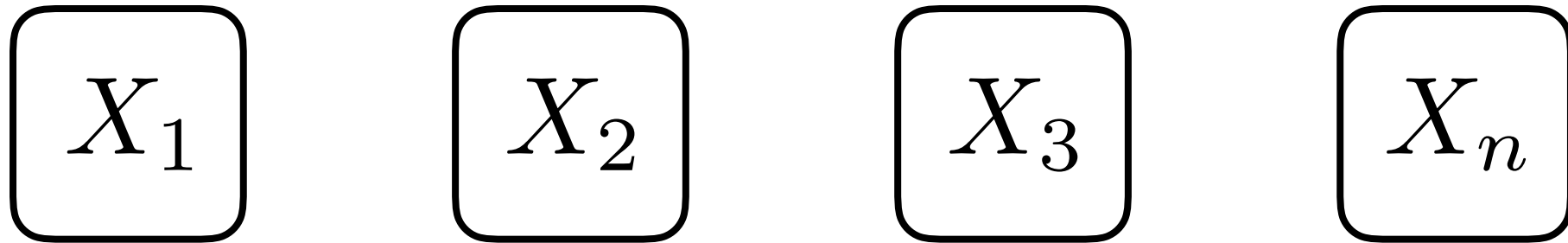


# Introduction to Markov Chains

# What is a Markov **Chain**?

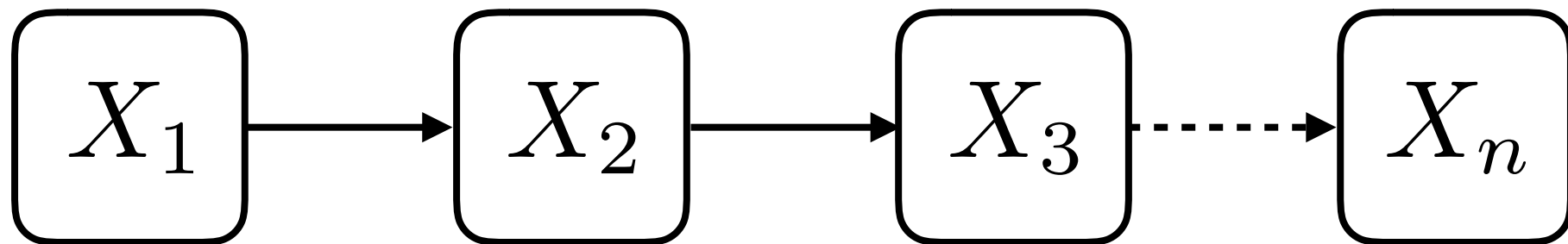


Random Variables

Could model as i.i.d.  
(independent and identically distributed)

Realistic? What if index is time?

# What is a Markov **Chain**?



Let's add a dash of dependence  
(but not too much!)

# The Markov Property

$$P(X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = P(X_{n+1} = j | X_n = i)$$

# The Markov Property

Everything Before

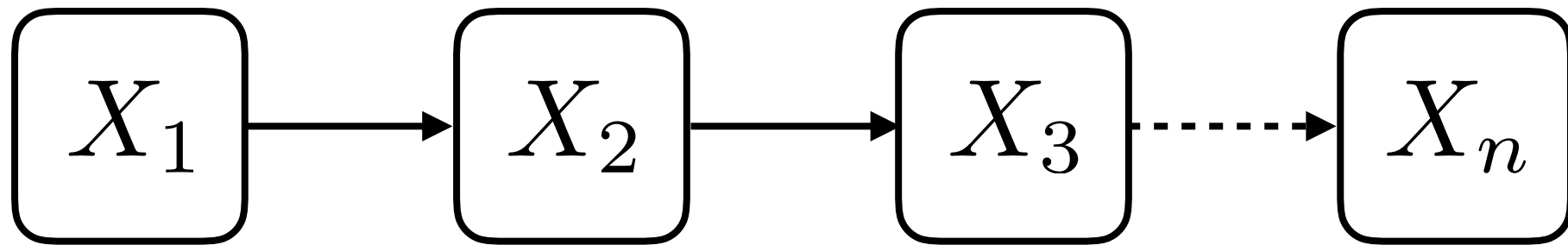
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Next	Now	Previous	First	Next	Now
------	-----	----------	-------	------	-----

$$P(X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \dots, X_0 = i_0) = P(X_{n+1} = j | X_n = i)$$

Memoryless!

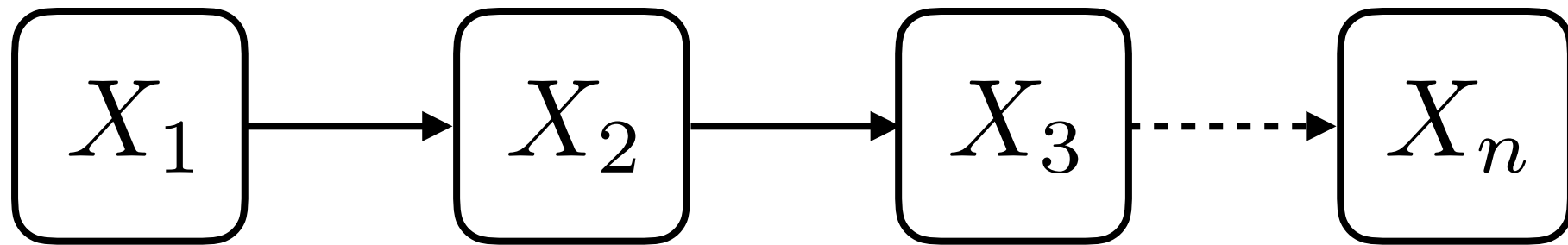
# State Space



$$X_i \in \{Rainy, Sunny\}$$

<http://setosa.io/ev/markov-chains/>

# State Spaces



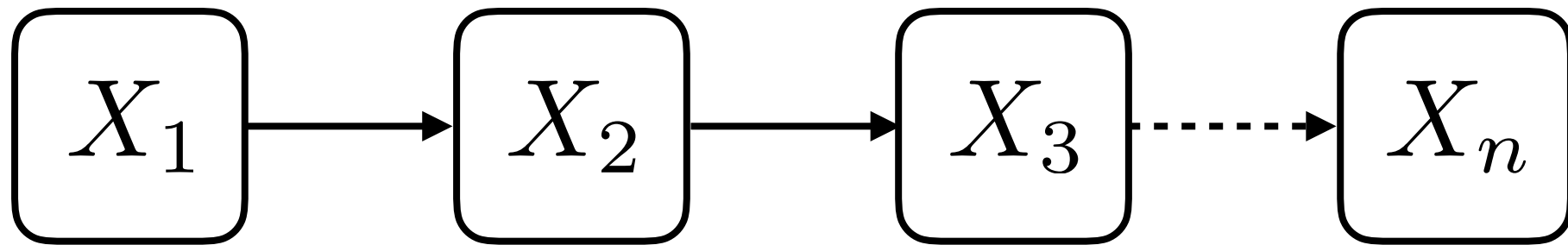
$$X_i \in \{Rainy, Sunny\}$$

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

$$X_i \in \{A, C, G, T\}$$

$$X_i \in \{AAA, AAC, AAG, \dots, TTG, TTT\}$$

# State Spaces (Discrete)



$$X_i \in \{Rainy, Sunny\}$$

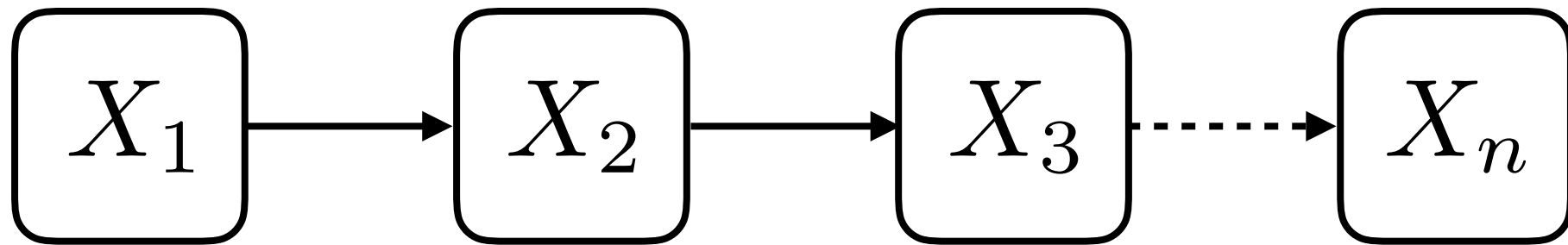
$$X_i \in \{1, 2, 3, 4, 5, 6\}$$

$$X_i \in \{A, C, G, T\}$$

$$X_i \in \{AAA, AAC, AAG, \dots, TTG, TTT\}$$



# State Spaces (Continuous)



$$X_i \in \mathbb{R}$$

$$X_i \in \mathbb{R}_{>0}$$

$$X_i \in [0, 1]$$

What sorts of continuous state spaces might we have in phylogenetics?

# Transition Matrix

$$\begin{array}{c} R \\ S \end{array} \begin{array}{cc} R & S \\ \left( \begin{array}{cc} 0.7 & 0.3 \\ 0.3 & 0.7 \end{array} \right) \end{array}$$

# Transition Matrix

To

From

$$\begin{array}{c} R \\ S \end{array} \begin{pmatrix} R & S \\ 0.7 & 0.3 \\ 0.3 & 0.7 \end{pmatrix}$$

		To	
		$R$	$S$
From	$R$	0.7	0.3
	$S$	0.3	0.7

$$P(X_{n+1} = R | X_n = R) = 0.7$$

$$P(X_{n+1} = S | X_n = R) = 0.3$$

		To	
		$R$	$S$
From	$R$	0.7	0.3
	$S$	0.3	0.7

$$P(X_{n+1} = R | X_n = R) = 0.7$$

$$P(X_{n+1} = S | X_n = R) = 0.3$$

$$P(X_{n+1} = R | X_n = S) = 0.3$$

$$P(X_{n+1} = S | X_n = S) = 0.7$$

# In-Class Exercise (pairs)

(1) Create a Markov chain class with these values:

- Number of steps (positive integer)
- State space (list)
- Transition matrix (list of lists of floats - or own class!)
- Sampled states (list)

and these methods:

- run (sample states for each step)
- clear (remove any sampled states)

(2) Create a list (or lists) to hold frequencies of states for different runs. For the {Rainy,Sunny} example, start each run in S. Now run 100 chains for 1 step. Record state frequencies across chains. Then run 100 chains for 2 steps. Record state frequencies. Then 5, then 10.

# Transition Matrix

$$Q = \begin{pmatrix} 0.7 & 0.3 \\ 0.3 & 0.7 \end{pmatrix}$$

$$q_{ij} = P(X_{n+1} = j | X_n = i)$$

$$q_{11} = q_{RR} = 0.7$$

**$Q$**  and  **$q$**  give us a sense for what will happen in the next step. But what about 2,3,4,...,100 steps in the future?

$$q_{ij}^{(100)} = ?$$

# Transition Matrix

$$Q = \begin{pmatrix} 0.7 & 0.3 \\ 0.3 & 0.7 \end{pmatrix}$$

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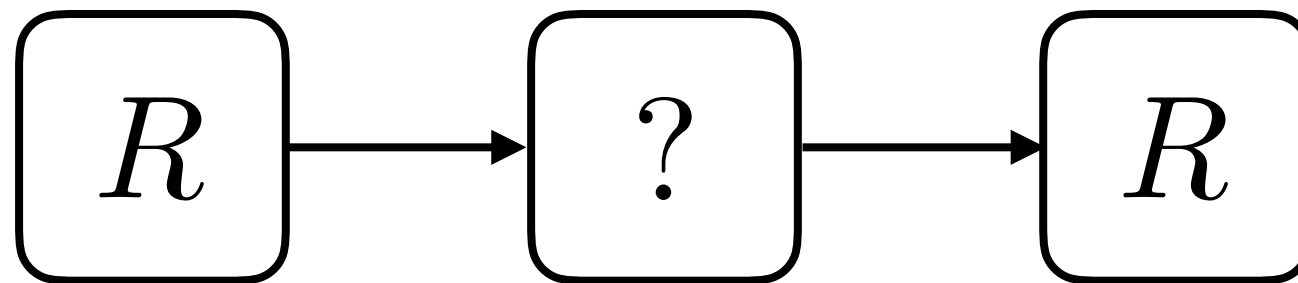
**$Q$**  and  **$q$**  give us a sense for what will happen in the next step. But what about 2,3,4,...,100 steps in the future?

$$q_{ij}^{(100)} \neq (q_{ij})^{100}$$



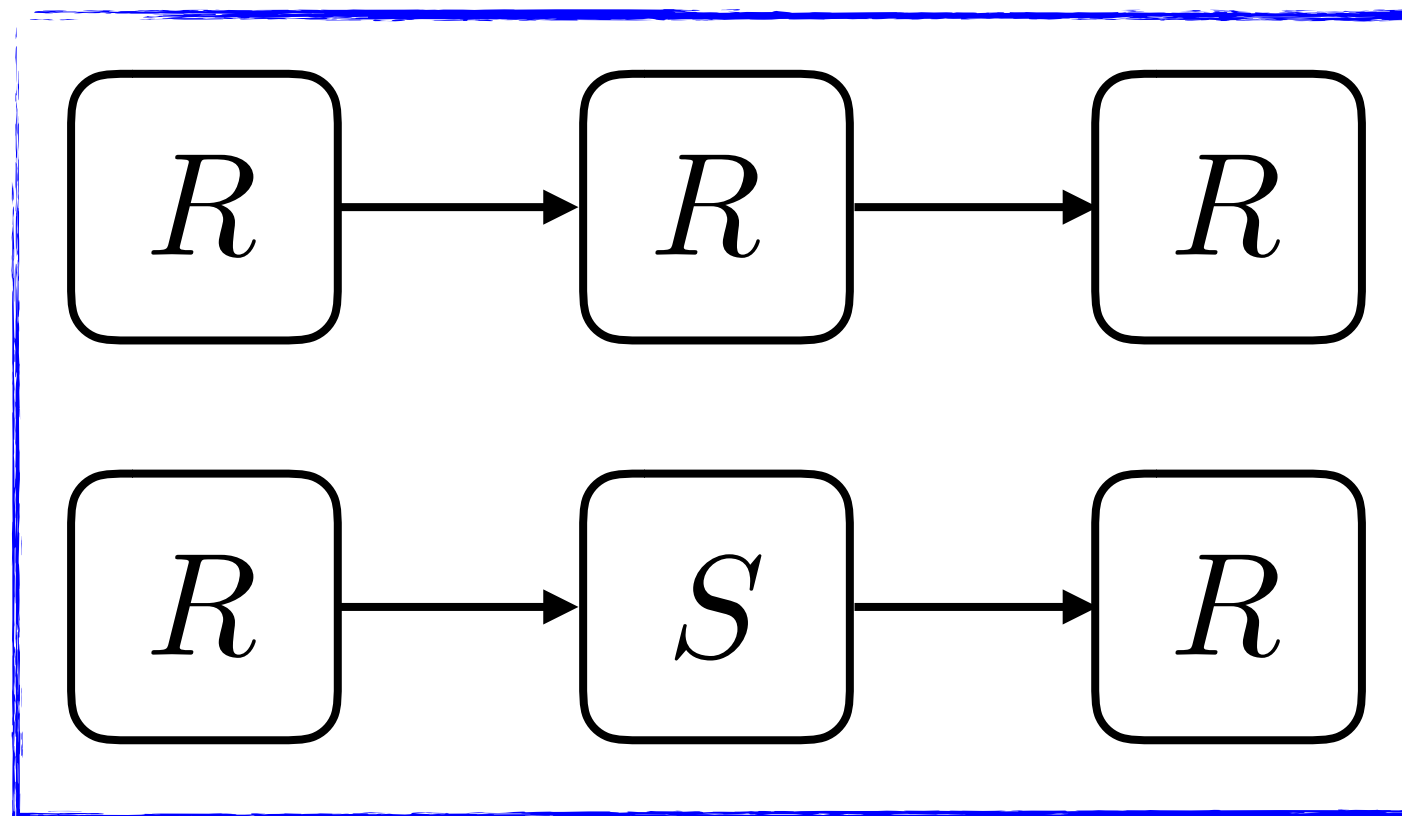
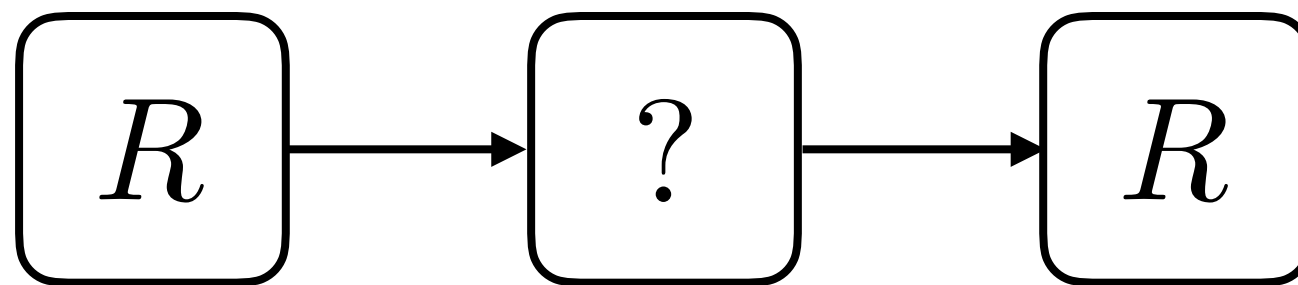
# Transition Matrix

