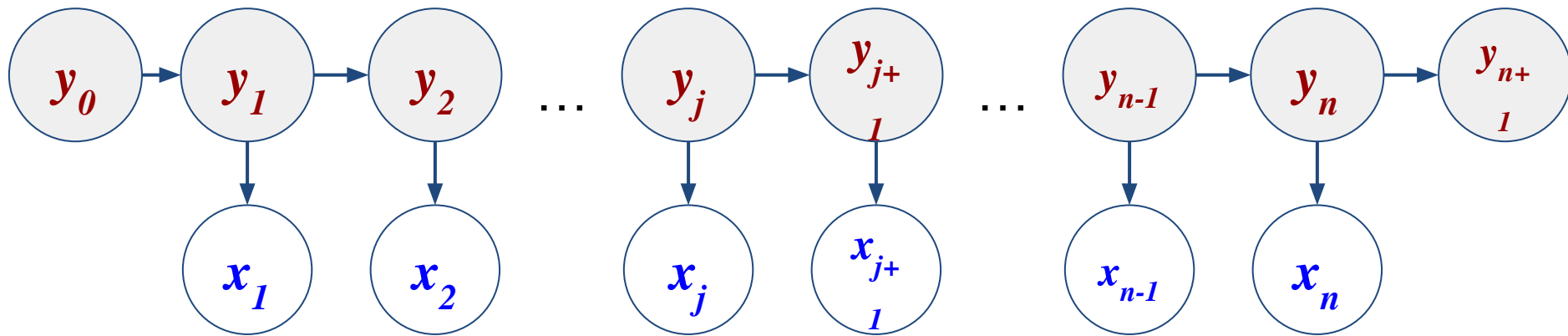
Sequence Labeling



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

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

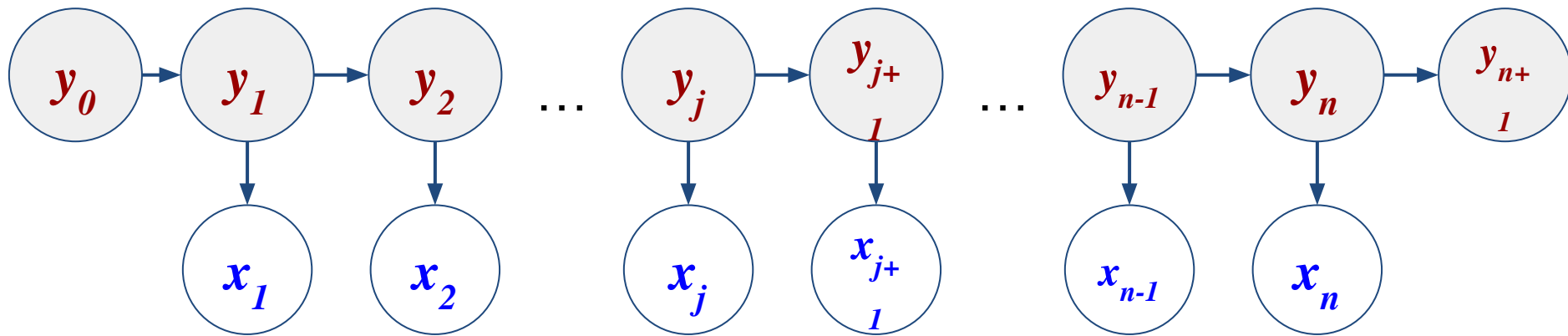
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Sequence Labeling



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

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 END states
 - \mathcal{O} : a set of observation symbols
 - θ : Transition and emission parameters $a_{u,v}$, and $b_u(o)$

Hidden Markov Model (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 (Example)

$a_{u,v}$

$u \backslash v$	A	B	STOP
START	1.0	0.0	0.0
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$b_u(o)$

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



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

Hidden Markov Model (Example)

