

# Probabilistic Graphical Models

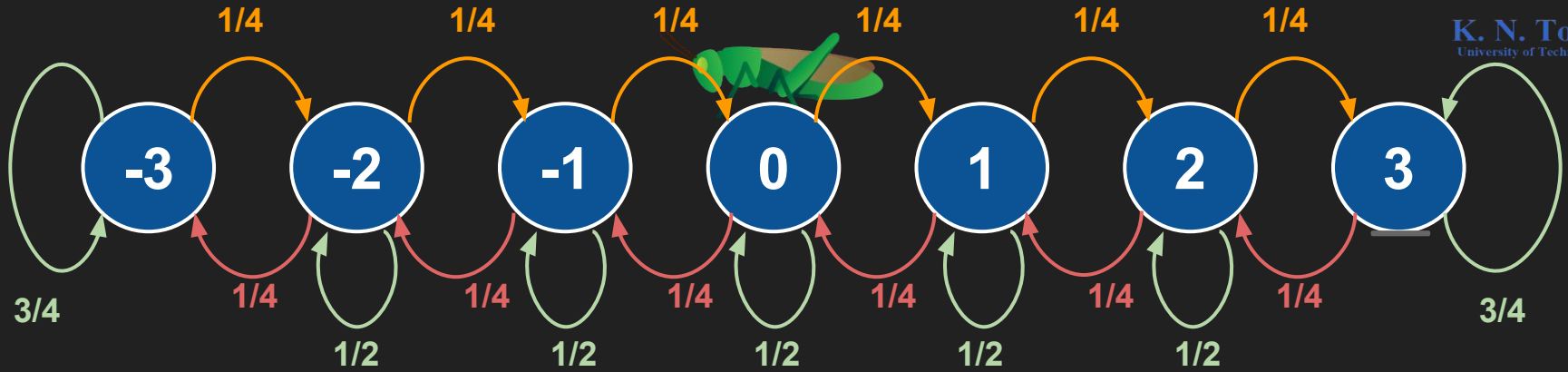
## Lectures 21

Markov Chain Monte Carlo  
Gibbs Sampling

# Sampling Using a Markov Chain (Koller)



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University of Technology

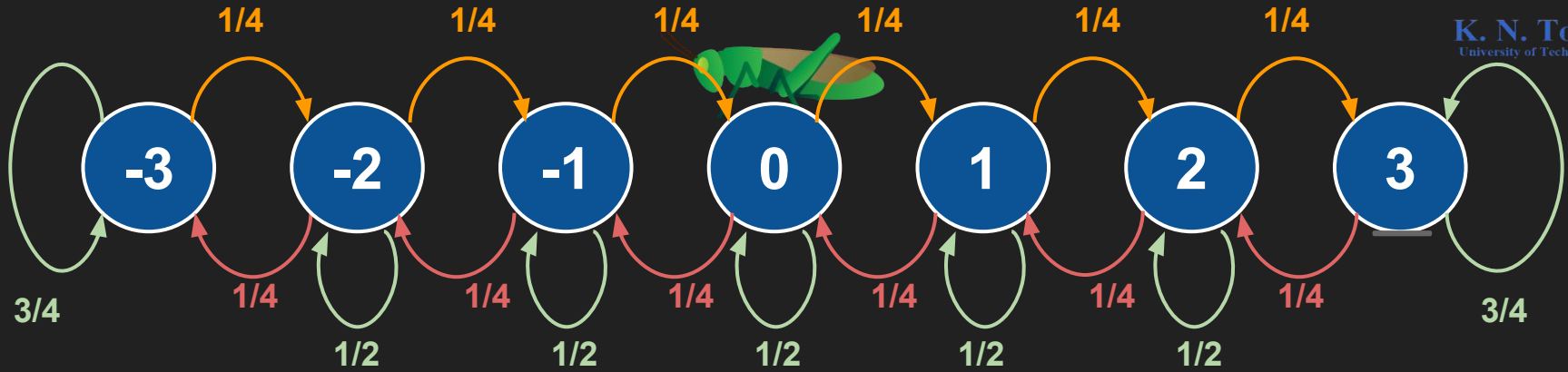


	-3	-2	-1	0	1	2	3
t=0	0	0	0	1	0	0	0
t=1							
t=2							

# Sampling Using a Markov Chain (Koller)



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University of Technology