$$P(X_{n+2} = R | X_n = R)$$



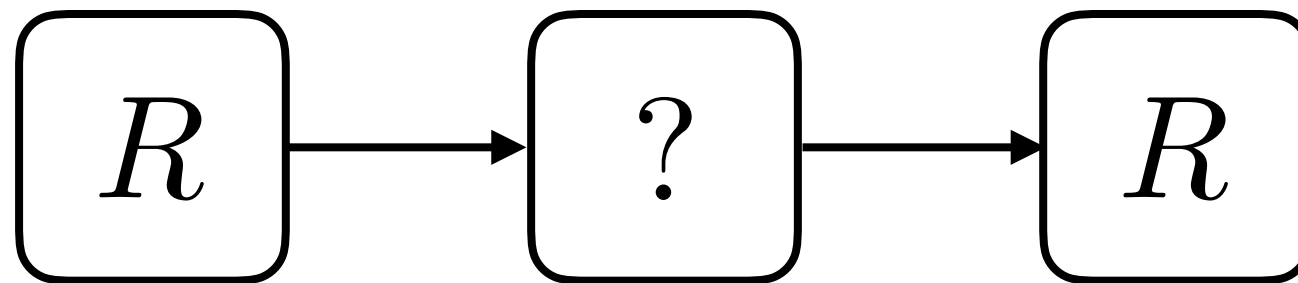
# Transition Matrix

$$P(X_{n+2} = R | X_n = R)$$

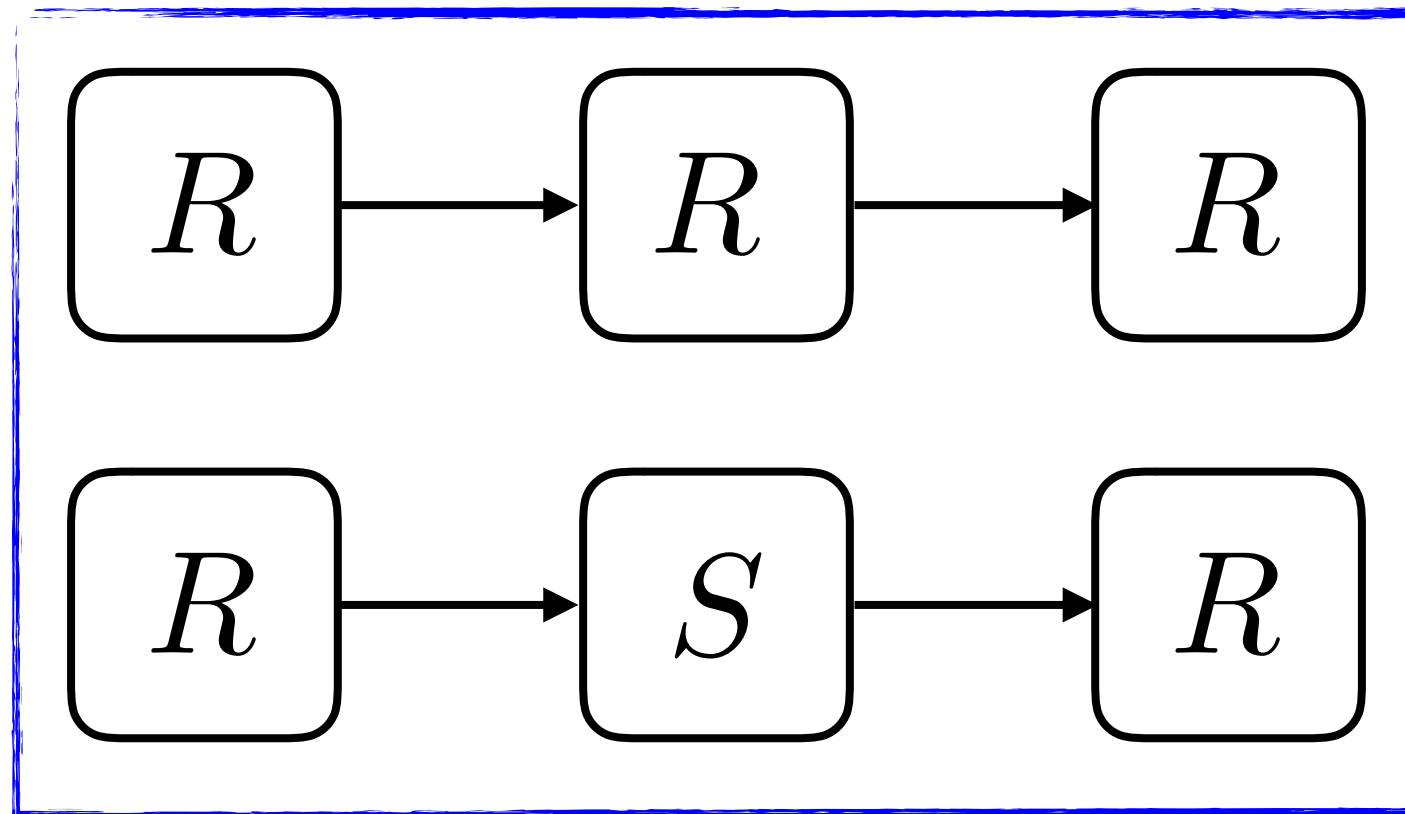


# Transition Matrix

$$P(X_{n+2} = R | X_n = R)$$

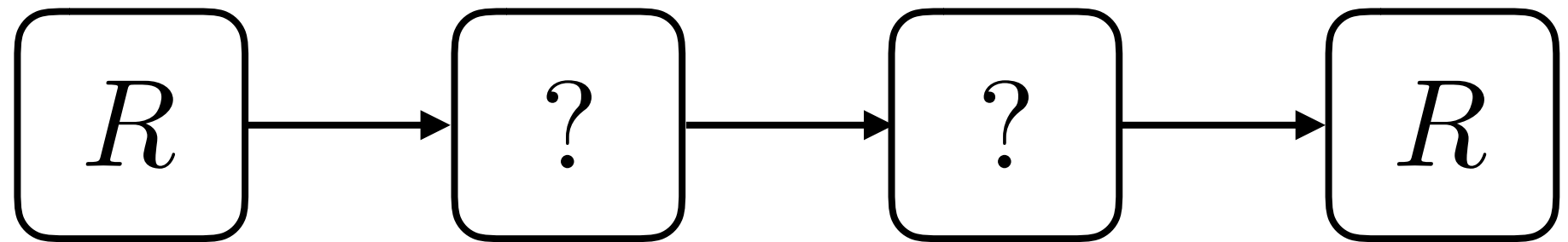


$$(q_{RR})^2 =$$

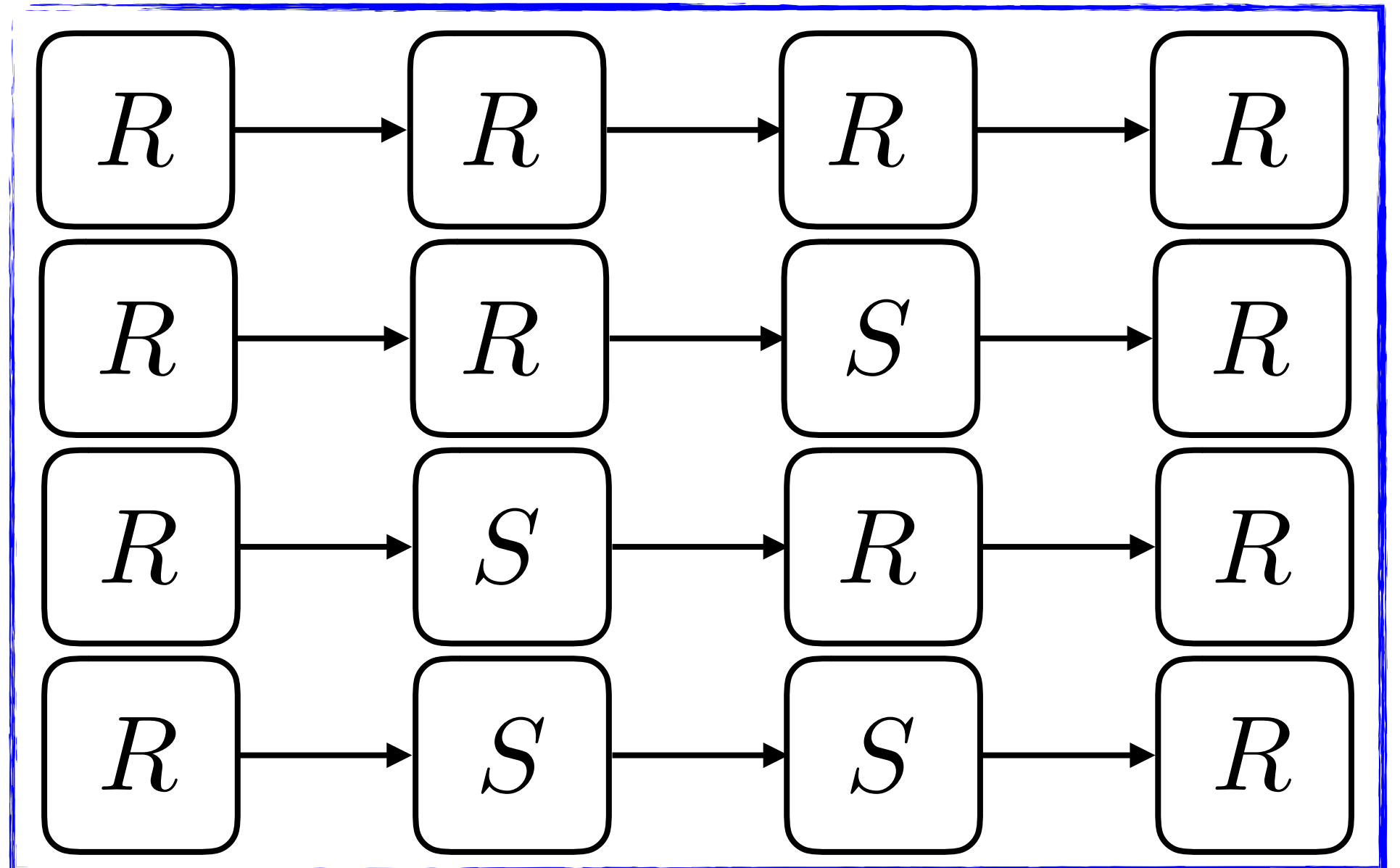


# Transition Matrix

$$P(X_{n+3} = R | X_n = R)$$



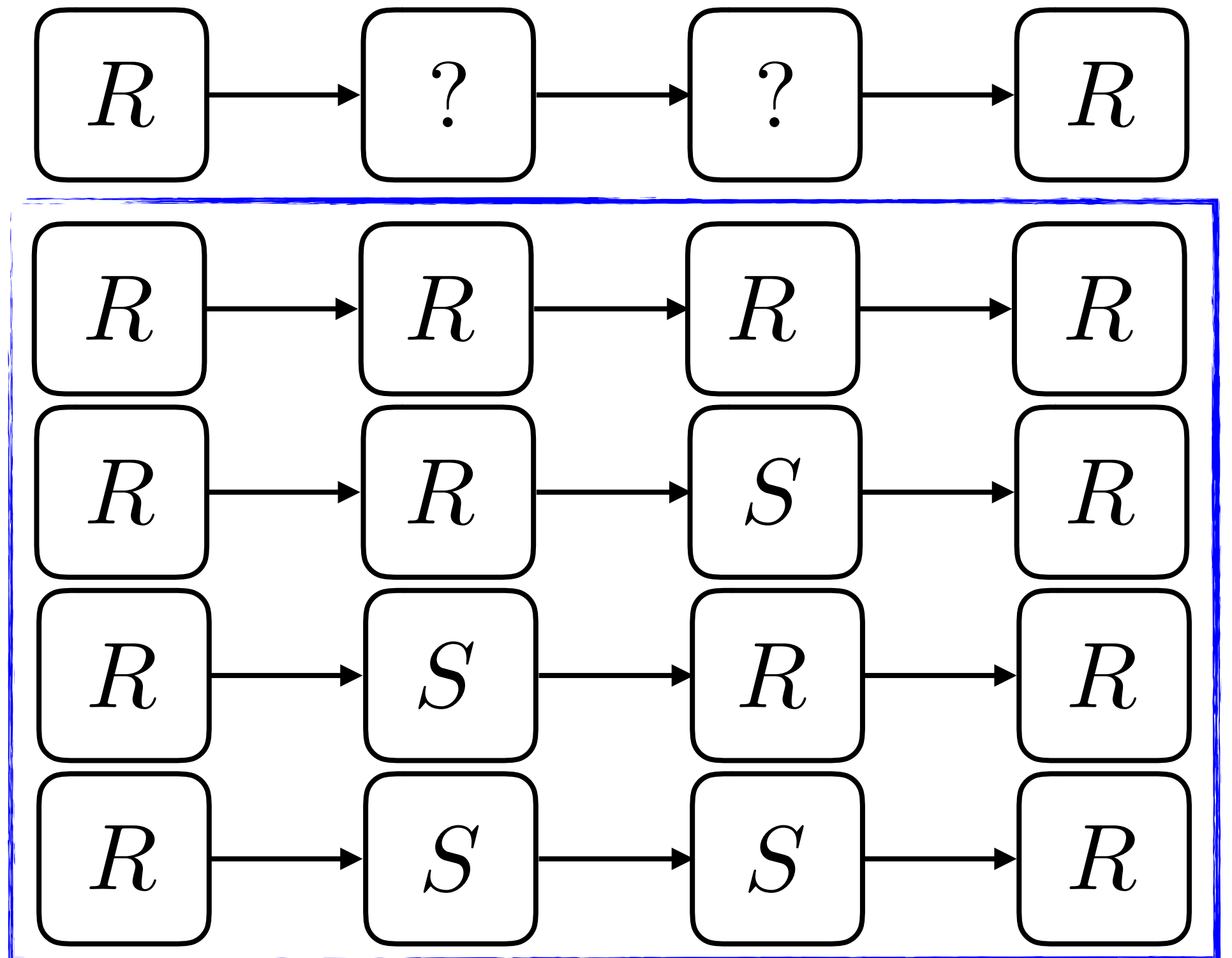
$$(q_{RR})^3 =$$



# Transition Matrix

$$P(X_{n+3} = R | X_n = R)$$

$$q_{RR}^{(3)} =$$



# Transition Matrix

$q_{ij}^{(n)}$  is the  $(i, j)$  entry of  $Q^n$

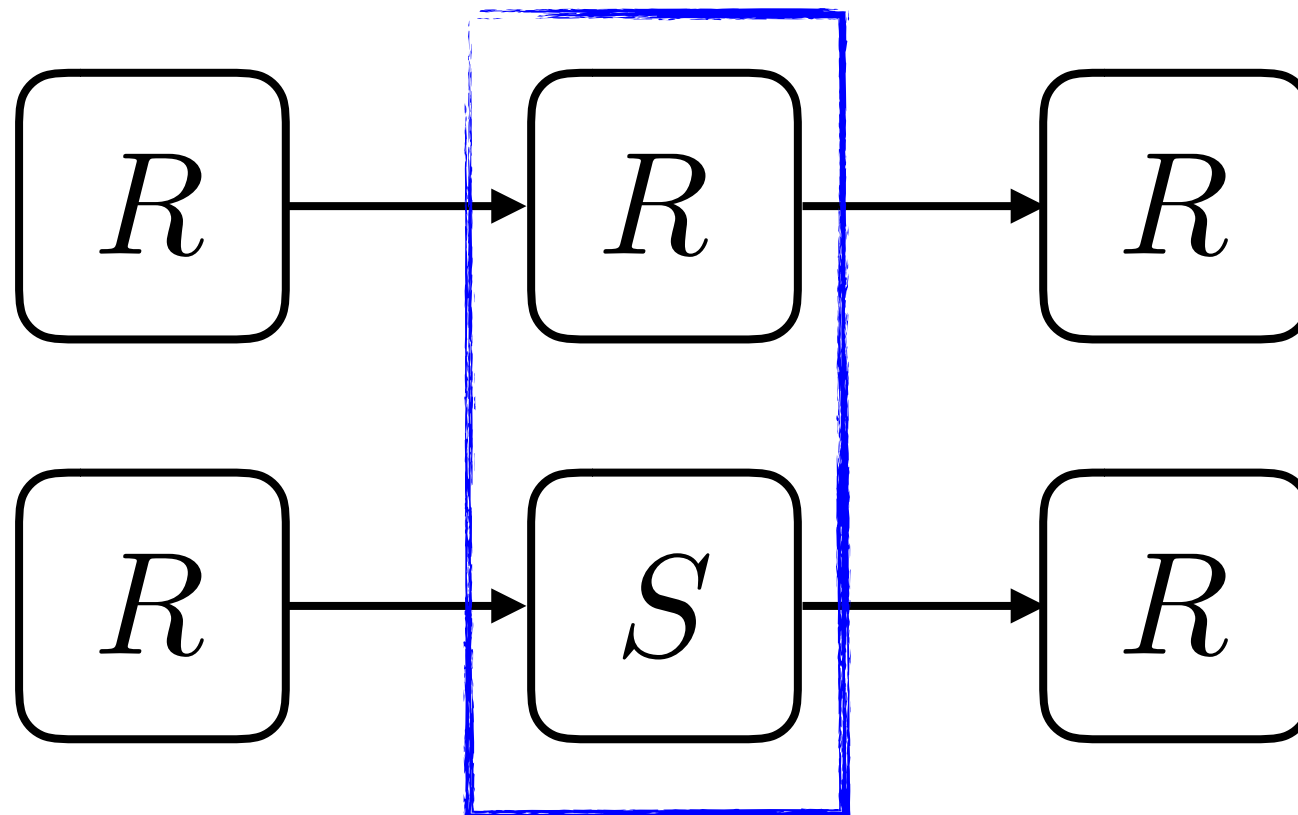
$$q_{ij}^{(2)} = \sum_k q_{ik} q_{kj}$$

# Transition Matrix

$q_{ij}^{(n)}$  is the  $(i, j)$  entry of  $Q^n$

$$q_{ij}^{(2)} = \sum_k q_{ik} q_{kj}$$

$k$   
↓



# Stationary Distribution

A row vector  $\mathbf{s} = (s_1, \dots, s_M)$  such that  $s_i \geq 0$  is a **stationary distribution** for a Markov chain with transition matrix  $Q$  if  $\sum_i s_i q_{ij} = s_j$  for all  $j$ .  
Equivalently,  $\mathbf{s}Q = \mathbf{s}$ .



# Stationary Distribution

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Equivalently,  $\mathbf{s}Q = \mathbf{s}$ .

What does this mean??

# Stationary Distribution

A row vector  $\mathbf{s} = (s_1, \dots, s_M)$  such that  $s_i \geq 0$  is a **stationary distribution** for a Markov chain with transition matrix  $Q$  if  $\sum_i s_i q_{ij} = s_j$  for all  $j$ .  
Equivalently,  $\mathbf{s}Q = \mathbf{s}$ .

Simply put, if the states have certain probabilities of appearing in one iteration, they will have those same probabilities in the next iteration. The **probabilities do not change!**

# Stationary Distribution

Using the Markov chain simulator you wrote above, try using this  $Q$  matrix:

$$\begin{array}{cc} & \begin{array}{cc} R & S \end{array} \\ \begin{array}{c} R \\ S \end{array} & \left( \begin{array}{cc} 0.99 & 0.01 \\ 0.01 & 0.99 \end{array} \right) \end{array}$$

Start 100 chains in  $R$ . Now calculate the frequencies of  $R$  and  $S$  at regular intervals for 100 generations.

What do you notice? How does this compare to the transition matrix you were using before? What are the stationary frequencies in each case?

# Reversibility

$$s_i q_{ij} = s_j q_{ji}$$

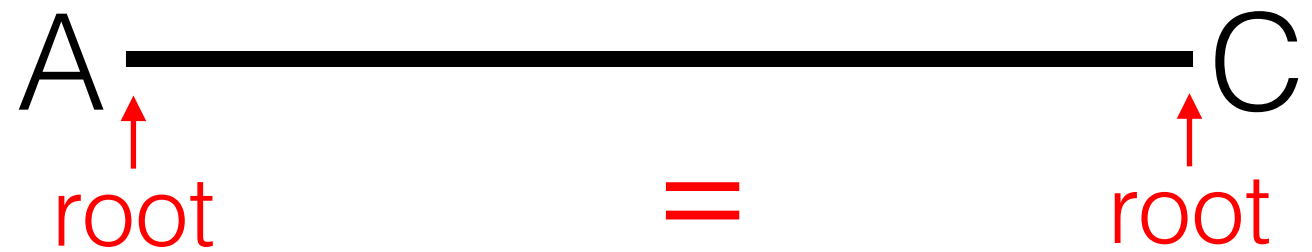
## Detailed Balance Equation

The probability of a series of states in the chain is the same forward, as it is in reverse? Why might this be important for phylogenetics?

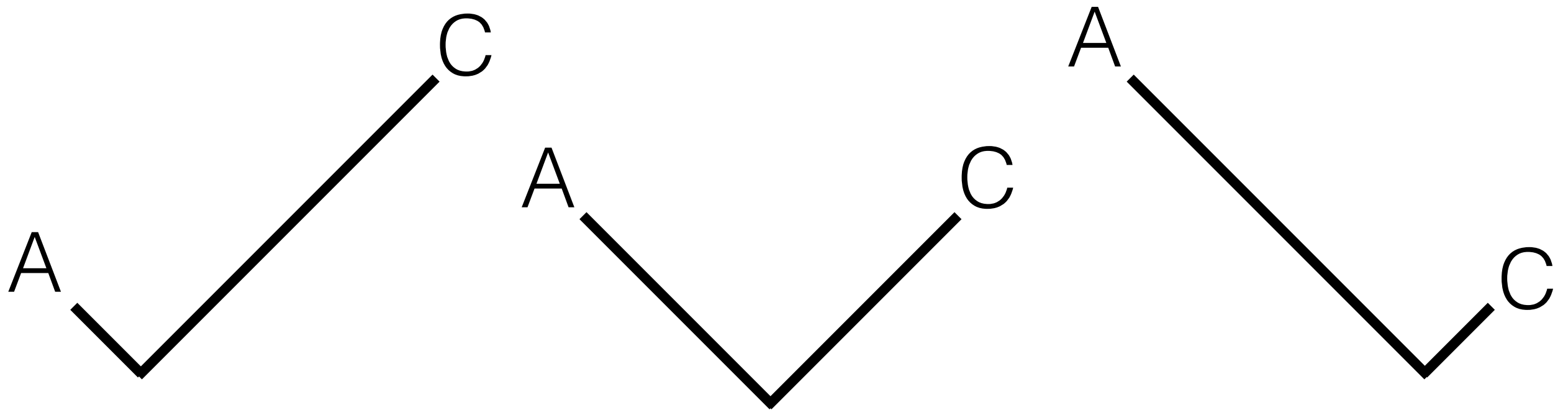
# The Pulley Principle



# The Pulley Principle

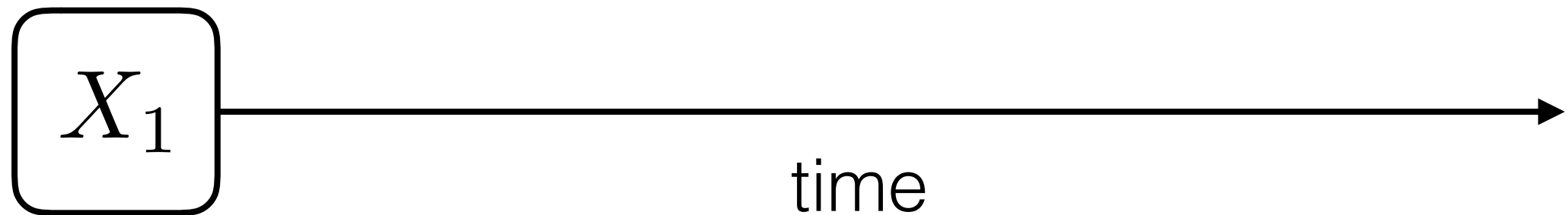


# The Pulley Principle



If the chain is reversible, the likelihood will be the same no matter where we put our “root”. This is known as the pulley principle (Felsenstein 1981).

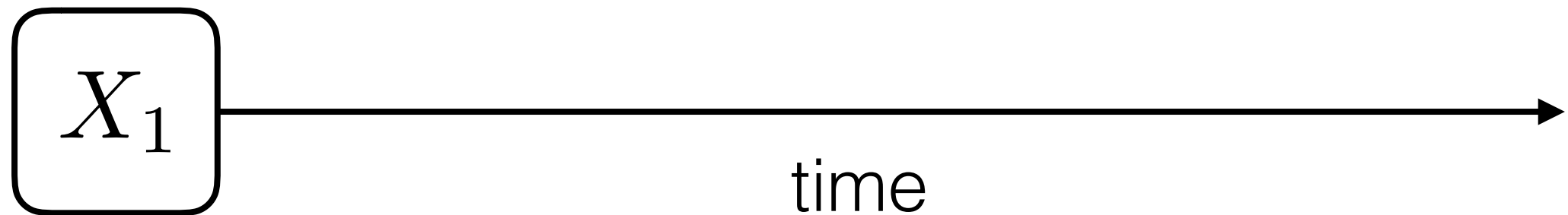
# Continuous Time Markov Chains



For a continuous-time Markov chain, time does not proceed in iterations. Rather, it is a continuous variable and state changes can occur at any point. Think of a discrete-time chain where the time between iterations is very short (too short to discern) and we go through many of them.

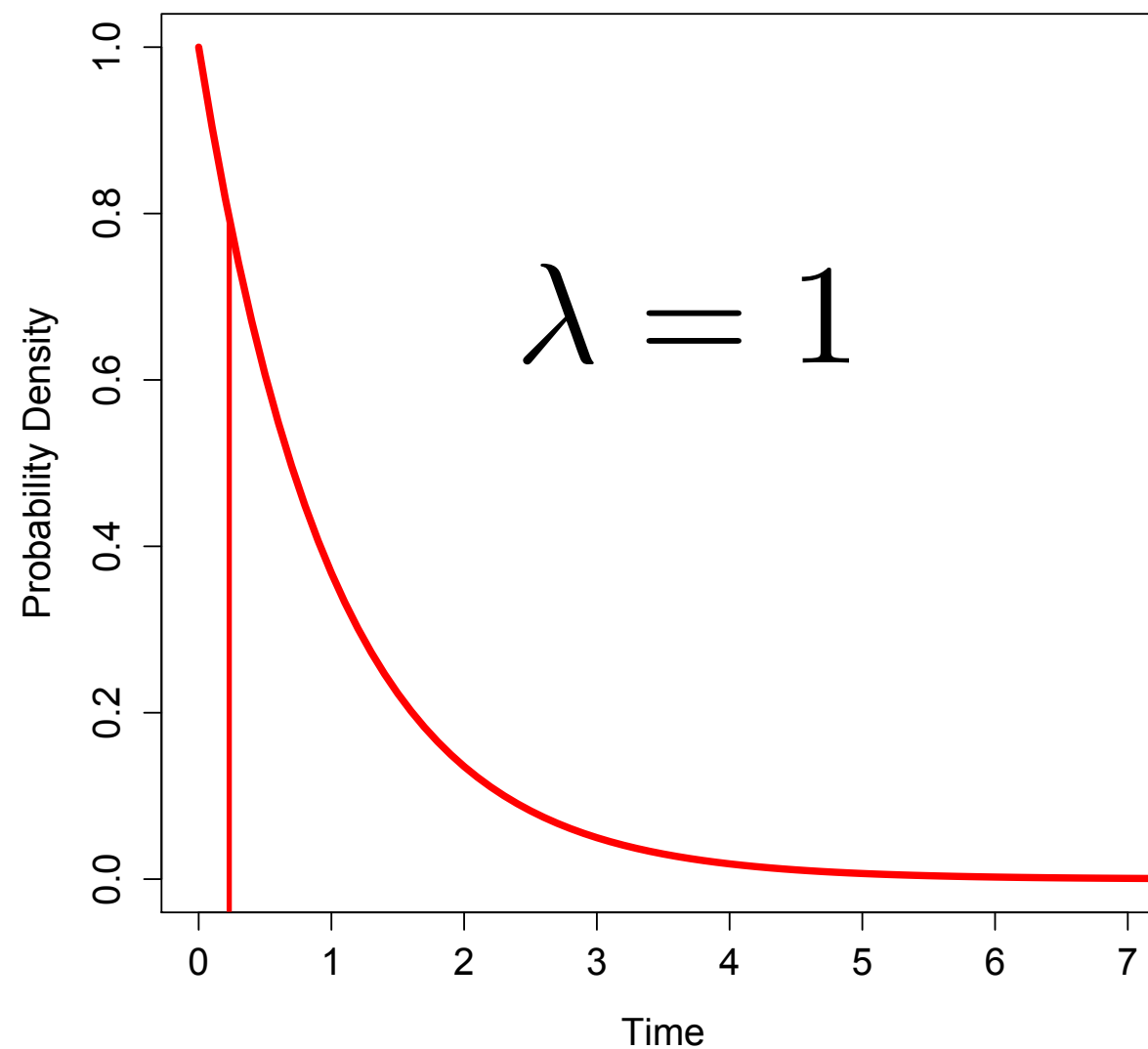
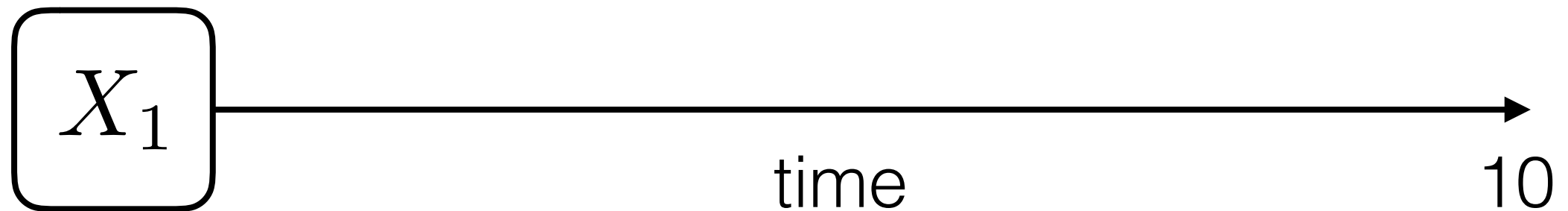