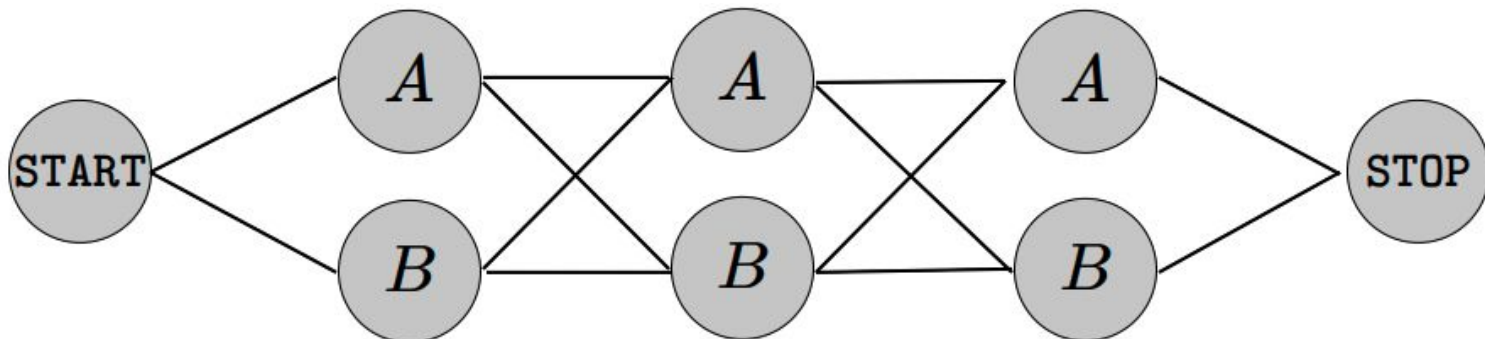
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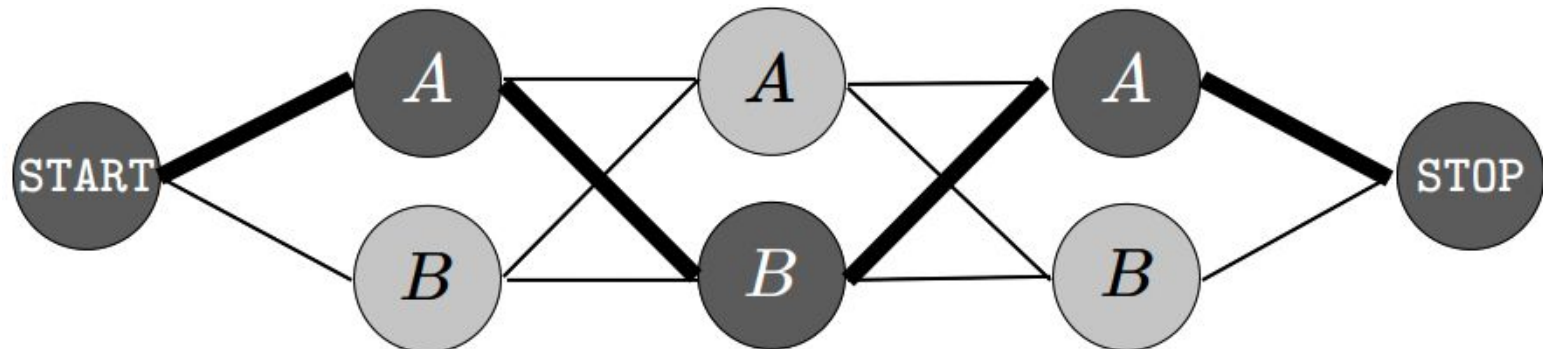
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$a_{\text{START},A}$

Hidden Markov Model (Example)