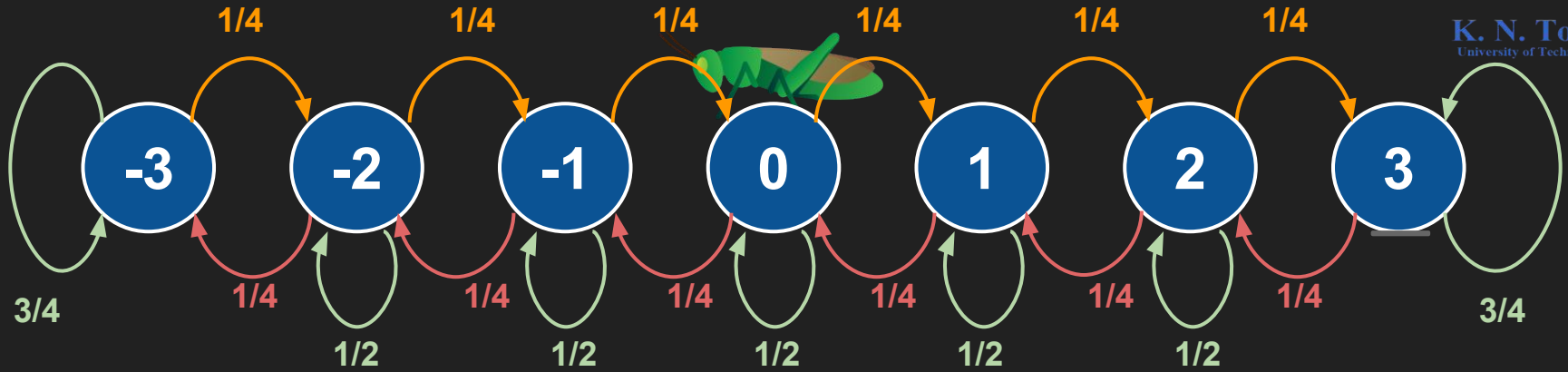


	-3	-2	-1	0	1	2	3
t=0	0	0	0	1	0	0	0
t=1	0	0	1/4	1/2	1/4	0	0
t=2							

# Sampling Using a Markov Chain (Koller)



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University of Technology

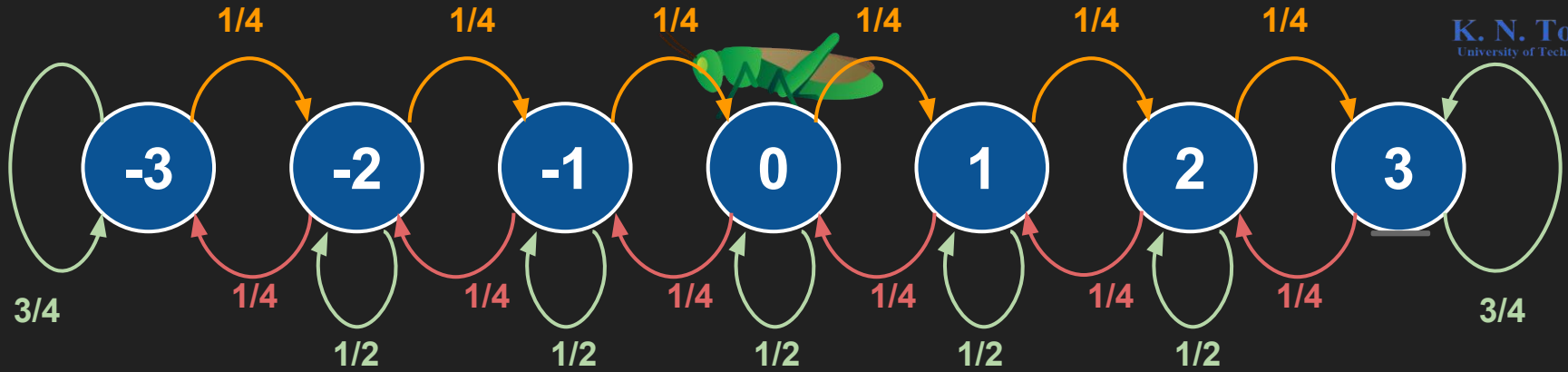


	-3	-2	-1	0	1	2	3
t=0	0	0	0	1	0	0	0
t=1	0	0	1/4	1/2	1/4	0	0
t=2	0	1/16	1/4	3/8	1/4	1/16	0