# Continuous Time Markov Chains

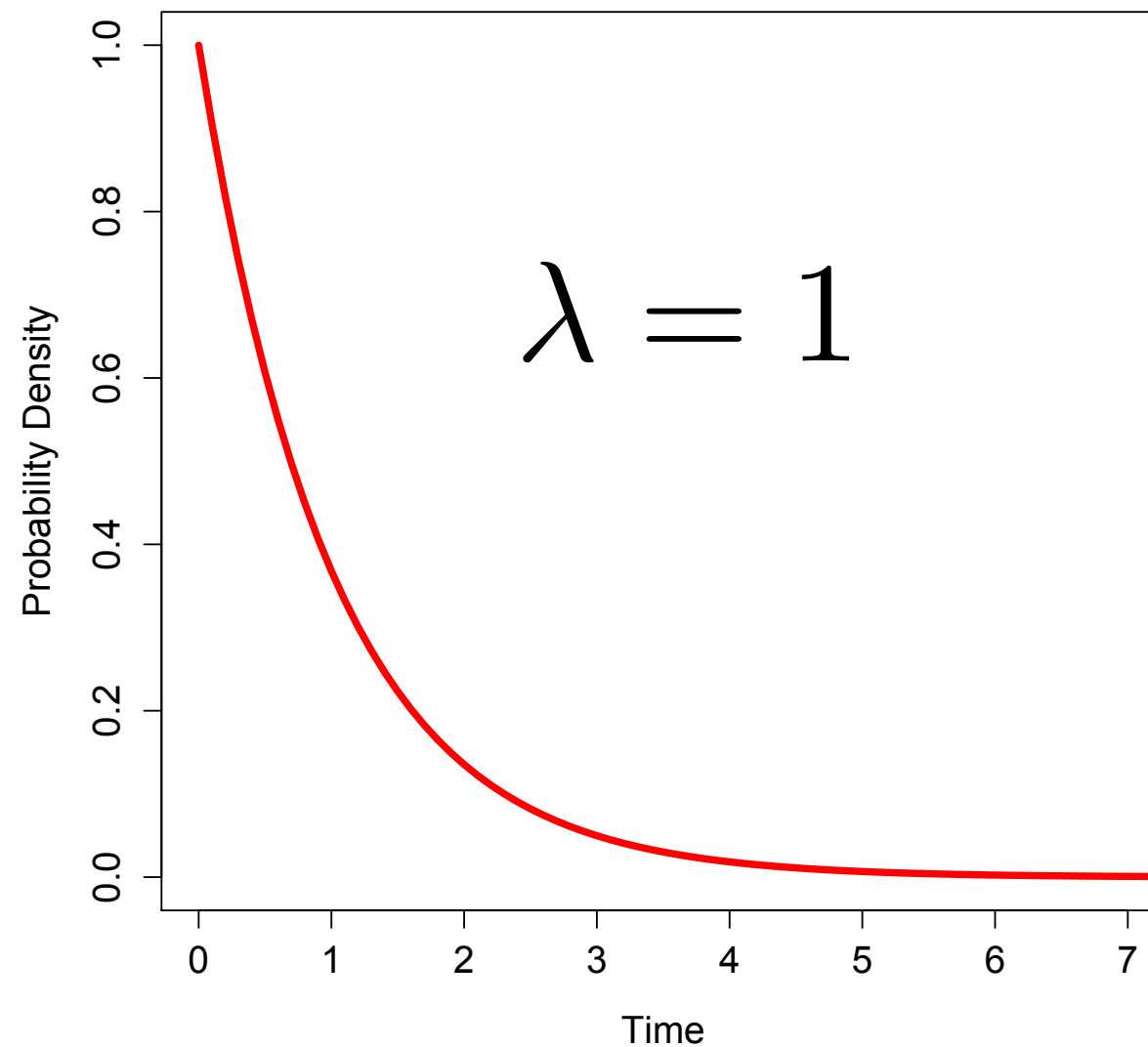
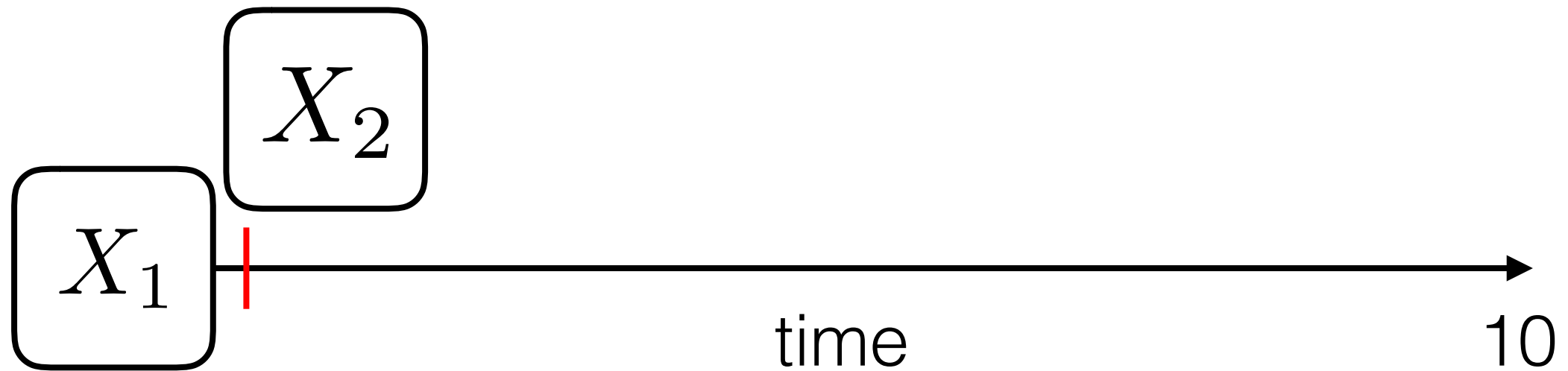


The waiting times between events (state changes) in a continuous-time Markov chain are exponentially distributed. The rate parameter ( $\lambda$ ) determines how frequently those events occur.