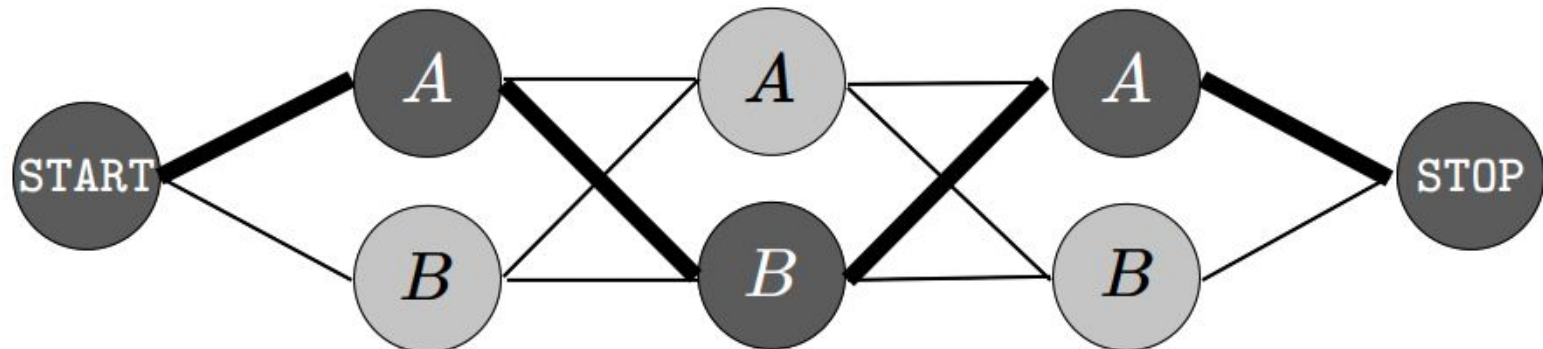
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$a_{\text{START},A} \times b_A(\text{“the”})$

Hidden Markov Model (Example)

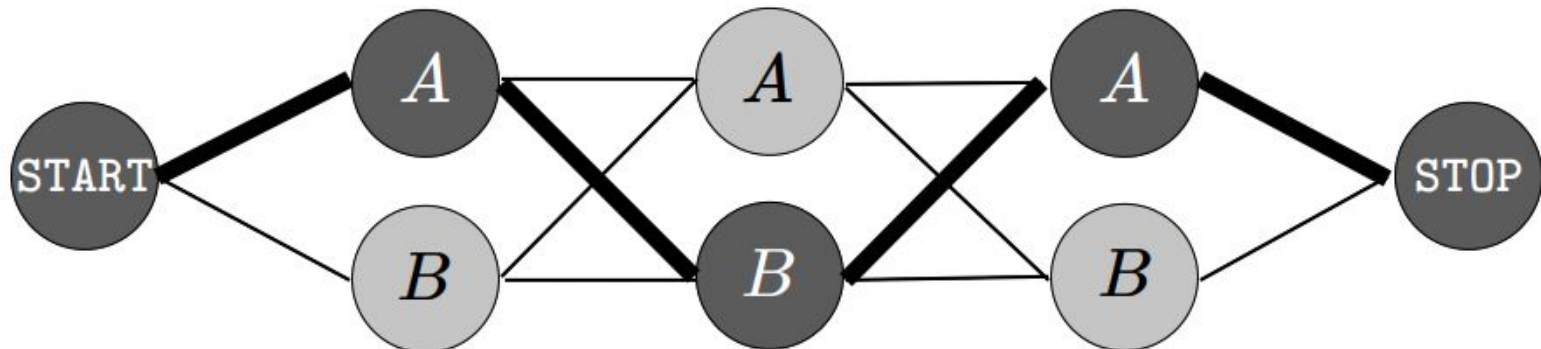
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$(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$



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

Hidden Markov Model (Example)

