

# Markov Chains

CS70 Summer 2016 - Lecture 6B/C

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UC Berkeley

# Agenda

What are Markov Chains? State machine  
and matrix representations.

Hitting Time

Convergence, limiting and stationary  
distributions



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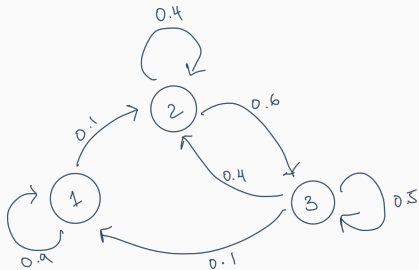
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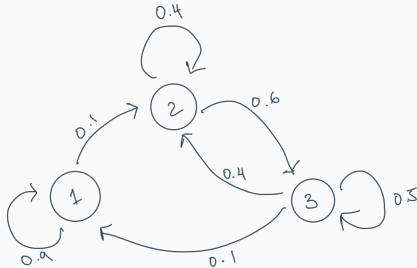
Solution: Markov chains!

# Intuition



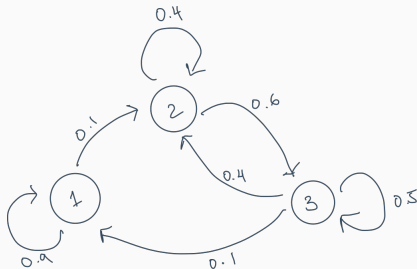


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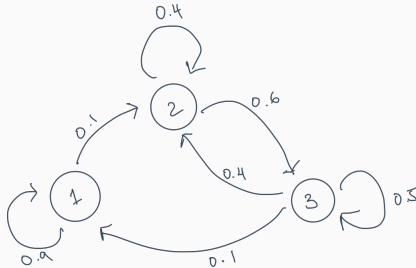
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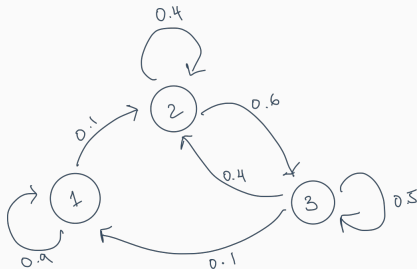


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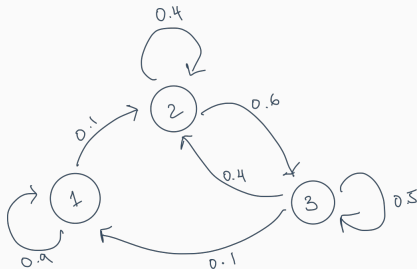
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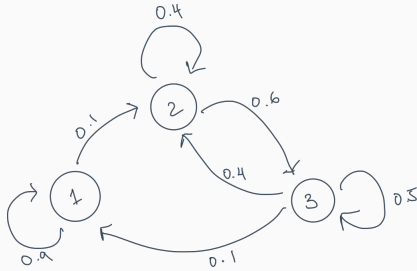
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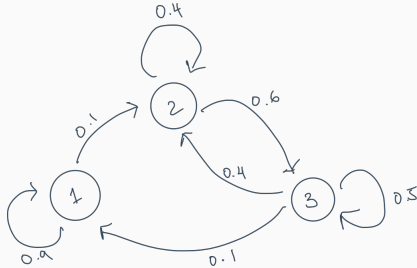
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Markov chains are **memoryless** - they don't remember anything other than what state they are.

# Formally Speaking...

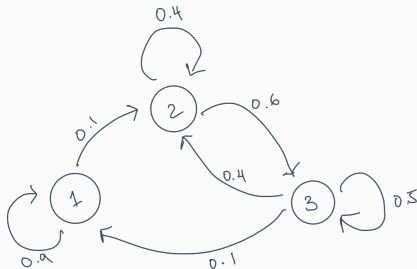


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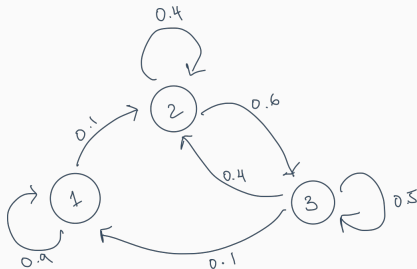