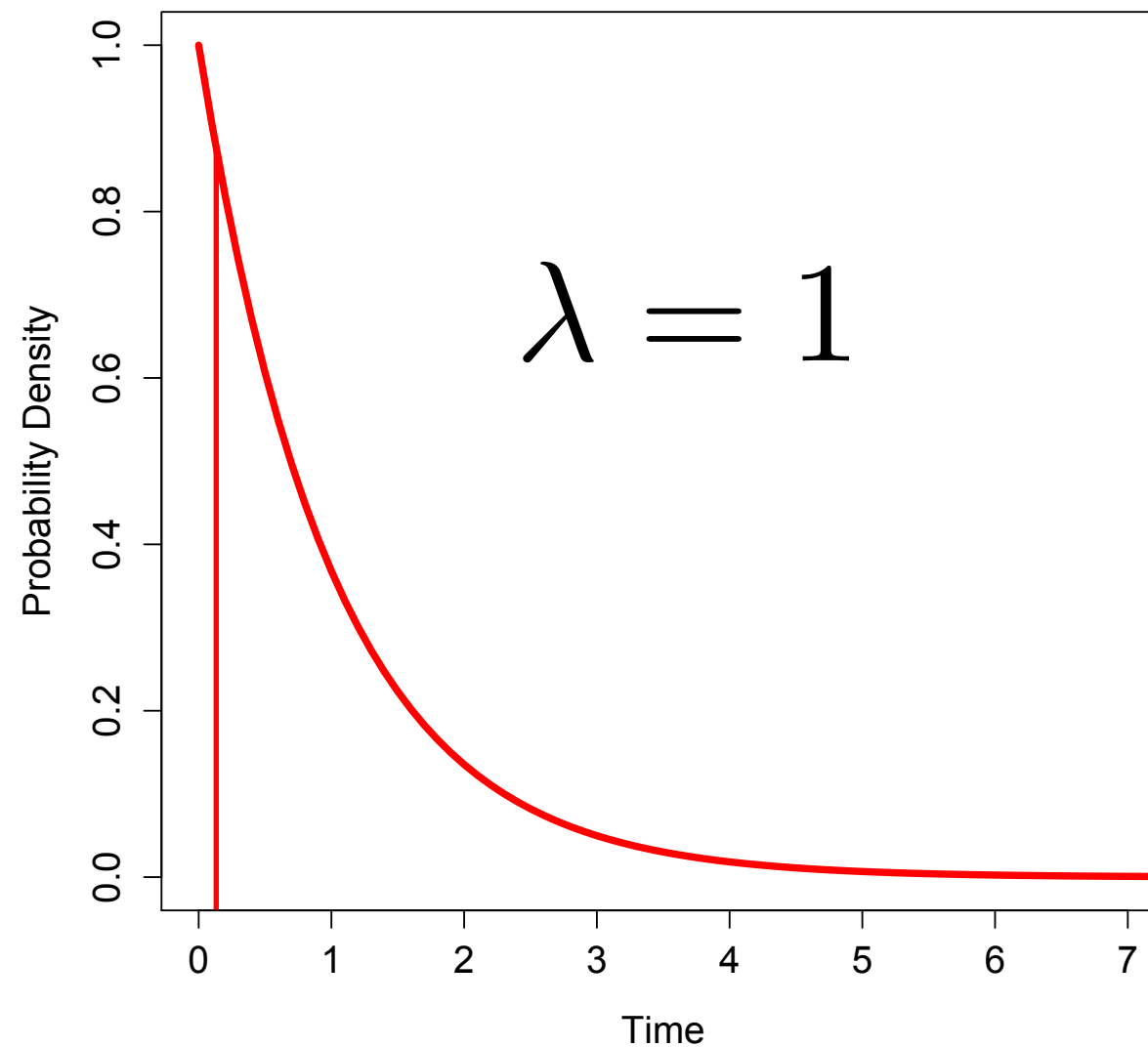
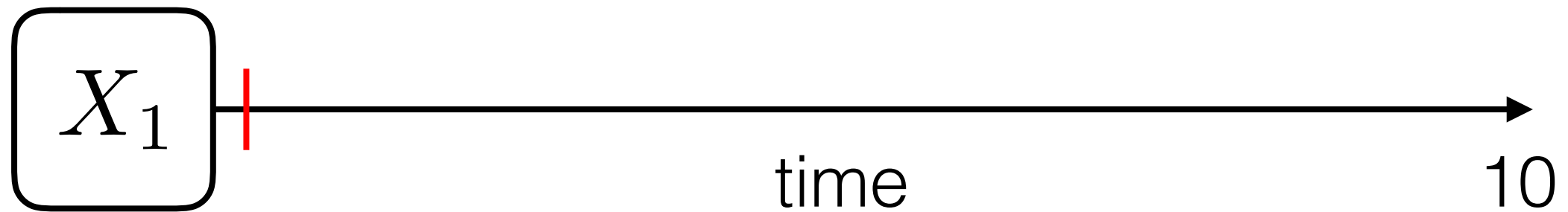
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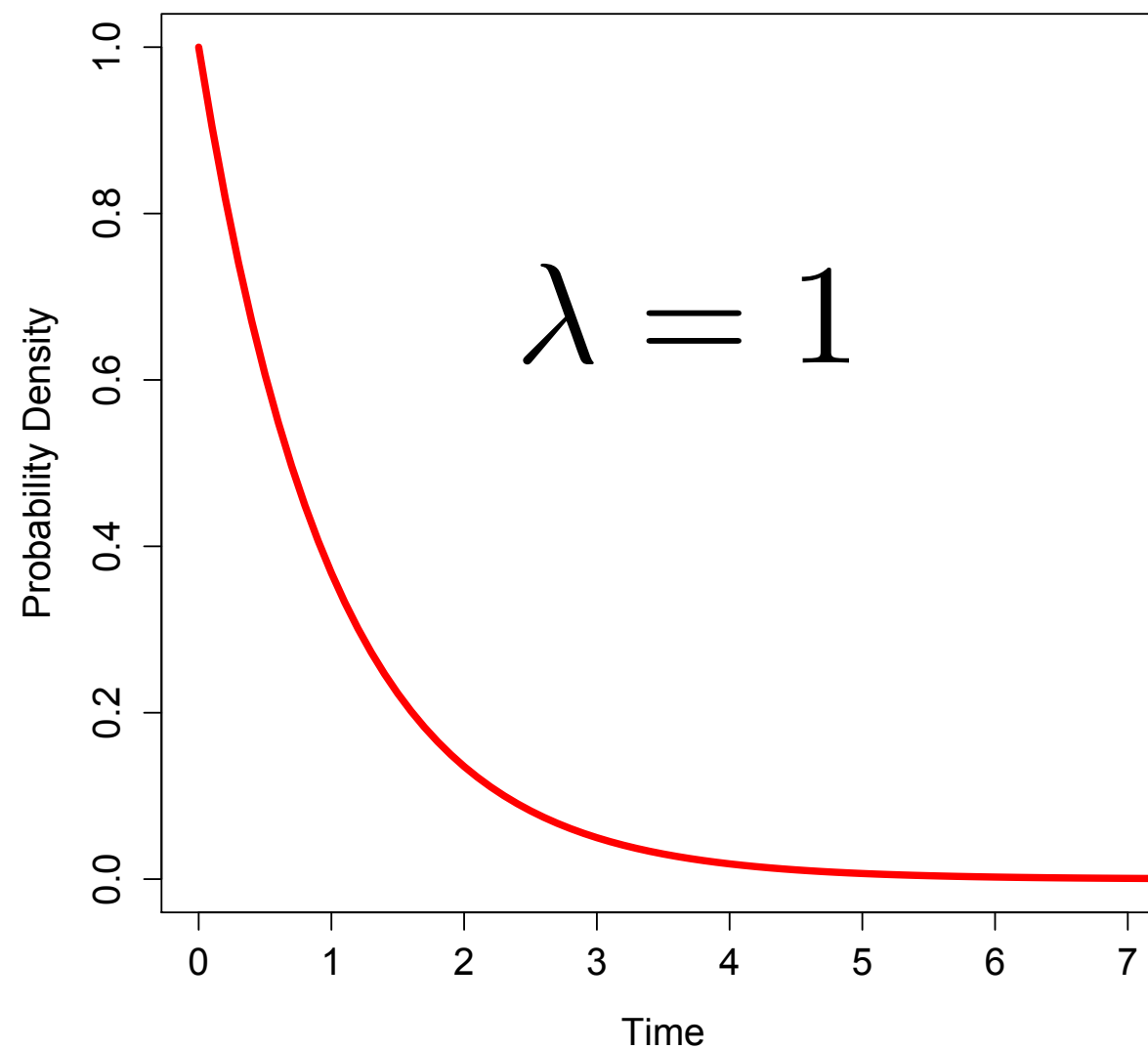
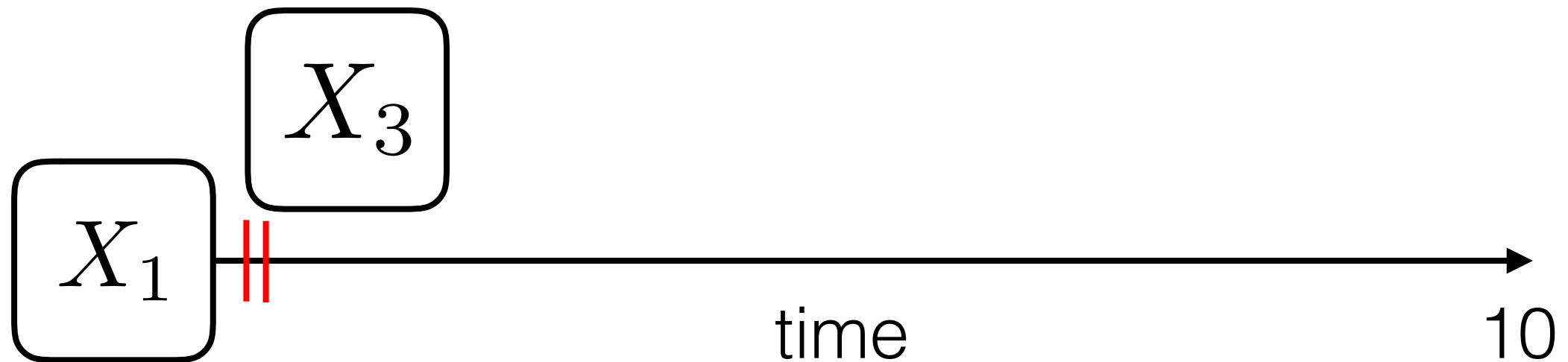
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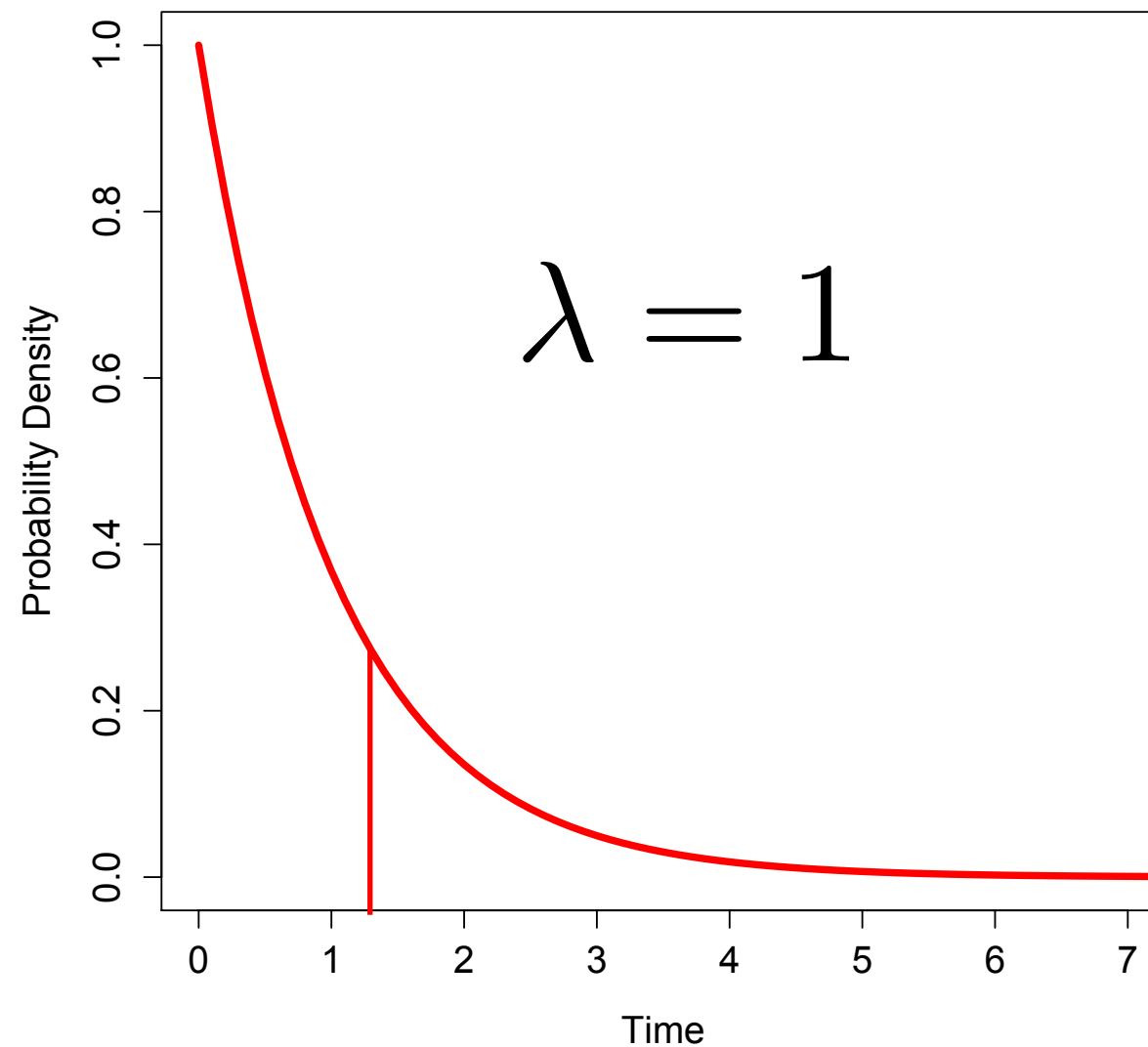
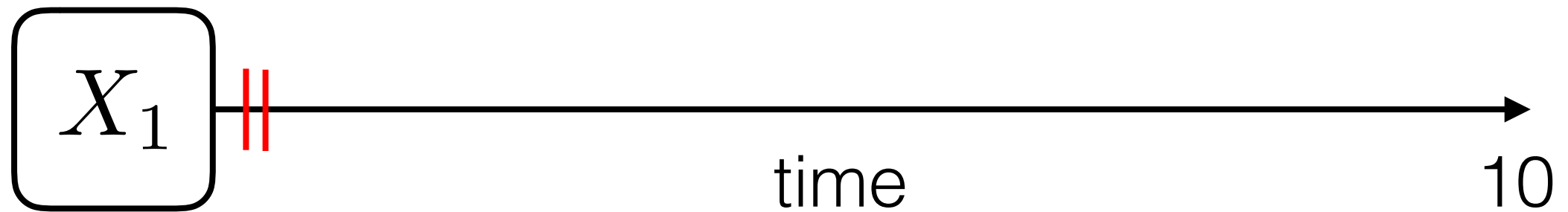
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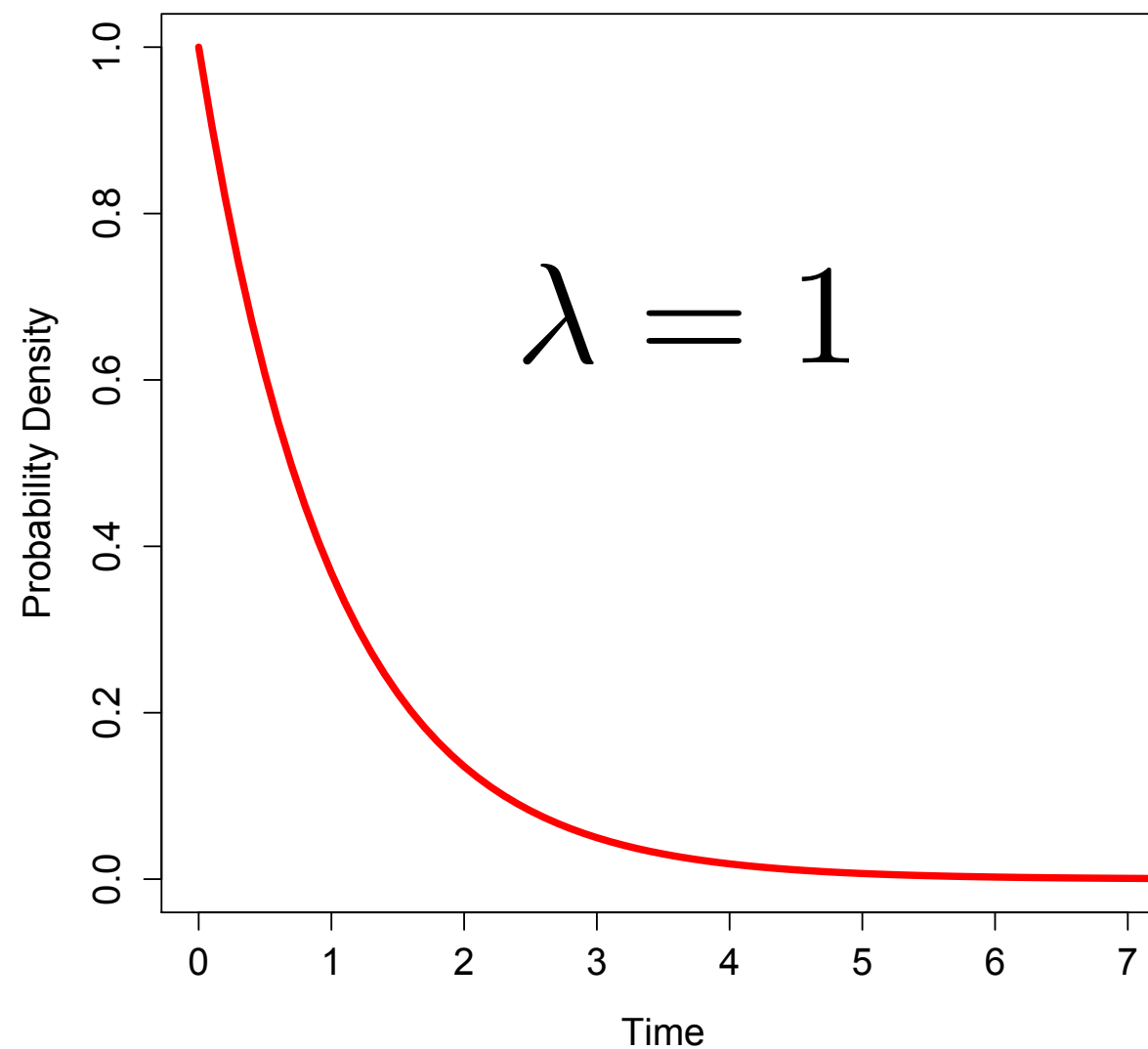
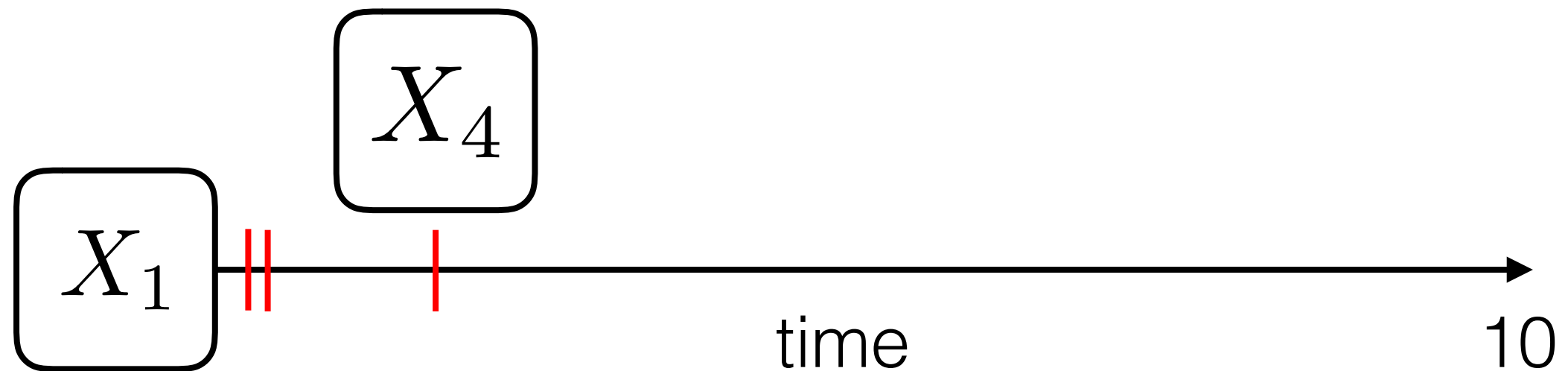
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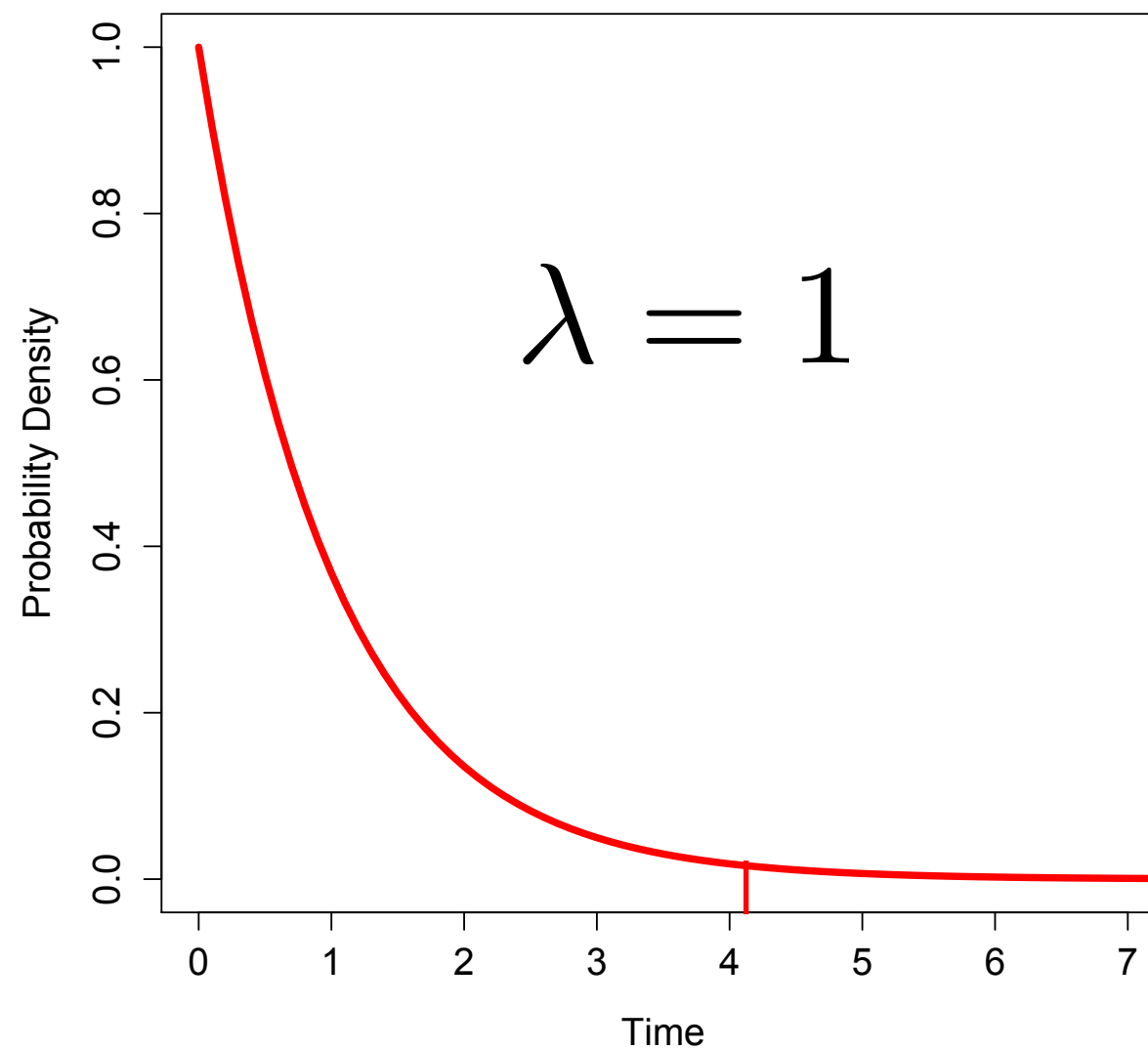
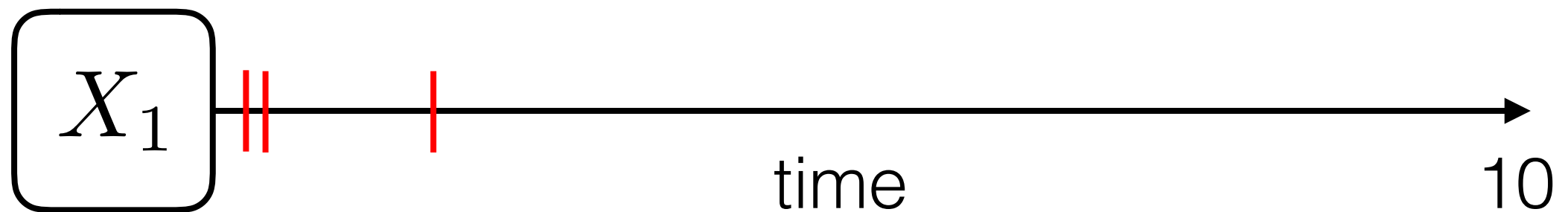
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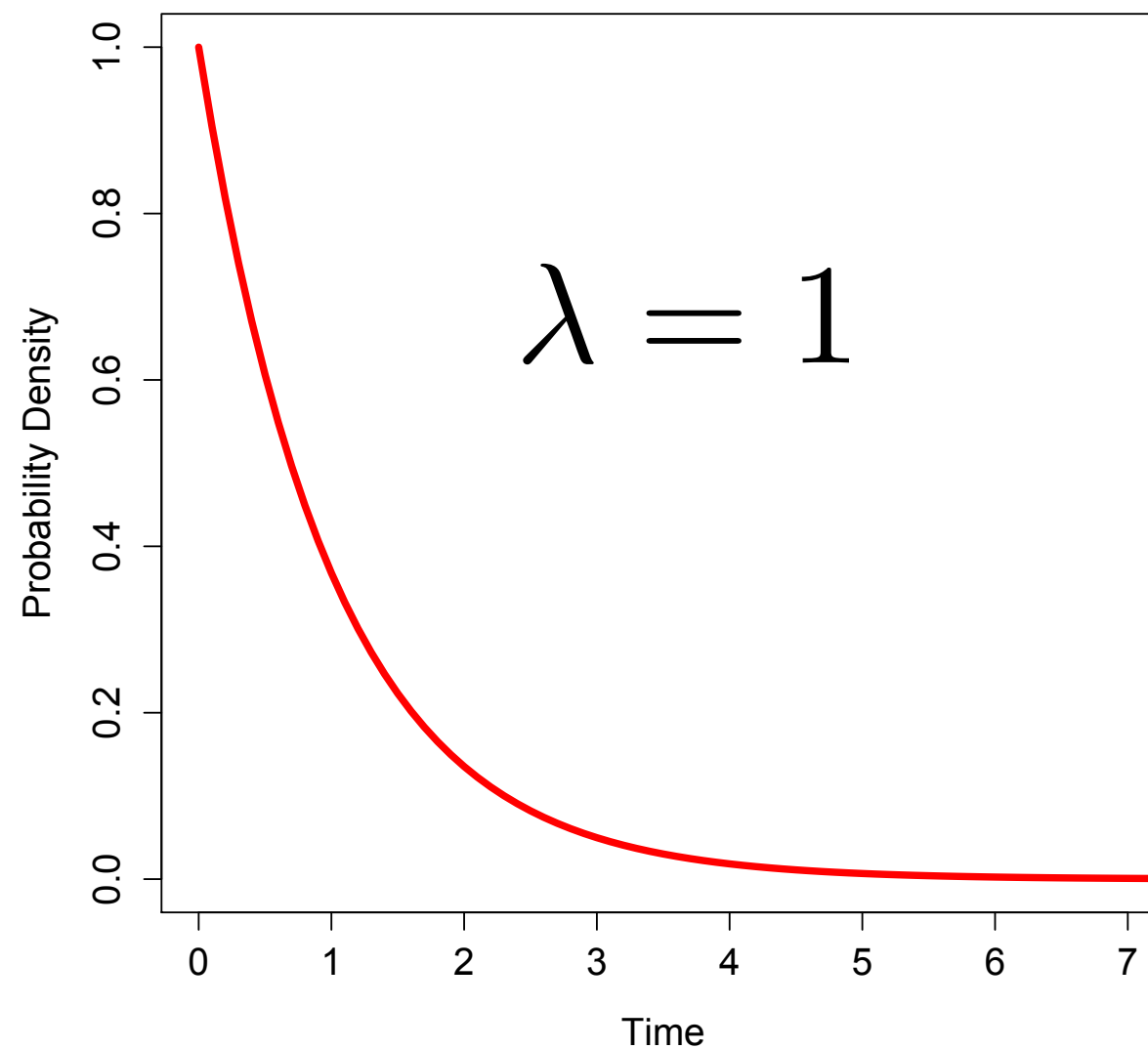
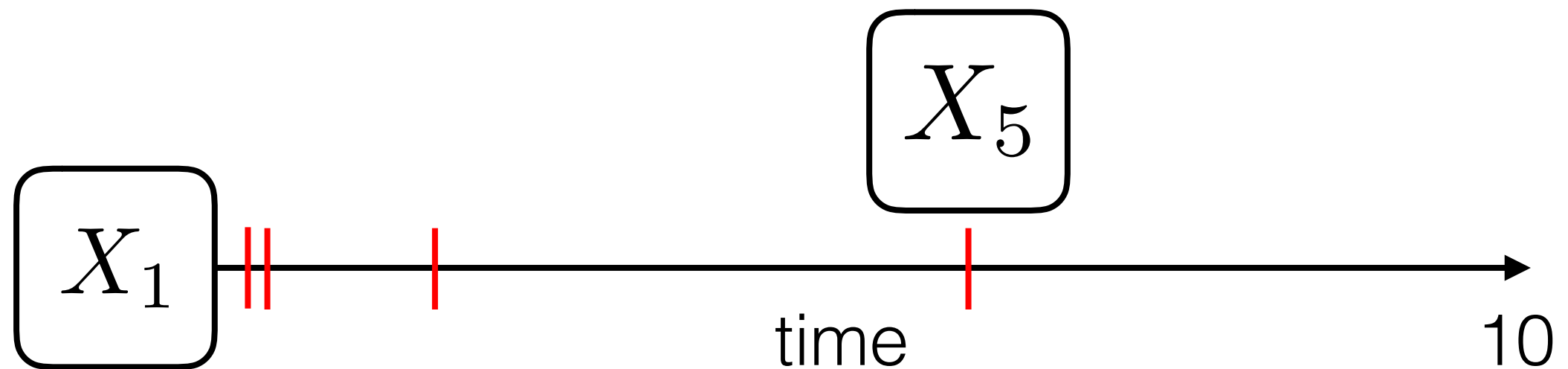