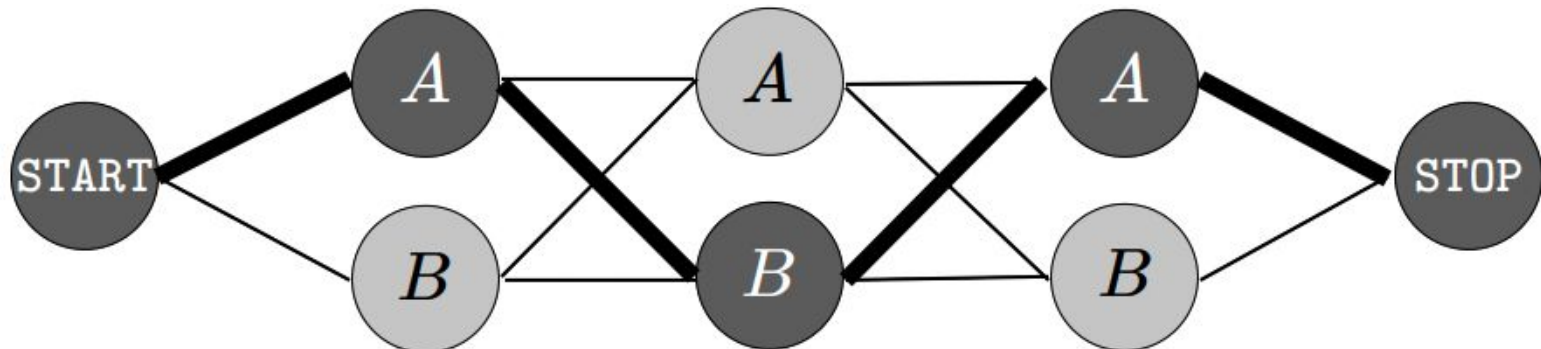
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$$a_{\text{START},A} \times b_A(\text{“the”}) \times a_{A,B} \times b_B(\text{“dog”})$$

Hidden Markov Model (Example)

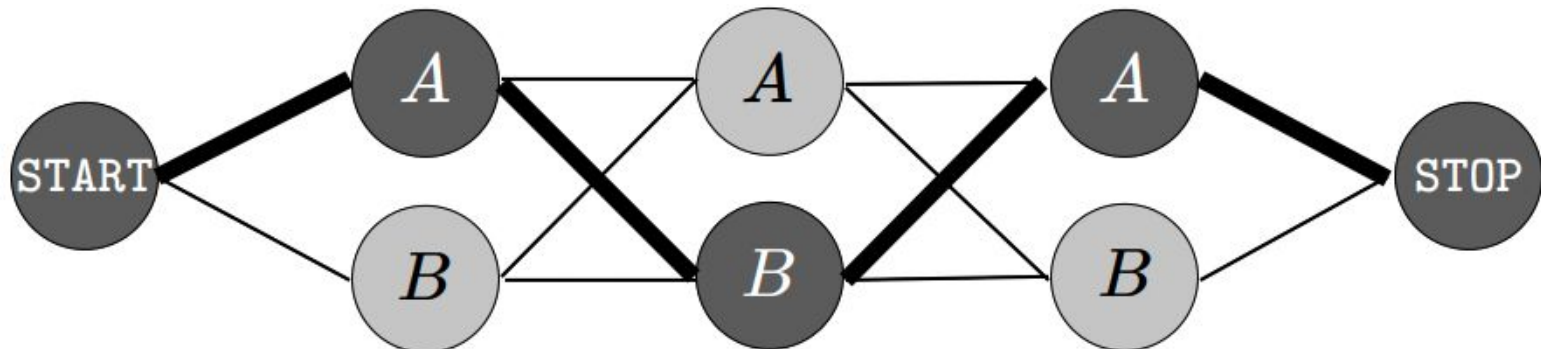
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$$a_{\text{START},A} \times b_A(\text{“the”}) \times a_{A,B} \times b_B(\text{“dog”}) \times a_{B,A}$$

Hidden Markov Model (Example)

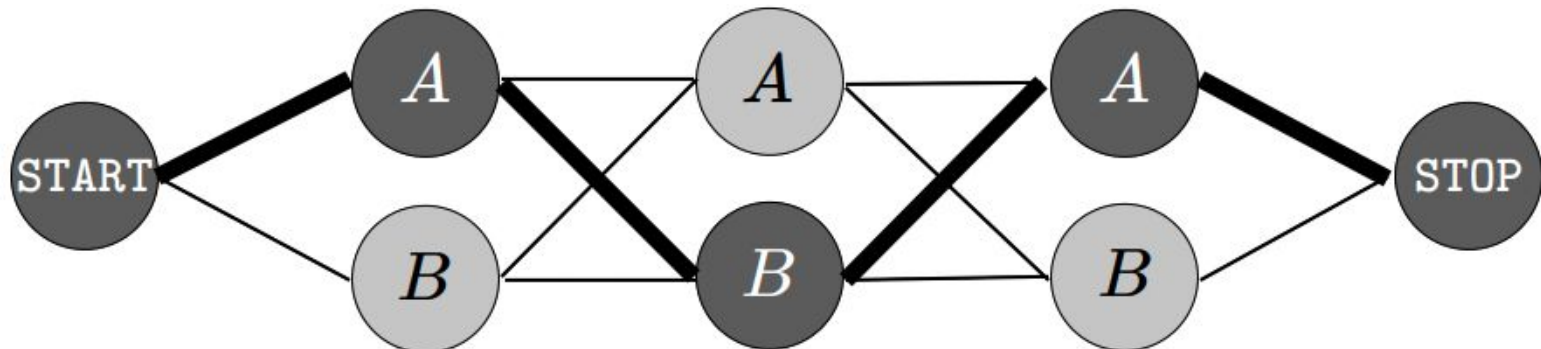
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$(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$



