

# Markov Chains I

## Lec.26

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# Markov Chains: Fundamental Idea

We now wish to model sequences of random variables  $X_0, X_1, X_2, \dots$ . You can think of  $X_n$  as the state of a system at time  $n$ .

We will be working on the setting where time is discrete, and each  $X_i$  can only take on a finite set of values. This finite set of values is denoted  $\mathcal{X}$  and is called the state space.

# Markov Property

Think of  $X_n$  be the present/current state, and  $X_{n+1}$  as the future state. The Markov Property is:

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

This property is not saying the future is independent of the past. This property is saying that the past and future are *conditionally independent* given the present.

We call  $\Pr(X_{n+1} = j | X_n = i) = P(i, j)$  the transition probability from state  $i$  to state  $j$ .

In this class, we will only deal with time homogeneous Markov chains.

# Transition Probability Matrix

Let the state space  $\mathcal{X}$  be  $\{1, \dots, k\}$ . The transition probability matrix for a Markov chain  $P$  is a  $k$  by  $k$  matrix such that the entry in the  $i$ th row and  $j$  column is  $P(i, j)$ , and:

$$P(i, j) \geq 0 \quad \forall i, j \in \mathcal{X} \quad (1)$$

$$\sum_{j=1}^k P(i, j) = 1 \quad \forall i \in \mathcal{X} \quad (2)$$

# Markov Chain Example

# Distribution Over States

We use  $\pi_i$  to represent the distrution of our random variable  $X_i$  over the states in  $\mathcal{X}$ . The entries in  $\pi_i$  must be probabilities that sum up to 1.

$\pi_0$  is called our initial distribution.  $\pi_0$ , in conjunction with  $P$  and  $\mathcal{X}$  fully specifies our Markov chain.

## Moving in Time

Suppose at time  $n$ ,  $X_n$  has distribution  $\pi_n$ . Then, by the Law of Total Probability,

$$\Pr(X_{n+1} = j) = \sum_i \Pr(X_{n+1} = j | X_n = i) \Pr(X_n = i) \quad (3)$$

$$= \sum_i P(i, j) \pi_n(i) \quad (4)$$

But  $\sum_i P(i, j) \pi_n(i)$  is the  $j$ th entry of  $\pi_n P$ . So,

$$\pi_{n+1} = \pi_n P \quad (5)$$

$$\pi_{n+2} = \pi_{n+1} P = \pi_n P P = \pi_n P^2 \quad (6)$$

$P^k$  is the probability transition matrix where the entry in the  $i$ th row  $j$ th column is the probability of going from state  $i$  to state  $j$  in  $k$  steps.

# Hitting Time Example



# Probability of A before B Example

# Invariant Distribution Definition

A distribution  $\pi$  is *invariant* for the transition probability matrix  $P$  if it satisfies the following *balance equations*:

$$\pi = \pi P \tag{7}$$

# Stationary Distribution Existence

Let  $P$  be the probability transition matrix for a Markov chain.

The rows of  $P$  add up to 1. Let  $\mathbf{1}$  be a column vector of ones. This means  $P\mathbf{1} = \mathbf{1} = 1 \cdot \mathbf{1}$ .

This means  $P$  has a right eigenvector corresponding to eigenvalue 1. Since the right and left eigenvalues of a square matrix are the same, this means there exists some left eigenvector  $\pi$  such that  $\pi P = 1 \cdot \pi$ .

Note that this does not say anything about the uniqueness of the stationary distribution.

# Stationary Distribution Example