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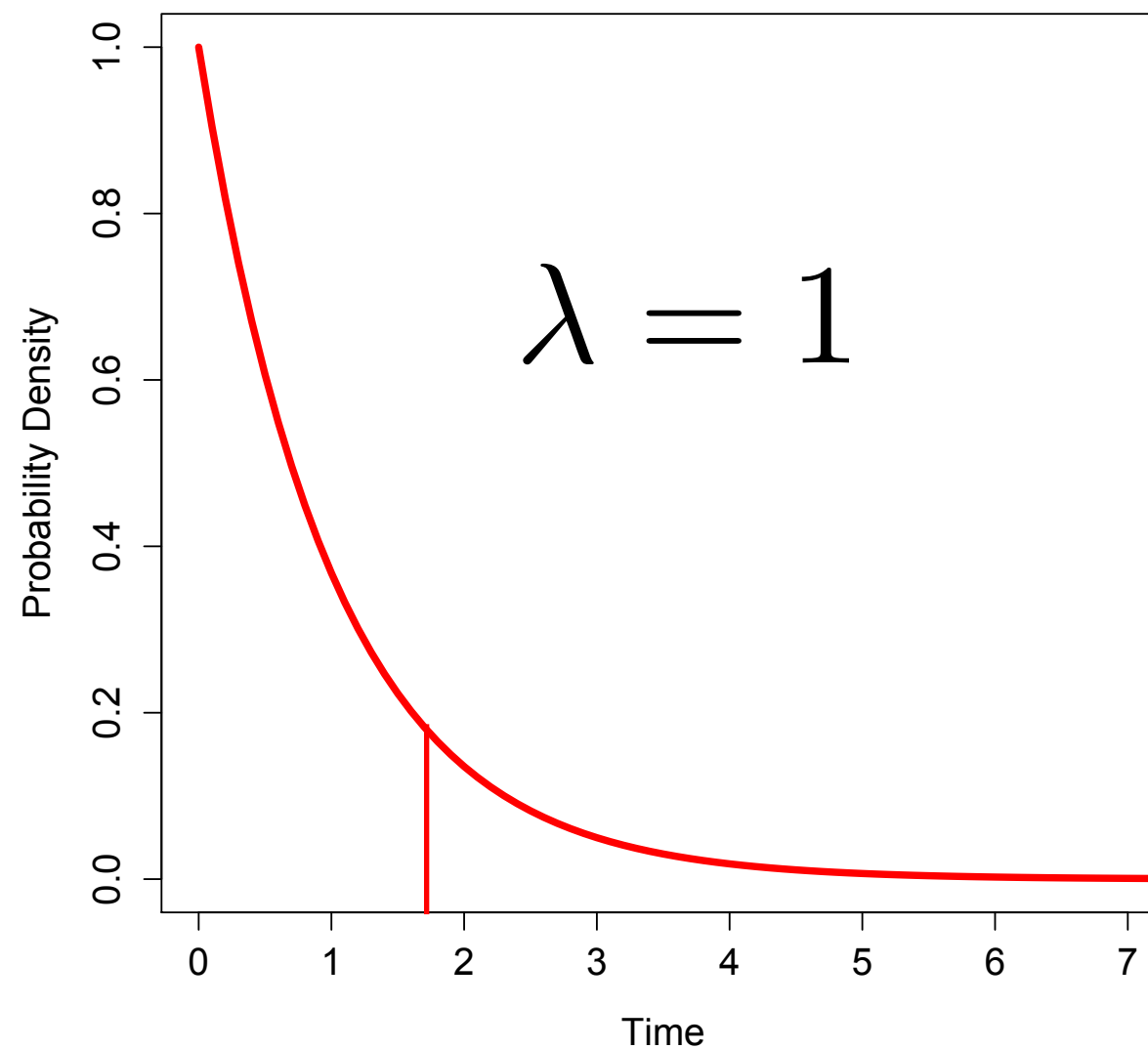
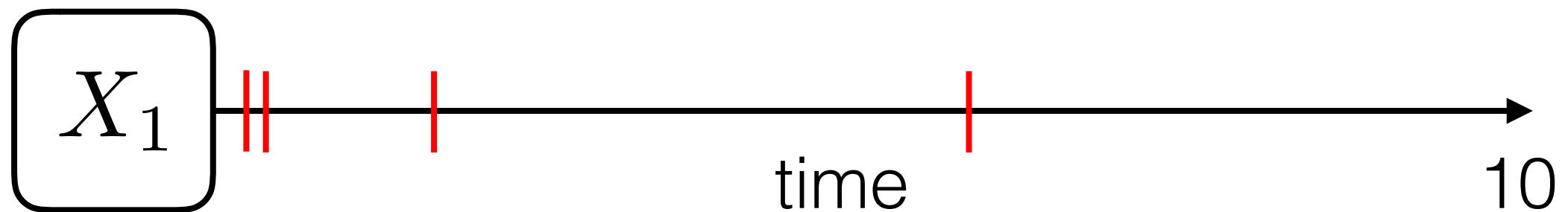