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

Hidden Markov Model (Example)

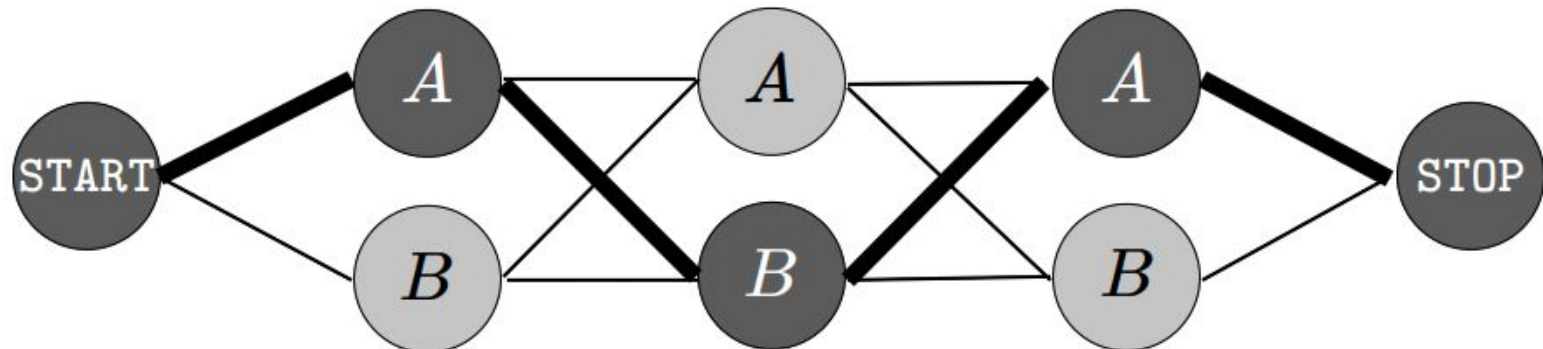
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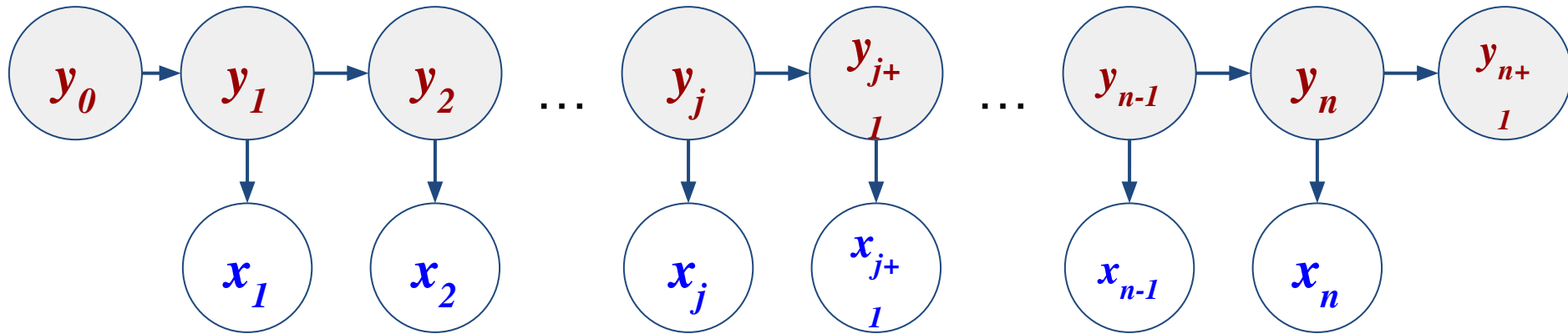
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A	0.9	0.1
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$(\mathbf{x}, \mathbf{y}) = \text{the}/A, \text{dog}/B, \text{the}/A$