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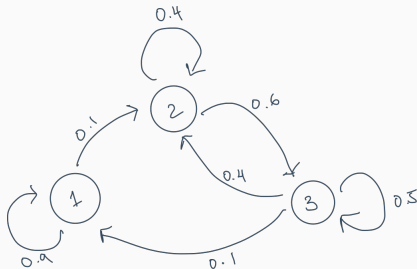
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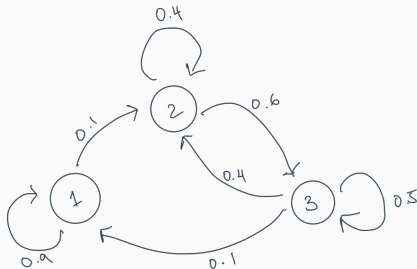


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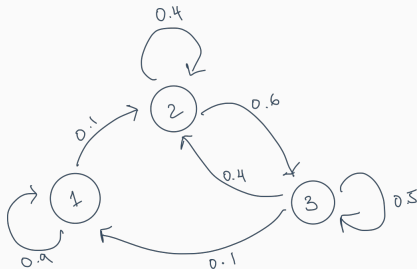
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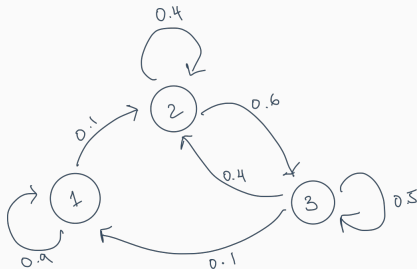
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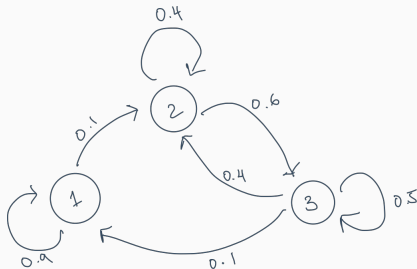
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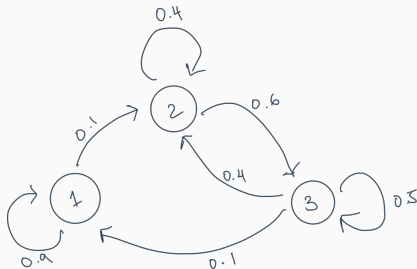
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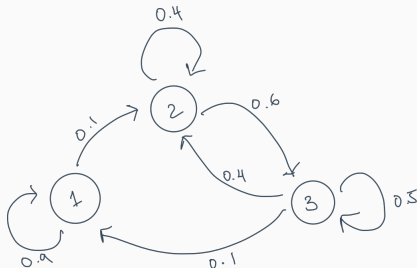
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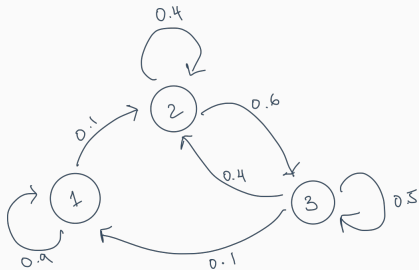
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- $Pr[X_{n+1} = j \mid X_0, \dots, X_n = i] = P(i, j), i, j \in \mathcal{X}.$

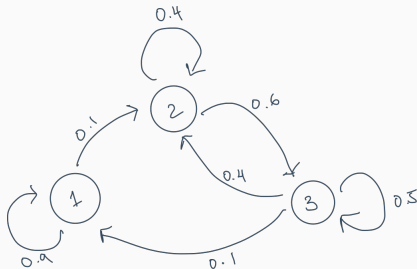


## One Small (Time)step for a State



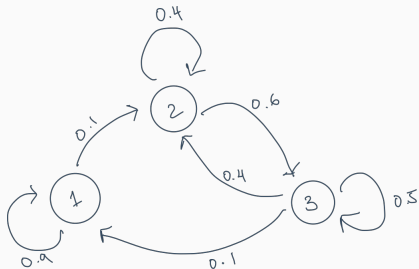
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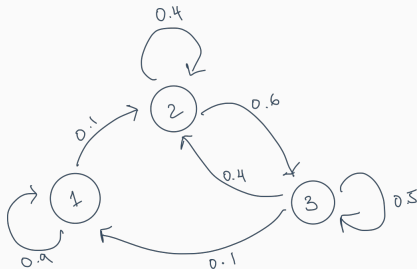


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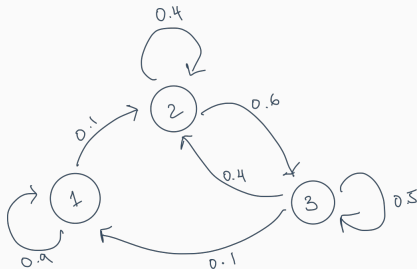
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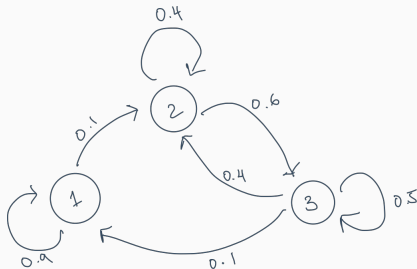
Probability depends on the previous state, but is independent of how it got to the previous state. (It's not independent of states before the previous state - but any dependence is captured in the previous state.)