# Sampling Using a Markov Chain (Koller)

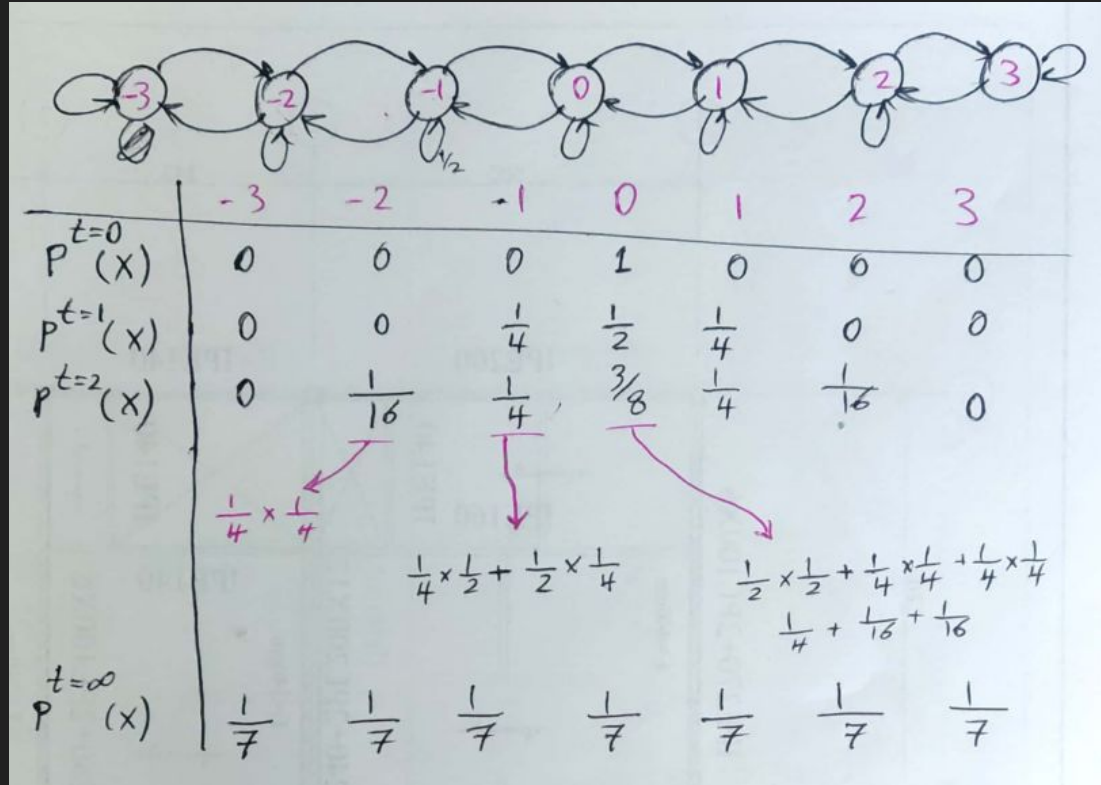


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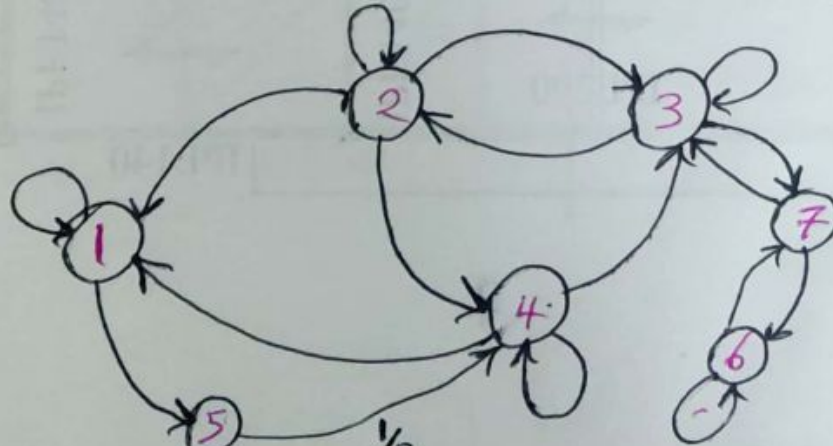