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

Hidden Markov Model

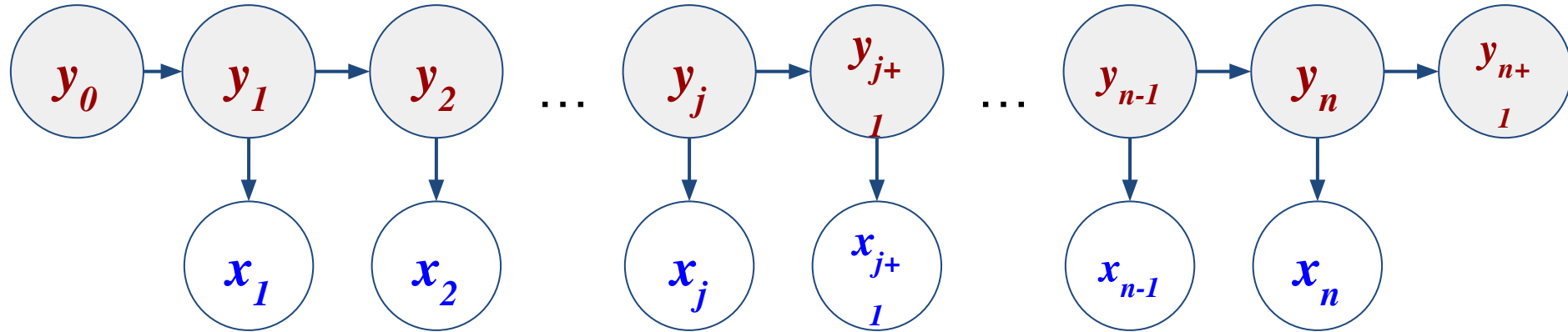


$$p(\mathbf{x}, \mathbf{y}) = \underbrace{\prod_{j=0}^n a_{y_j, y_{j+1}}}_{\text{Transition probabilities}} \times \underbrace{\prod_{j=1}^n b_{y_j}(x_j)}_{\text{Emission probabilities}}$$



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

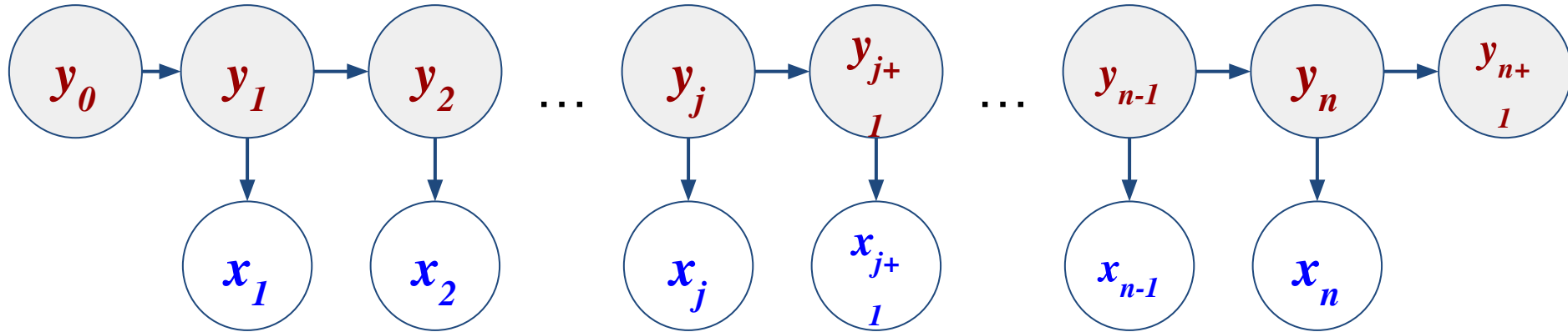
Hidden Markov Model



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

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

Hidden Markov Model



Number of times we see
a transition from u to v

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

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

Number of times we see
observation o generated from 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