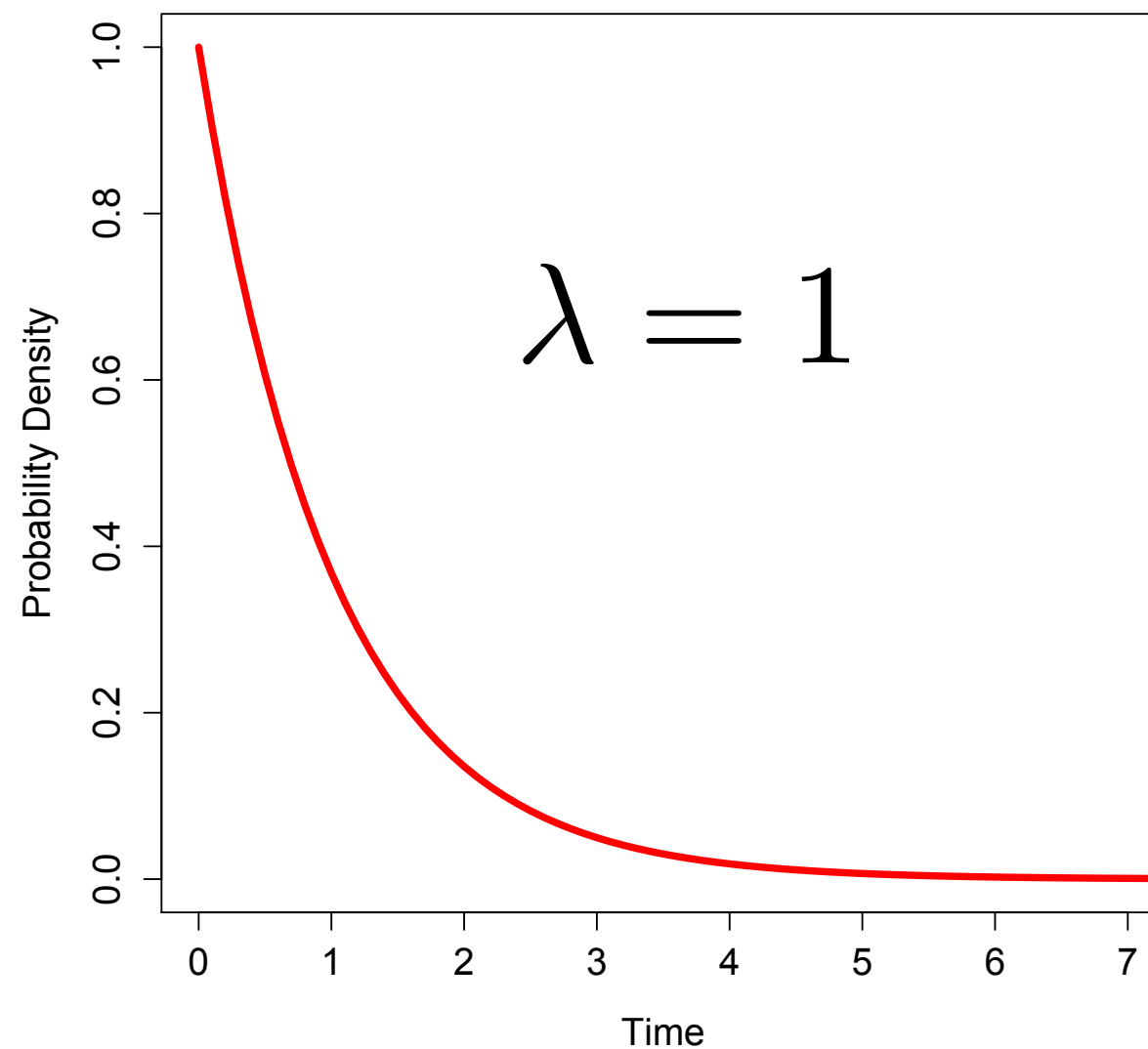
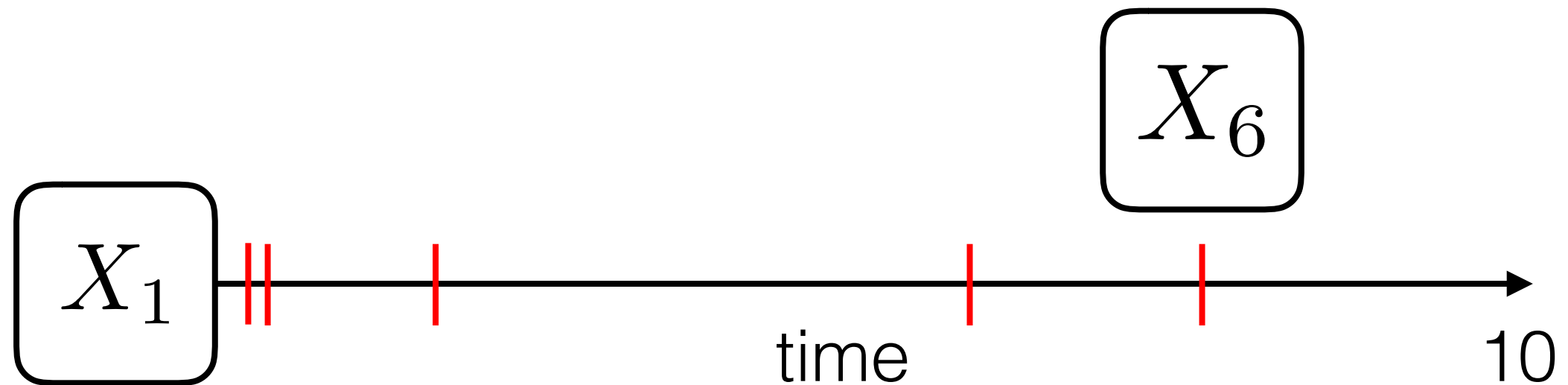
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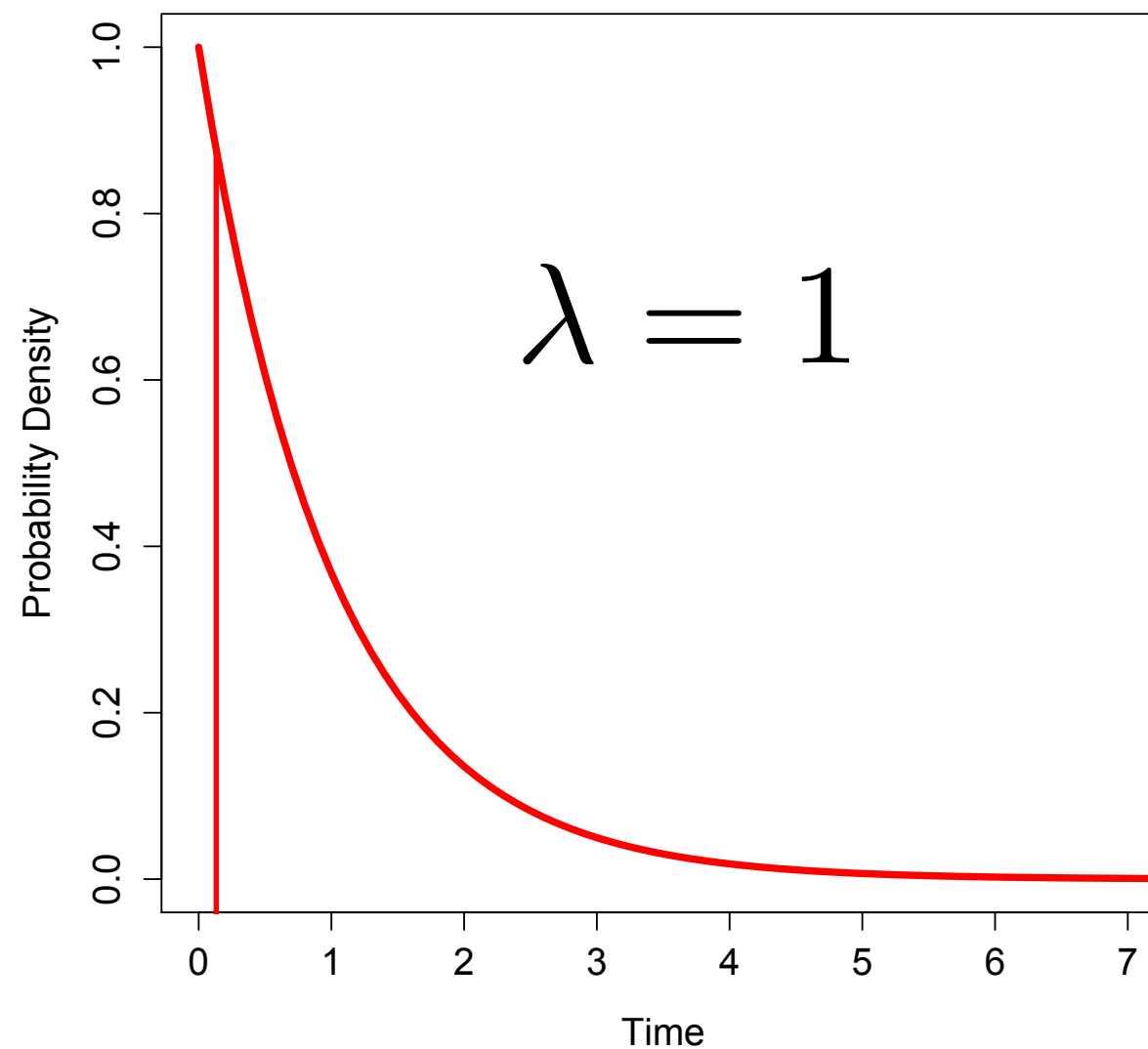
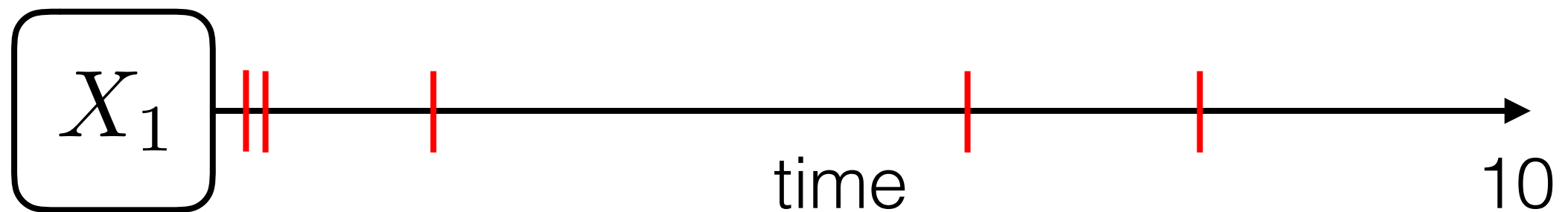
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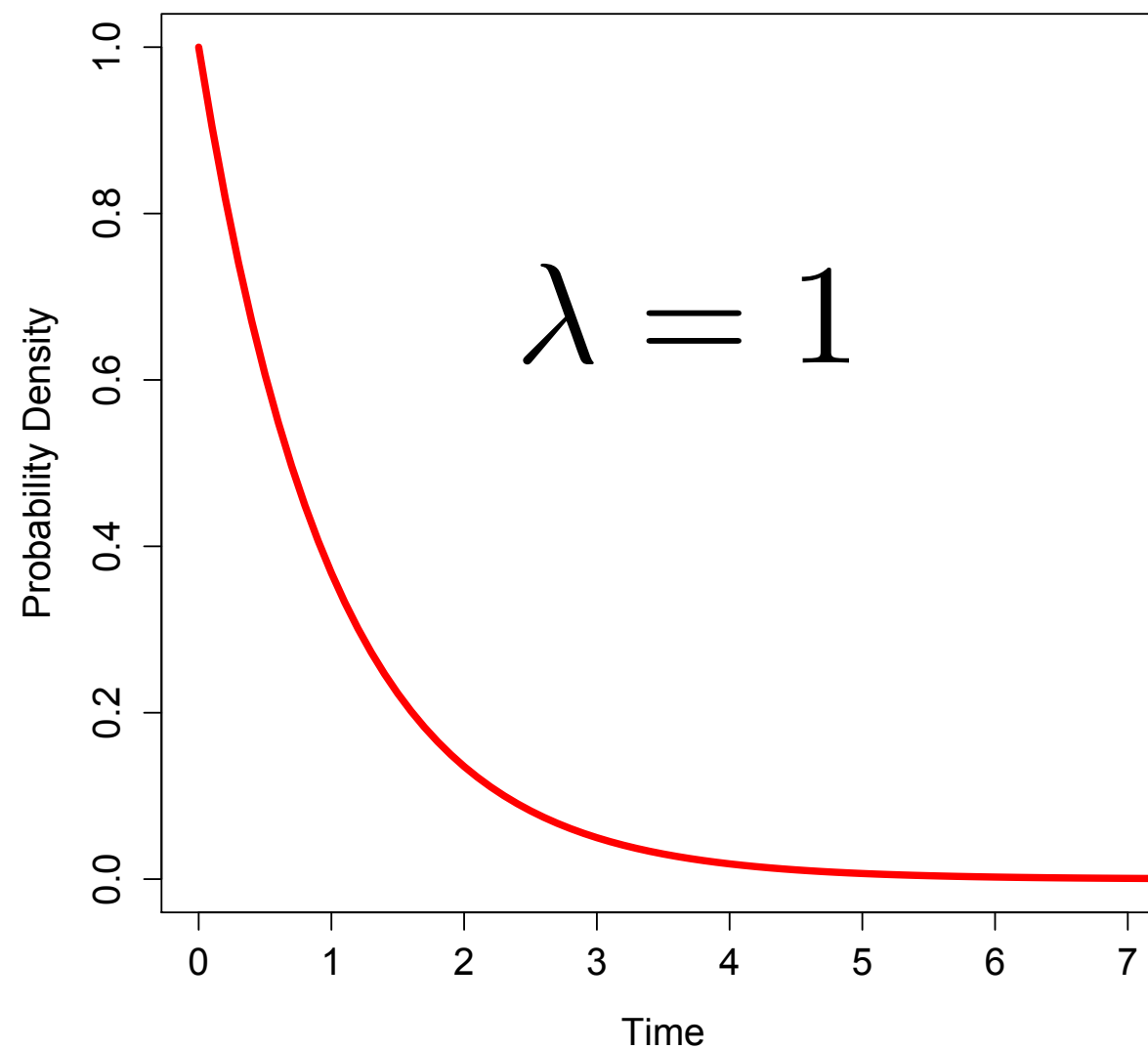
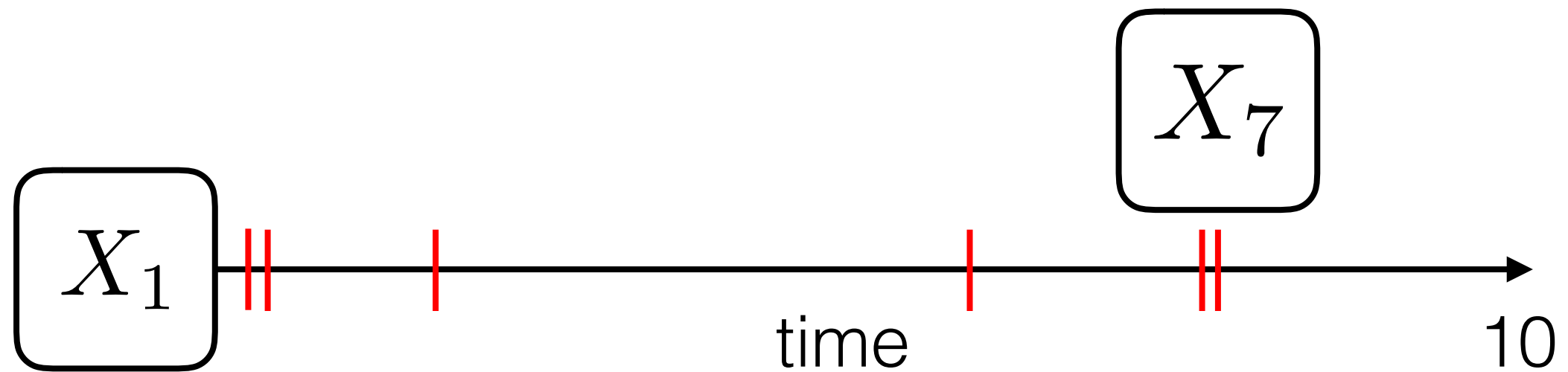
