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# A review of countable time MC

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## Some definitions on MC

**Definition** A *discrete time stochastic process* is a collection of random variables  $\{X_0, X_1, X_2, \dots\}$  defined on a common sample space and state space.

**Definition** A (time homogeneous) *Markov chain* is a stochastic process such that for all  $n \in \{0, 1, \dots\}$  and  $x_0, x_1, \dots, x_n, y \in S$ ,

$$P(X_{n+1} = y | X_0 = x_0, X_1 = x_1, \dots, X_n = x_n) = P(X_{n+1} = y | X_n = x_n).$$

[All Markov chains in this course will be time homogeneous unless explicitly stated otherwise.]

## Finite State MC

**Definition** Given a Markov chain with a finite state space  $S$ , a *transition matrix* is a matrix whose entry in the  $i$ th row and  $j$ th column is

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

**Definition** Given a Markov chain with finite state space  $S$ , the *transition graph* has vertex set  $S$ , and has directed edges  $(i, j)$  with weight

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

whenever this weight is positive.

**Definition**  $\pi$  is a *stationary* or *invariant* distribution for a Markov chain if  $\sum_{y \in S} \pi_y p(y, x) = \pi_x$ .

**Definition** For countable state Markov chains, if

$$\sum_{x \in S} \pi_x P(X_{t+1} = y | X_t = x) = \pi_y$$

then  $\pi$  is a stationary distribution. These are called the *balance equations*.

**Definition**  $\pi$  is a *limiting* distribution for a countable state Markov chain if

$$\lim_{n \rightarrow \infty} P(X_n = i | X_0 = j) = \pi_i,$$

for all states  $i$  and  $j$ .

**Definition** States  $x$  and  $y$  of a Markov chain communicate if for some  $n$  and some  $m$ ,  $P(X_n = y|X_0 = x) > 0$  and  $P(X_m = x|X_0 = y) > 0$ .

**Definition** A Markov chain is *irreducible* if all states communicate. Otherwise it is reducible.

**Definition** The *period* of an irreducible Markov chain is

$$\gcd\{n : P(X_n = x|X_0 = x) > 0\}$$

for any state  $x$ . A chain with period 1 is called *aperiodic*.

## Ergodic Theorem for finite state Markov chains

For irreducible aperiodic finite state Markov chains, a unique stationary distribution exists with  $\pi_x > 0$  for all  $x \in S$ , and this will also be the limiting distribution. In addition, the expected time of return from  $x$  to itself will be  $1/\pi_x$ .

## Countable State MC

**Definition** Let

$$R_x = \inf\{t > 0 : X_t = x | X_0 = x\}$$

be the *return time* for the state  $x$ . Then state  $x$  is *recurrent* if  $P(R_x < \infty) = 1$ . If any state in an irreducible chain is recurrent, they all are, and it is a *recurrent chain*.

**Definition** A state that is not recurrent is *transient*. An irreducible chain which is not recurrent is a *transient chain*.

**Fact** A state  $x$  is transient iff  $E(N(x) | X_0 = x) < \infty$  where  $N(x) = \sum_{m=1}^{\infty} 1_{\{X_m=x\}}$ .

**Definition** Consider a chain that is recurrent and aperiodic. If there exist states  $x$  and  $y$  in  $S$  such that  $\lim_{n \rightarrow \infty} P(X_n = y | X_0 = x) = 0$ , the chain is *null recurrent*. When the limit is positive, it is *positive recurrent*.

**Fact** Let  $R$  be the time needed to return to state  $x$  given  $X_0 = x$ . For null recurrent chains,  $E(R) = \infty$  and  $P(R < \infty) = 1$ .



## Ergodic Thm for countable state space

For an irreducible aperiodic positive recurrent chain on a countable state space, there exists a unique stationary distribution  $\pi$  with  $\pi_i > 0$ . Also,  $\pi$  is the limiting distribution, and if  $R$  is the time for return to  $x$  starting from  $x$ ,  $E(R) = 1/\pi_x$ . If the chain is null recurrent or transient, there is no stationary distribution  $\pi$ .

**Definition** A *branching process* is a special Markov chain on  $\{0, 1, 2, \dots\}$  such that if  $\xi_1^n, \xi_2^n, \dots$  are i.i.d. draws from a distribution on the nonnegative integers with a mean  $\mu$ , then

$$X_{n+1} = \sum_{i=1}^{X_n} \xi_i^n.$$

**Theorem:** If  $\mu \leq 1$  then the extinction probability equal to 1. If  $\mu > 1$  then the extinction probability is less than 1 and equal to the smallest positive root of  $a = \sum_{i=0}^{\infty} P(\xi = i)a^i$  with  $0 < a < 1$ .