$$\begin{matrix} y^{(1)} \\ x^{(1)} \end{matrix} = \begin{matrix} (A, B) \\ (e, g) \end{matrix}$$

$$\begin{matrix} y^{(2)} \\ x^{(2)} \end{matrix} = \begin{matrix} (A, B) \\ (e, h) \end{matrix}$$

$$\begin{matrix} y^{(3)} \\ x^{(3)} \end{matrix} = \begin{matrix} (A, B) \\ (f, h) \end{matrix}$$

$$\begin{aligned} & a_{\text{START},A} \times b_A(e) \times a_{A,B} \times b_B(g) \times a_{B,\text{STOP}} \\ & \times a_{\text{START},A} \times b_A(e) \times a_{A,B} \times b_B(h) \times a_{B,\text{STOP}} \\ & \times a_{\text{START},A} \times b_A(f) \times a_{A,B} \times b_B(h) \times a_{B,\text{STOP}} \end{aligned}$$

(1) Write down the likelihood

Hidden Markov Model

$$\begin{array}{lll} y^{(1)} = (A, B) & y^{(2)} = (A, B) & y^{(3)} = (A, B) \\ x^{(1)} = (e, g) & x^{(2)} = (e, h) & x^{(3)} = (f, h) \end{array}$$

$$\begin{aligned} & a_{\text{START},A} \times b_A(e) \times a_{A,B} \times b_B(g) \times a_{B,\text{STOP}} \\ & \times a_{\text{START},A} \times b_A(e) \times a_{A,B} \times b_B(h) \times a_{B,\text{STOP}} \\ & \times a_{\text{START},A} \times b_A(f) \times a_{A,B} \times b_B(h) \times a_{B,\text{STOP}} \end{aligned}$$

Hidden Markov Model

$$\begin{array}{lll} y^{(1)} &= & (A, B) \\ x^{(1)} &= & (e, g) \end{array} \quad \begin{array}{lll} y^{(2)} &= & (A, B) \\ x^{(2)} &= & (e, h) \end{array} \quad \begin{array}{lll} y^{(3)} &= & (A, B) \\ x^{(3)} &= & (f, h) \end{array}$$

$$\begin{aligned} & (a_{\text{START},A})^3 \times (a_{A,B})^3 \times (a_{B,\text{STOP}})^3 \\ & \times (b_A(f))^1 \times (b_A(e))^2 \\ & \times (b_B(h))^2 \times (b_B(g))^1 \end{aligned}$$

Hidden Markov Model

$$\begin{array}{l} y^{(1)} \\ x^{(1)} \end{array} = \begin{array}{l} (A, B) \\ (e, g) \end{array} \quad \begin{array}{l} y^{(2)} \\ x^{(2)} \end{array} = \begin{array}{l} (A, B) \\ (e, h) \end{array} \quad \begin{array}{l} y^{(3)} \\ x^{(3)} \end{array} = \begin{array}{l} (A, B) \\ (f, h) \end{array}$$

$$(a_{\text{START},A})^3 \times (a_{A,B})^3 \times (a_{B,\text{STOP}})^3$$

$$\times (b_A(f))^1 \times (b_A(e))^2$$

$$\times (b_B(h))^2 \times (b_B(g))^1$$

Hidden Markov Model

$$\begin{array}{ccc} y^{(1)} & = & (A, B) \\ x^{(1)} & = & (e, g) \end{array} \quad \begin{array}{ccc} y^{(2)} & = & (A, B) \\ x^{(2)} & = & (e, h) \end{array} \quad \begin{array}{ccc} y^{(3)} & = & (A, B) \\ x^{(3)} & = & (f, h) \end{array}$$

$$\begin{aligned} & (a_{\text{START}, A})^{\text{Count}(\text{START}, A)} \\ & \times (a_{A, B})^{\text{Count}(A, B)} \\ & \times (a_{B, \text{STOP}})^{\text{Count}(B, \text{STOP})} \end{aligned}$$