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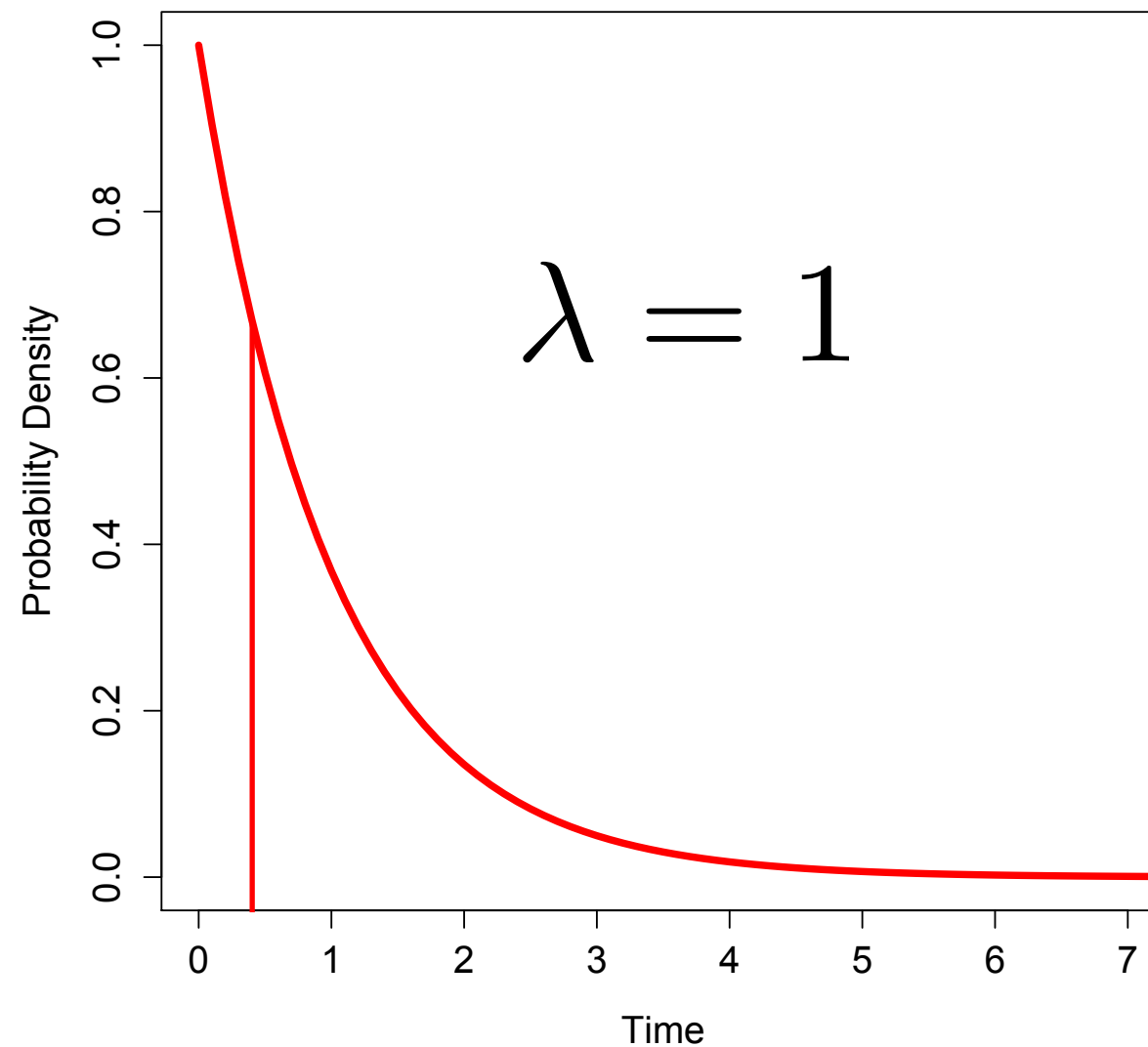
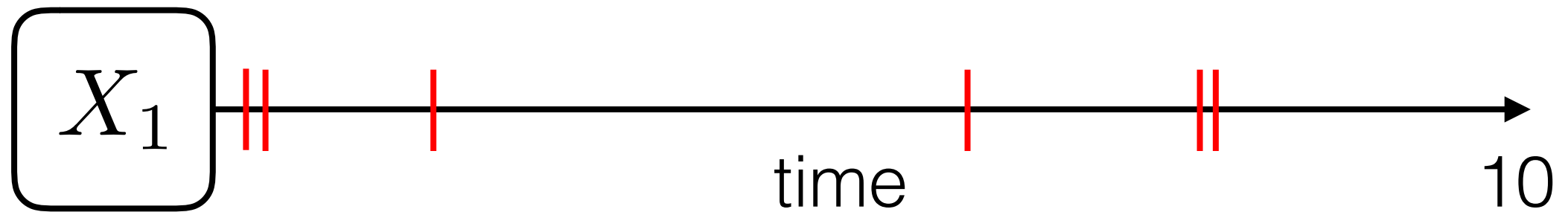
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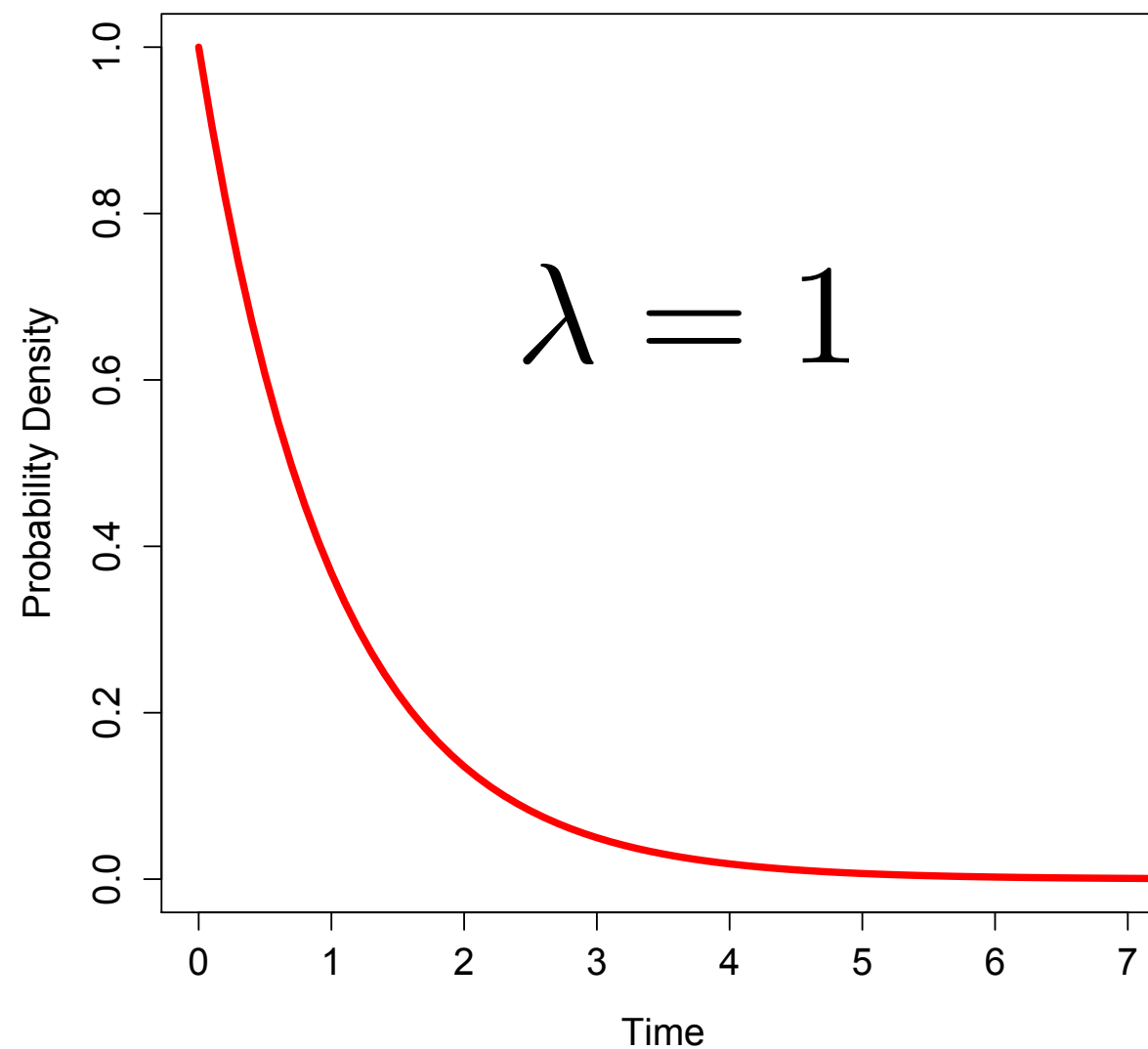
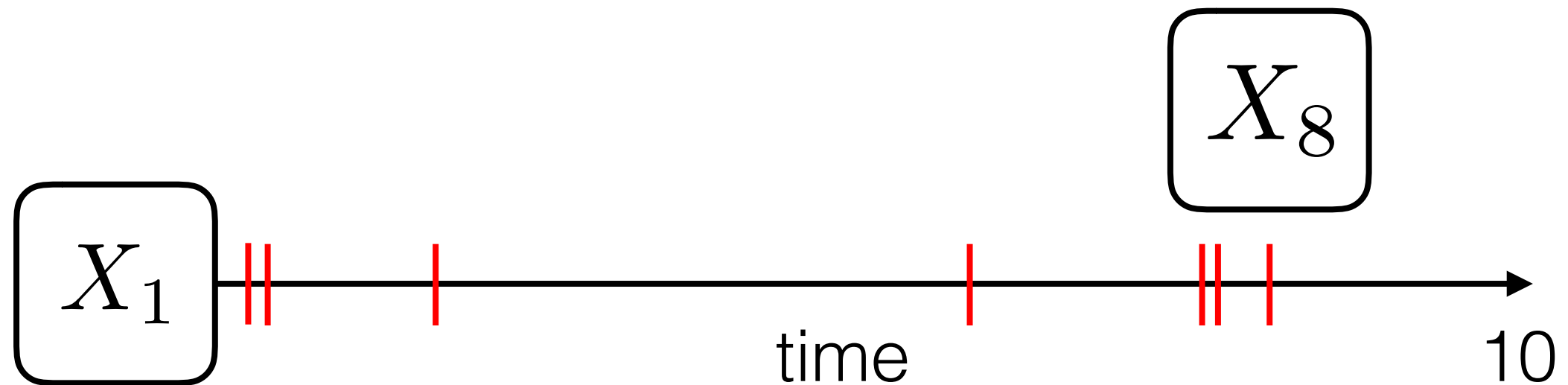
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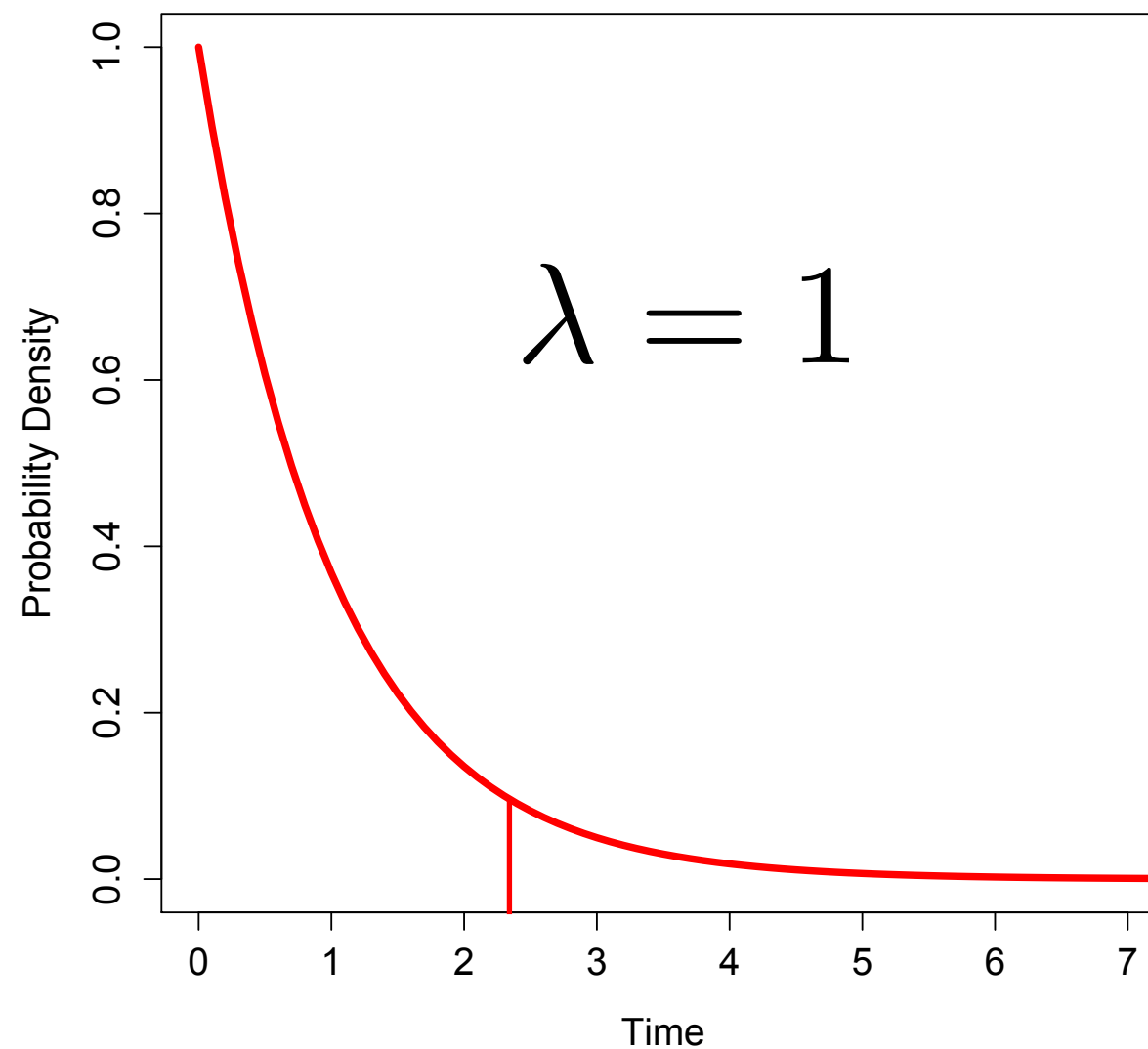
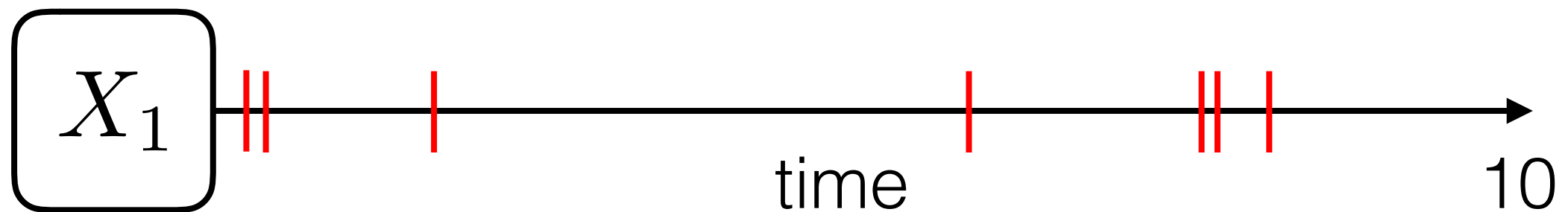
# Continuous Time Markov Chains