# One Giant Leap with Conditional Probability



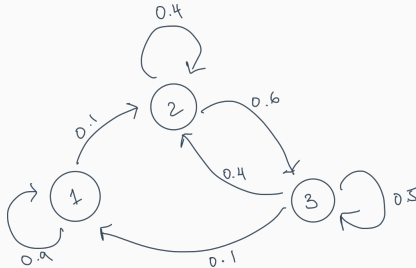
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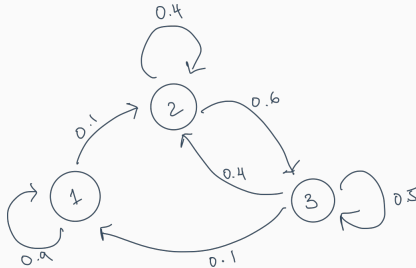
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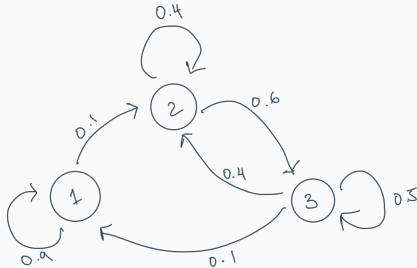


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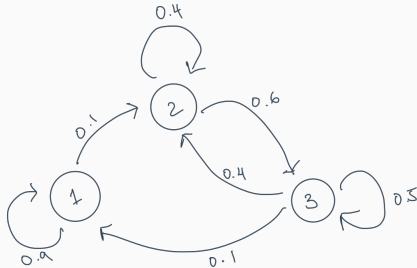
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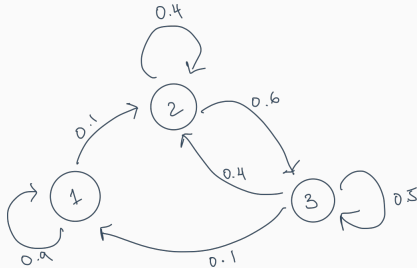
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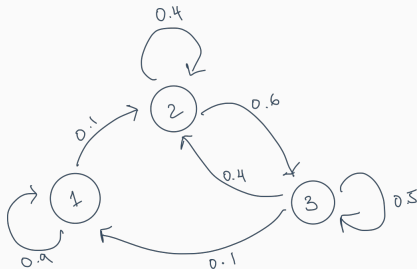
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Rest of distribution for  $X_{t+1}$  can be found similarly.

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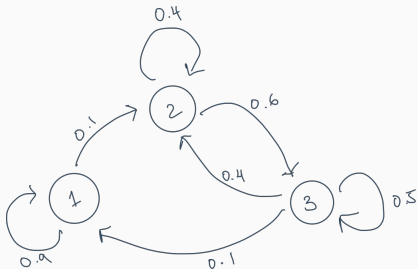
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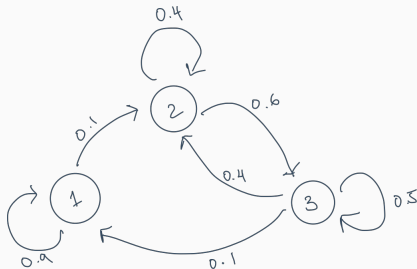


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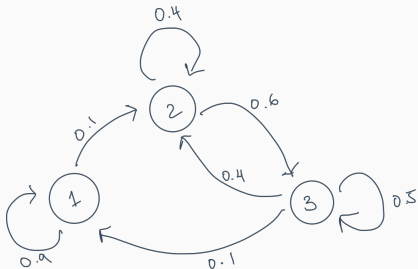


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$$\begin{bmatrix} 0.2 * 0.9 + 0.3 * 0 + 0.5 * 0.1 \\ 0.2 * 0.1 + 0.3 * 0.4 + 0.5 * 0.4 \\ 0.2 * 0 + 0.3 * 0.6 + 0.5 * 0.5 \end{bmatrix}^T$$