Hidden Markov Model

$$\begin{matrix} y^{(1)} \\ x^{(1)} \end{matrix} = \begin{pmatrix} A, B \\ e, g \end{pmatrix}$$

$$\begin{matrix} y^{(2)} \\ x^{(2)} \end{matrix} = \begin{pmatrix} A, B \\ e, h \end{pmatrix}$$

$$\begin{matrix} y^{(3)} \\ x^{(3)} \end{matrix} = \begin{pmatrix} A, B \\ f, h \end{pmatrix}$$

$$\prod_{u,v} (a_{u,v})^{\text{Count}(u,v)}$$

Hidden Markov Model

$$\begin{matrix} y^{(1)} \\ x^{(1)} \end{matrix} = \begin{pmatrix} A, B \\ e, g \end{pmatrix}$$

$$\begin{matrix} y^{(2)} \\ x^{(2)} \end{matrix} = \begin{pmatrix} A, B \\ e, h \end{pmatrix}$$

$$\begin{matrix} y^{(3)} \\ x^{(3)} \end{matrix} = \begin{pmatrix} A, B \\ f, h \end{pmatrix}$$

$$\prod_{u,v} (a_{u,v})^{\text{Count}(u,v)} \\ \times \prod_{u,o} (b_u(o))^{\text{Count}(u \rightarrow o)}$$

(2) This is the likelihood. We can consider the log-likelihood.

Hidden Markov Model

$$\begin{array}{lll} y^{(1)} &= & (A, B) \\ x^{(1)} &= & (e, g) \end{array} \quad \begin{array}{lll} y^{(2)} &= & (A, B) \\ x^{(2)} &= & (e, h) \end{array} \quad \begin{array}{lll} y^{(3)} &= & (A, B) \\ x^{(3)} &= & (f, h) \end{array}$$

$$\sum_{u,v} \text{Count}(u, v) \log(a_{u,v}) \\ + \sum_{u,o} \text{Count}(u \rightarrow o) \log(b_u(o))$$

(3) Next, take the partial derivative with respect to each individual parameter, and set it to zero. Solve the equation.

Hidden Markov Model

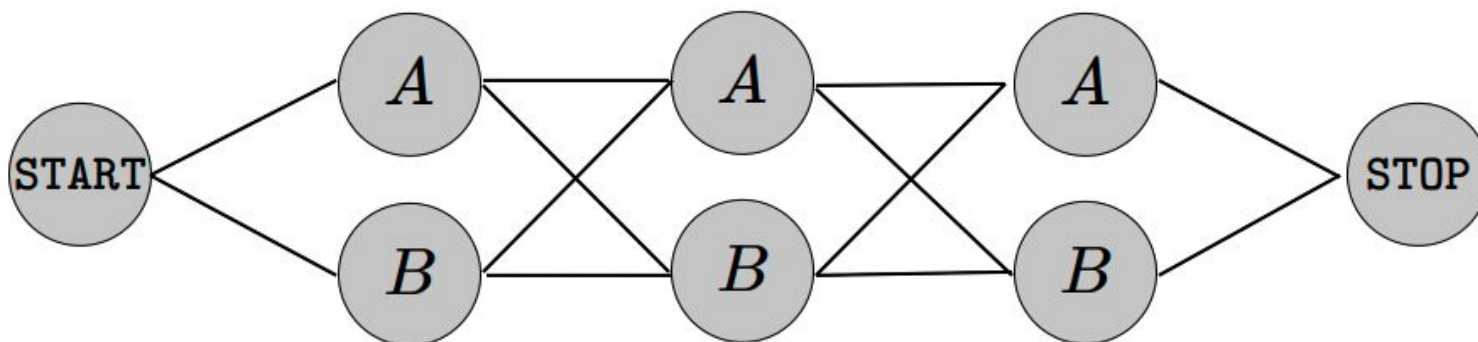
$a_{u,v}$

$u \backslash v$	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

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



Which label sequence \mathbf{y} is the most probable given the word sequence \mathbf{x} ?