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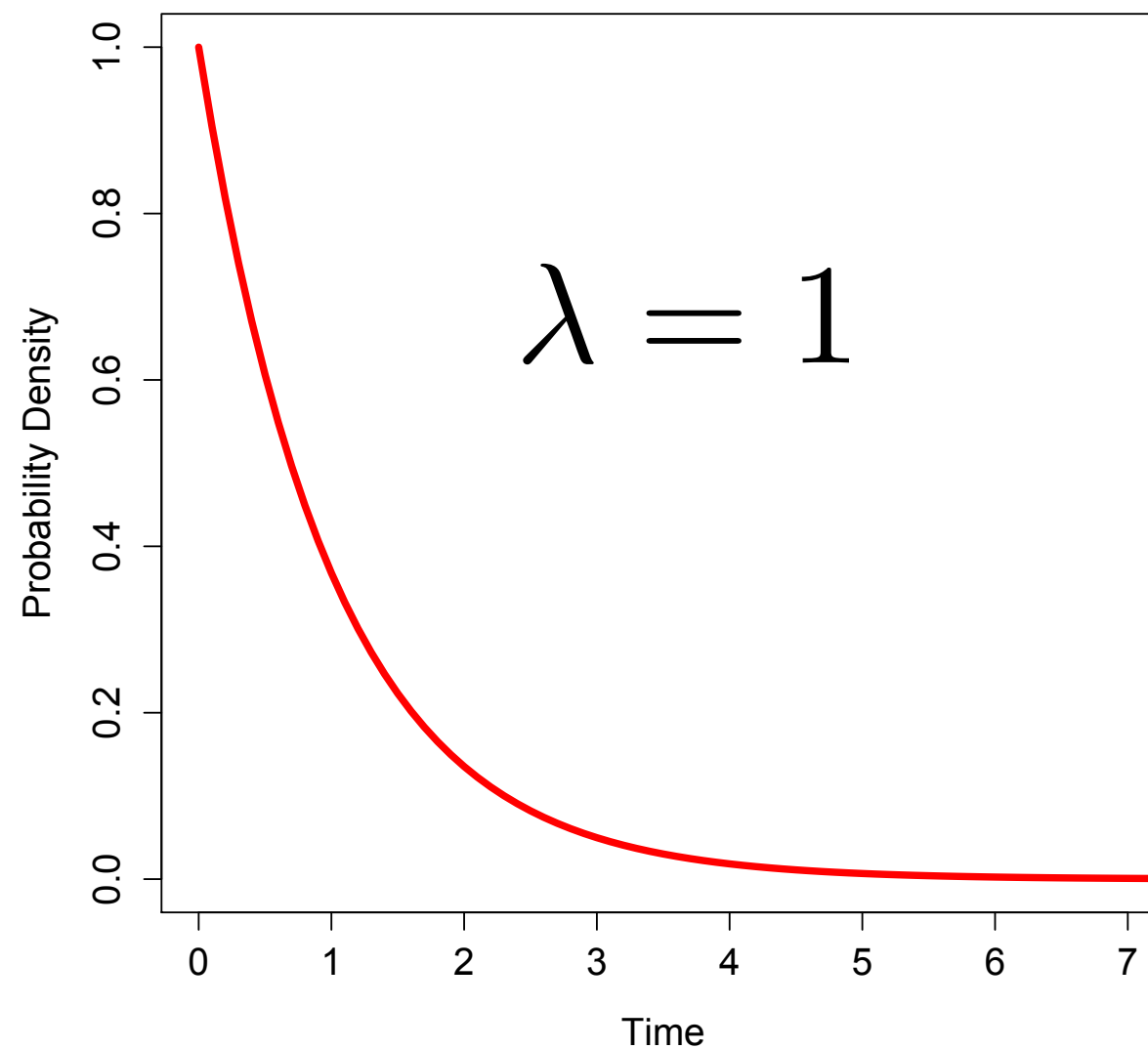
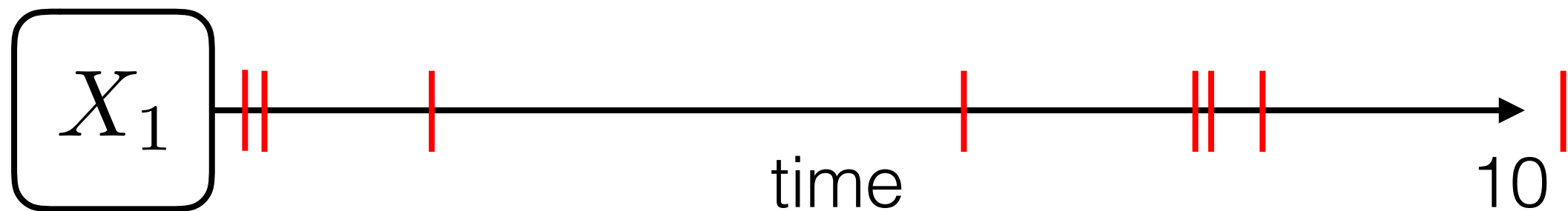


# Continuous Time Markov Chains





# Continuous Time Markov Chains



# CTMC Transition Matrix

$$\begin{array}{c} A \\ C \\ G \\ T \end{array} \begin{array}{c} A \\ C \\ G \\ T \end{array} \begin{pmatrix} -1 & 1/3 & 1/3 & 1/3 \\ 1/3 & -1 & 1/3 & 1/3 \\ 1/3 & 1/3 & -1 & 1/3 \\ 1/3 & 1/3 & 1/3 & -1 \end{pmatrix}$$

Jukes and Cantor (1969)


# CTMC Transition Matrix

$$\begin{array}{c} A \\ C \\ G \\ T \end{array} \begin{array}{c} A \\ C \\ G \\ T \end{array} \begin{pmatrix} -1 & 1/3 & 1/3 & 1/3 \\ 1/3 & -1 & 1/3 & 1/3 \\ 1/3 & 1/3 & -1 & 1/3 \\ 1/3 & 1/3 & 1/3 & -1 \end{pmatrix}$$

Jukes and Cantor (1969)

# CTMC Transition Matrix

Exponential Rate  
for State A


$$\begin{matrix} & A & C & G & T \\ \begin{matrix} A \\ C \\ G \\ T \end{matrix} & \begin{pmatrix} -1 & 1/3 & 1/3 & 1/3 \\ 1/3 & -1 & 1/3 & 1/3 \\ 1/3 & 1/3 & -1 & 1/3 \\ 1/3 & 1/3 & 1/3 & -1 \end{pmatrix} \end{matrix}$$

Jukes and Cantor (1969)

# CTMC Transition Matrix

Relative  
Probabilities of  
Transition

$$\begin{matrix} & A & C & G & T \\ \begin{matrix} A \\ C \\ G \\ T \end{matrix} & \begin{pmatrix} -1 & 1/3 & 1/3 & 1/3 \\ 1/3 & -1 & 1/3 & 1/3 \\ 1/3 & 1/3 & -1 & 1/3 \\ 1/3 & 1/3 & 1/3 & -1 \end{pmatrix} \end{matrix}$$

Jukes and Cantor (1969)