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$$\begin{bmatrix} 0.2 * 0.9 + 0.3 * 0 + 0.5 * 0.1 \\ 0.2 * 0.1 + 0.3 * 0.4 + 0.5 * 0.4 \\ 0.2 * 0 + 0.3 * 0.6 + 0.5 * 0.5 \end{bmatrix}^T = \begin{bmatrix} 0.23 & 0.34 & 0.43 \end{bmatrix}$$

# Stepping with Multiplication

$$P = \begin{bmatrix} 0.9 & 0.1 & 0 \\ 0 & 0.4 & 0.6 \\ 0.1 & 0.4 & 0.5 \end{bmatrix}$$

Distributions are vectors. Suppose that  $X_t$  is distributed 1 w.p. 0.2, 2 w.p. 0.3, and 3 w.p. 0.5. Write distribution as vector!

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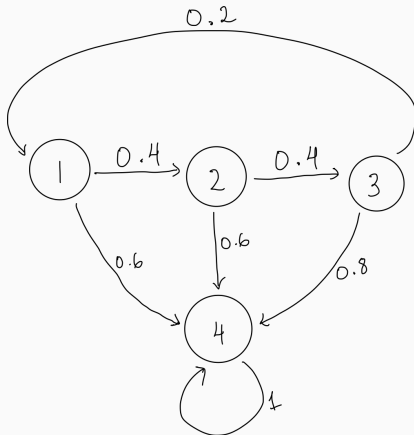
This is the distribution of  $X_{t+1}$ .

## An Example

California driving test: you get 3 retakes before you have to start the application process all over again. Suppose someone passes a driving test w.p. 0.6, unless it's their final retake, in which case they're more careful and pass w.p. 0.8.

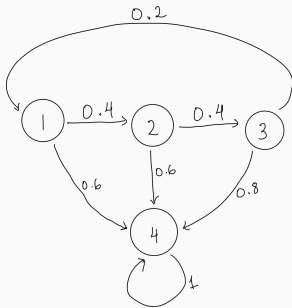
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# An Example



Initial distribution?  $\pi_0 = [1 \ 0 \ 0 \ 0]$

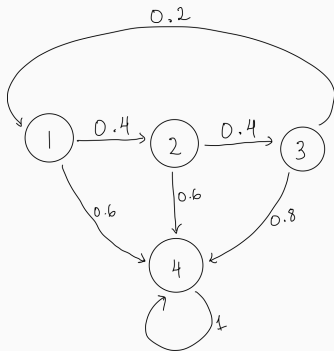
Transition matrix?

$$T = \begin{bmatrix} 0 & .4 & 0 & .6 \\ 0 & 0 & .4 & .6 \\ .2 & 0 & 0 & .8 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

## Hitting Time

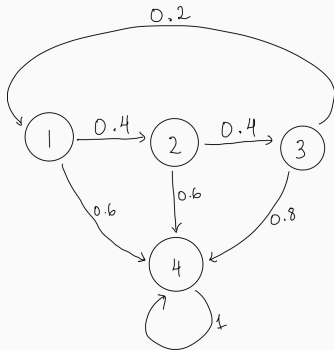
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# Motivation



How long does it take to get a driver's license, in expectation?

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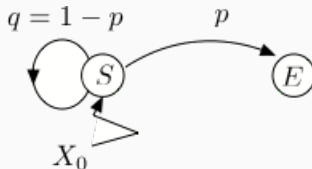


How long does it take to get a driver's license, in expectation?

Generally: given a Markov chain and an initial distribution, how many timesteps do we expect to take before reaching a particular state?

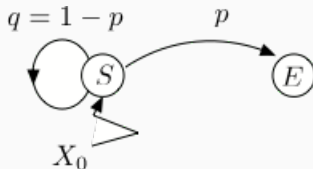
## A Simple Example

Let's flip a coin with  $\Pr[H] = p$  until we get  $H$ . How many flips, on average?



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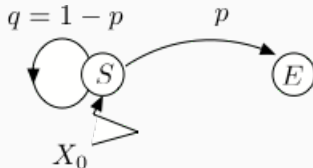
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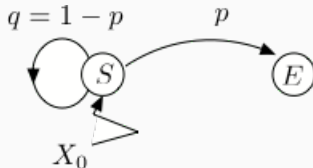