	-3	-2	-1	0	1	2	3
$t=0$	0	0	0	1	0	0	0
:	:	:	:	:	:	:	:
$t \rightarrow \infty$	$1/7$	$1/7$	$1/7$	$1/7$	$1/7$	$1/7$	$1/7$

# Sampling Using a Markov Chain



# State Transition Graph



$P(X)$

$X \in \{1, 2, 3, 4, 5, 6, 7\}$

$X_t =$  ~~stat~~ state  
current  
at time  $t$

$T_{5 \rightarrow 5} = \frac{2}{3}$

$\frac{1}{3} = T_{5 \rightarrow 4}$

$T_{5 \rightarrow 4} = \Pr(X_{t+1} = 4 \mid X_t = 5)$  independent of  $t$   
 $= \Pr(X_t = 4 \mid X_{t-1} = 5)$

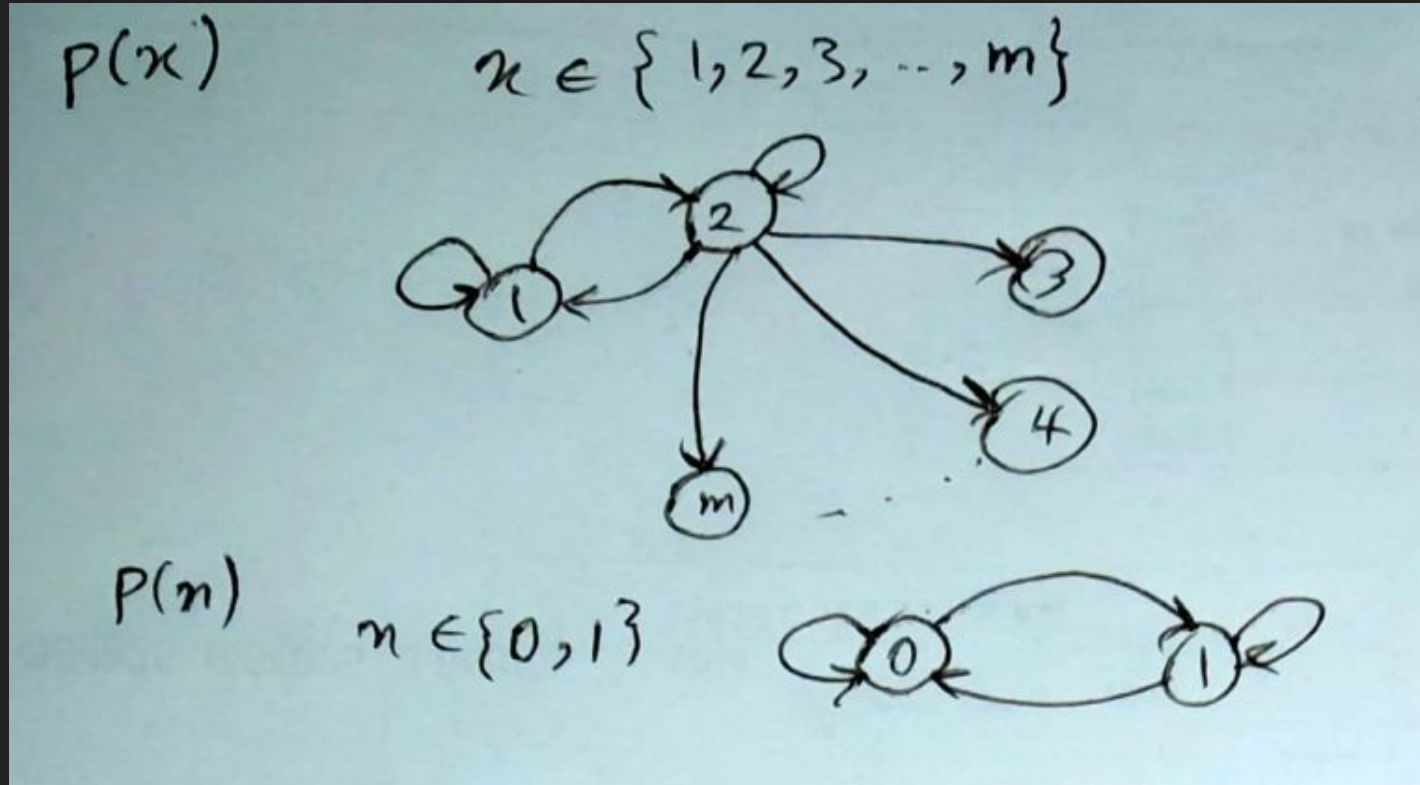
$\Pr(X_t = a) = \sum_{b=1}^7 P(X_t = a \mid X_{t-1} = b) P(X_{t-1} = b)$

$P(X_t = a \mid X_{t-1} = b) P(X_{t-1} = b)$

# State Transition Graph - Single Variable



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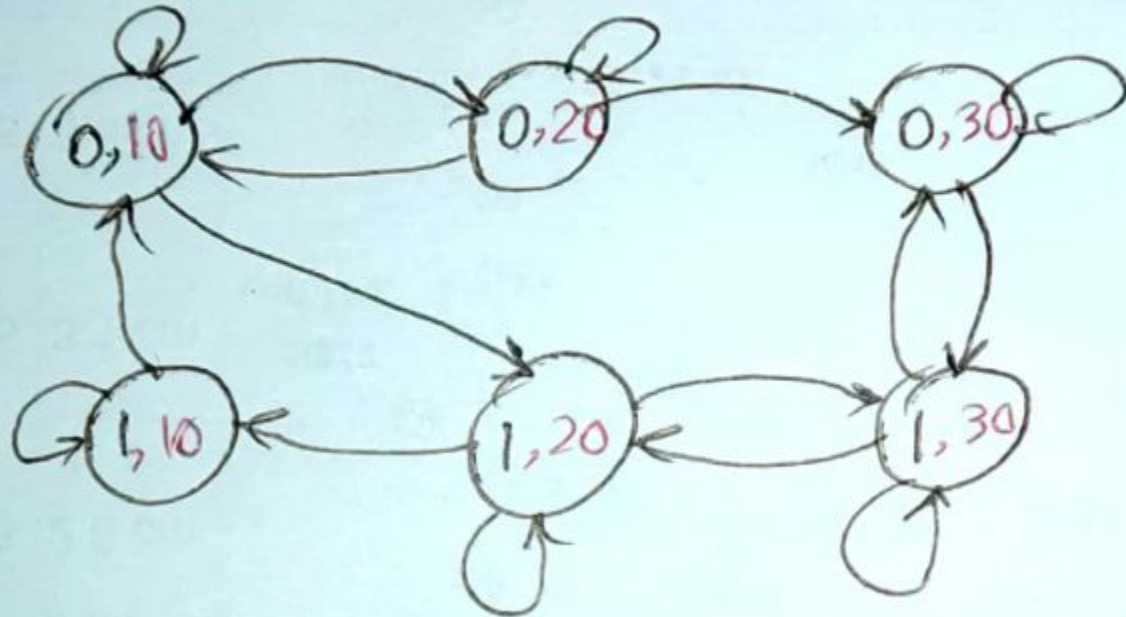


# State Transition Graph - Two Variables



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$P(x_1, x_2)$   $x_1 \in \{0, 1\}$   $x_2 \in \{10, 20, 30\}$