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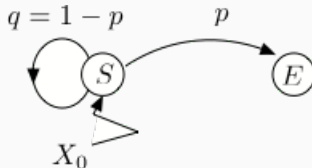
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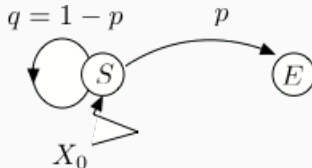
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Hence,

$$p\beta(S) = 1,$$

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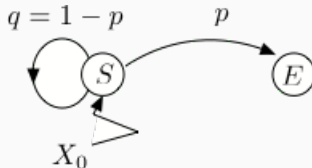
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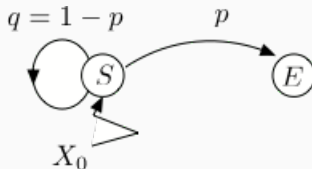
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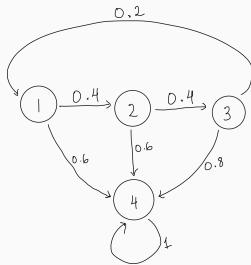
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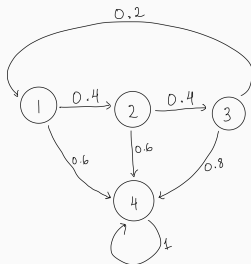
$$p\beta(S) = 1, \text{ so that } \beta(S) = 1/p.$$

Note: Time until  $E$  is  $G(p)$ . We have rediscovered that the mean of  $G(p)$  is  $1/p$ .

# How Long to Get a Driver's License?

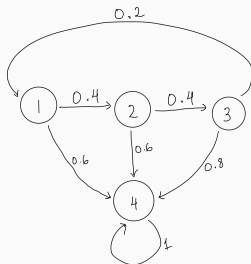


# How Long to Get a Driver's License?



Let  $\beta(S)$  denote expected time to get a driver's license from  $S$ .

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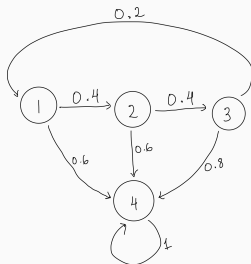
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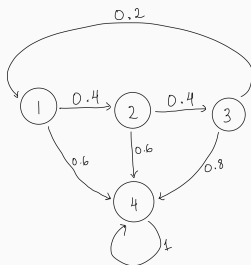
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Solves to  $\beta(1) \approx 0.61$ .



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Solves to  $\beta(1) \approx 0.61$ . Adding the first driving test: 1.61 driving tests.

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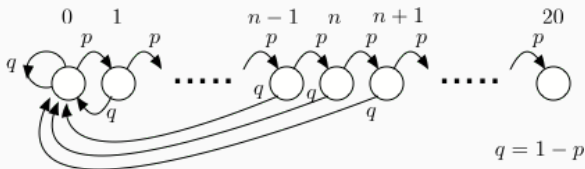
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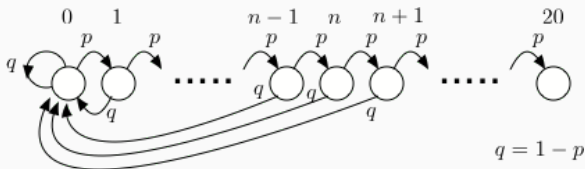
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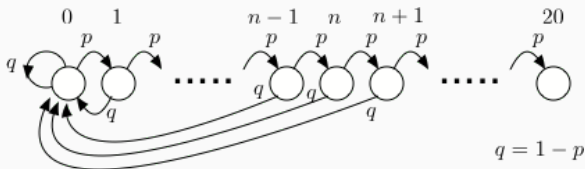
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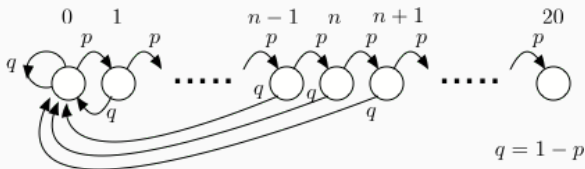
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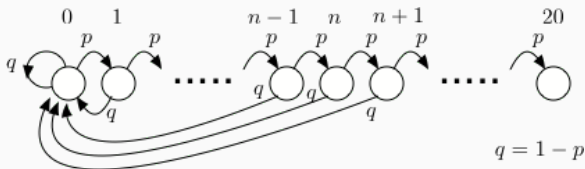
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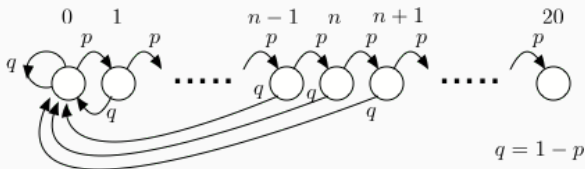
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See Lecture Note 24 for algebra.

Questions?