# State Transition Graph - Multiple Variables



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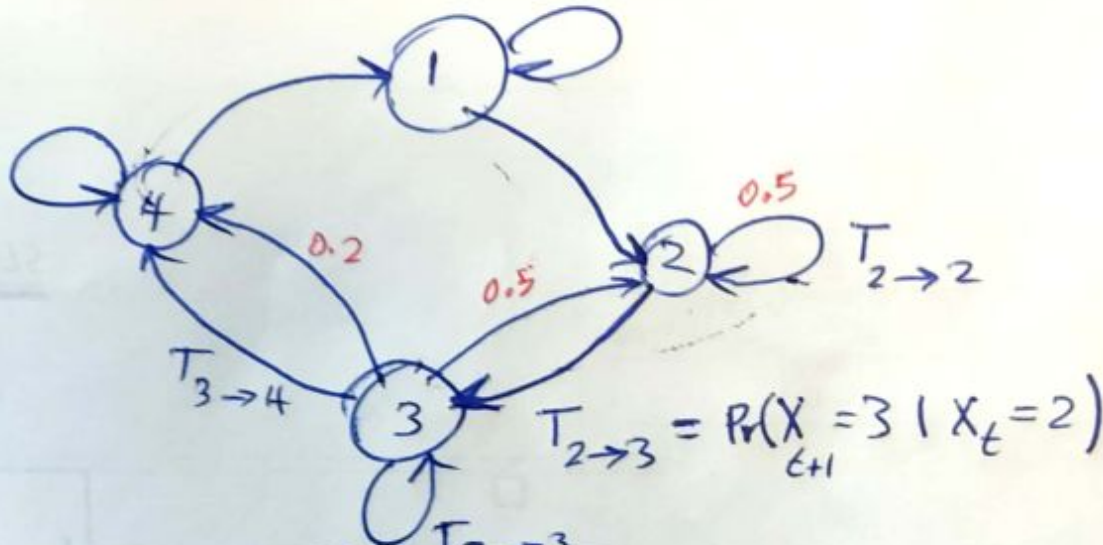
$$P(x_1, x_2, \dots, x_n) \approx x_i \in \{0, 1\}$$

$\Rightarrow$  there are  $2^n$  states in the state transition graph.

# State Transition Graph



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$X \in \{1, 2, 3, 4\}$

0.3  $T_{3 \rightarrow 3}$

$P^t(X)$ : prob. of being in state  $X$   
at time  $t$

# State Transition Graph



$X \in \{1, 2, 3, 4\}$

$P^t(X)$ : prob. of being in state  $X$  at time  $t$

$P^t(X) = \sum$

$P^t(a) = \sum_b \Pr(X_{t+1}=a | X_t=b) P^{t-1}(b)$

$P^t(a) = \sum_b T_{b \rightarrow a} P^{t-1}(b) \quad a = 1, 2, 3, 4$

# Stationary Distribution



$$p^t(a) = \sum_b \Pr(X_{t+1}=a | X_t=b) P^{t-1}(b)$$

$$p^t(a) = \sum_b T_{b \rightarrow a} P^{t-1}(b) \quad a=1,2,3,4$$

$$\lim_{t \rightarrow \infty} p^t(a) = P^\infty(a) = \pi(a) = \pi_a$$

if converge:

$$\lim_{t \rightarrow \infty} p^t(a) = \lim_{t \rightarrow \infty} \sum_b T_{b \rightarrow a} P^{t-1}(b)$$

$$\pi(a) = \sum_b T_{b \rightarrow a} \pi(b) \quad a=1,2,3,4$$

# Solving for the Stationary Distribution



$$\pi_a = \sum_b T_{b \rightarrow a} \pi_b \quad a=1,2,3,4$$

$$\pi_1 = \sum_b T_{b \rightarrow 1} \pi_b$$

$$\textcircled{I} \pi_1 = T_{1 \rightarrow 1} \pi_1 + T_{2 \rightarrow 1} \pi_2 + T_{3 \rightarrow 1} \pi_3 + T_{4 \rightarrow 1} \pi_4$$

$$\textcircled{II} \pi_2 = T_{1 \rightarrow 2} \pi_1 + T_{2 \rightarrow 2} \pi_2 + T_{3 \rightarrow 2} \pi_3 + T_{4 \rightarrow 2} \pi_4$$

$$\textcircled{III} \pi_3 = T_{1 \rightarrow 3} \pi_1 + T_{2 \rightarrow 3} \pi_2 + T_{3 \rightarrow 3} \pi_3 + T_{4 \rightarrow 3} \pi_4$$

$$\textcircled{IV} \pi_4 = T_{1 \rightarrow 4} \pi_1 + T_{2 \rightarrow 4} \pi_2 + T_{3 \rightarrow 4} \pi_3 + T_{4 \rightarrow 4} \pi_4$$

4 equation 4 unknowns ( $\pi_1, \pi_2, \pi_3, \pi_4$ )

3 independent equations

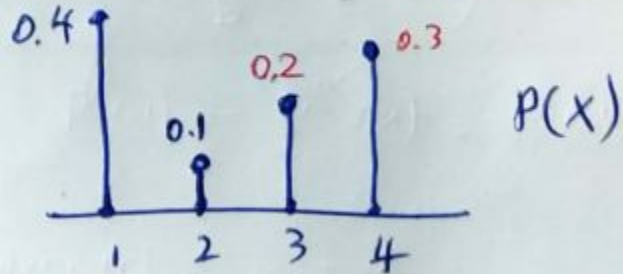
$$\textcircled{V} \boxed{\pi_1 + \pi_2 + \pi_3 + \pi_4 = 1}$$

# Solving for the Stationary Distribution



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Assume that  $\pi_1 = 0.4$     $\pi_2 = 0.1$     $\pi_3 = 0.2$     $\pi_4 = 0.3$



Stationary Distribution

# State Transition Graph - Two Variables



N. Toosi  
University of Technology

$$P_j^t = P(S_t = j) = \sum_{k=1}^m P(S_t = j, S_{t-1} = k)$$

$$= \sum_{k=1}^m P(S_t = j | S_{t-1} = k) P(S_{t-1} = k)$$

$$P_j^t = \sum_{k=1}^m$$

$T_{k \rightarrow j}$

$P_k^{t-1}$

$$P^t = (P_1^t, P_2^t, \dots, P_m^t)$$

if it converges

$\lim_{t \rightarrow \infty} P^t = ?$  exists? NOT Always  
what is it?



# Stationary Distribution



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$$\lim_{t \rightarrow \infty} P_j^t = \sum_{k=1}^m T_{k \rightarrow j} P_k^{t-1}$$

$$P_j^\infty = \sum_{k=1}^m T_{k \rightarrow j} P_k^\infty$$

$$\pi_j = \sum_{k=1}^m T_{k \rightarrow j} \pi_k \quad j = 1, 2, \dots, m$$

# Stationary Distribution



$$\pi_j = \sum_{k=1}^m T_{k \rightarrow j} \pi_k \quad j=1,2,\dots,m$$

Assume that  $T_{k \rightarrow j}$  is known for all  $k, j \in \{1, \dots, m\}$

Gives  $m$  equations in  $m$  unknowns  $\pi_1, \dots, \pi_m$

there are only  $m-1$  independent equations.

$$1 = \sum_{j=1}^m \pi_j = \sum_{j=1}^m \sum_{k=1}^m T_{k \rightarrow j} \pi_k = \sum_{k=1}^m \underbrace{\sum_{j=1}^m T_{k \rightarrow j}}_1 \pi_k = 1$$

$\left. \begin{array}{l} m-1 \text{ independent equations} \\ + \\ \pi_1 + \pi_2 + \dots + \pi_m = 1 \end{array} \right\} \Rightarrow \text{solve for } \pi_1, \pi_2, \dots, \pi_m$

# Stationary Distribution



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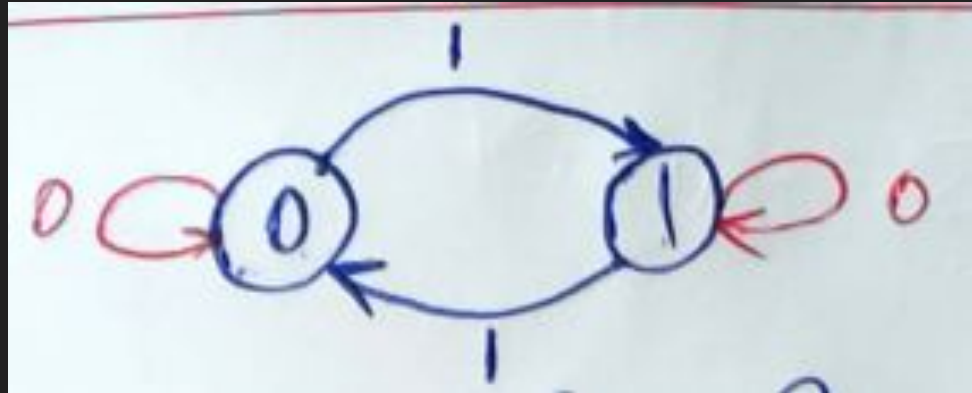
⇒ we have a distribution  $P_j^\infty = P(X_{t=\infty} = j)$

↪ if we move long enough in the state transition graph we have a sample from  $P(X_{t=\infty} = j) = P^\infty$

# Convergence is not always guaranteed



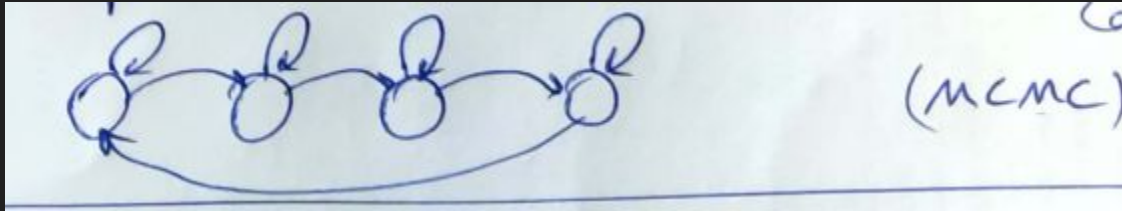
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# MCMC Convergence



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# MCMC Convergence



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# Stationary Distribution



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⇒ we have a distribution  $P_j^\infty = P(X_{t=\infty} = j)$

→ if we move long enough in the state transition graph we have a sample from  $P(X_{t=\infty} = j) = P_j^\infty$

# Stationary Distribution



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Main idea in MCMC:

→ we have a distribution

$$P(x)$$

→ create a state transition graph (explicit/implicit)

a set  $T_{i \rightarrow j}$  such that

(now we have  $\pi_k$ 's in  $\pi_j = \sum_{k \rightarrow j} T_{k \rightarrow j} \pi_k$  & we need to set  $T_{k \rightarrow j}$ )

$$P(x=k) = P(X=k)$$

Move in the state transition graph long enough to have a sample from  $P(x)$ .



# Gibbs Sampling



$$\begin{aligned} a^{t+1} &\sim P(A | B=b^t, C=c^t, D=d^t, E=e^t) \\ b^{t+1} &\sim P(B | A=a^{t+1}, C=c^t, D=d^t, E=e^t) \\ c^{t+1} &\sim P(C | A=a^{t+1}, B=b^{t+1}, D=d^t, E=e^t) \\ d^{t+1} &\sim P(D | A=a^{t+1}, B=b^{t+1}, C=c^{t+1}, E=e^t) \\ e^{t+1} &\sim P(E | A=a^{t+1}, B=b^{t+1}, C=c^{t+1}, D=d^{t+1}) \end{aligned}$$

The diagram illustrates the Gibbs sampling process. It shows five conditional probability distributions for variables  $a, b, c, d, e$  at iteration  $t+1$ . Each distribution is conditioned on the current values of the other variables. The variables are updated sequentially, with the updated value of one variable being used in the next distribution. The process starts with a set of current values  $(a^t, b^t, c^t, d^t, e^t)$  and iteratively updates them to  $(a^{t+1}, b^{t+1}, c^{t+1}, d^{t+1}, e^{t+1})$ .

# Computing conditionals



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University of Technology

$$P(A|B, C, D, E) = \frac{P(A, B, C, D, E)}{\sum_A P(A, B, C, D, E)}$$

# Computing conditionals



$$P(A, B, C, D, E) = \frac{1}{2} \phi_1(A) \phi_2(A, B) \phi_3(B, C) \phi_4(C, D, E)$$

$$P(A | b, c, d, e) = \frac{\frac{1}{2} \phi_1(A) \phi_2(A, b) \phi_3(b, c) \phi_4(c, d, e)}{\sum_a \frac{1}{2} \phi_1(a) \phi_2(a, b) \phi_3(b, c) \phi_4(c, d, e)}$$

$$\begin{aligned} P(A | b, c, d, e) &= \frac{\frac{1}{2} \phi_1(A) \phi_2(A, b) \phi_3(b, c) \phi_4(c, d, e)}{\sum_a \frac{1}{2} \phi_1(a) \phi_2(a, b) \phi_3(b, c) \phi_4(c, d, e)} \\ &= \frac{\phi_1(A) \phi_2(A, b)}{\sum_a \phi_1(a) \phi_2(a, b)} \end{aligned}$$

# Warm-up (burn-in) phase and mixing



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