

# Markov chains

A **Markov chain** is specified by a **state space**  $S$  and by a **transition matrix**  $P_{xy}$ ,  $x, y \in S$  such that

$$P_{xy} \geq 0, \quad \sum_{y \in S} P_{xy} = 1$$

The second condition ensures that, for each fixed  $x$ ,  $P_{xy}$  is a probability in  $y$ .

Two basic features:

- 1) the probability to be in  $y$  at time  $t+1$  depends only on the position  $x$  at time  $t$ ;
- 2) the probabilities are time independent.

In practice, the dynamics proceeds as follows:

- (a) at time  $t=0$  the system is in point  $x_0$ .
- (b)  $P_{x_0y}$  at fixed  $x_0$  is a probability  $p_y$ . The two conditions above imply  $p_y \geq 0$  and  $\sum_{y \in S} p_y = 1$  (they should be satisfied by a probability). Choose a point  $y$  with probability  $p_y$  and set  $x_1 = y$ .  $x_1$  is the state of the system at time  $t=1$ .
- (c)  $P_{x_1y}$  at fixed  $x_1$  is a probability  $p_y$ . Choose a point  $y$  with probability  $p_y$  and set  $x_2 = y$ .  $x_2$  is the state of the system at time  $t=2$ . We go on analogously generating  $x_3, \dots$

## Example

Let us consider two Ising spins  $s_1, s_2$ . An Ising spin is a variable which can assume the values  $\pm 1$ .

The **state space** has dimension 4. There are four different **states** or configurations  $(s_1, s_2)$ :

$$\begin{aligned} s_1 &= (+1, +1) \\ s_2 &= (+1, -1) \\ s_3 &= (-1, +1) \\ s_4 &= (-1, -1) \end{aligned}$$

**Dynamics.** The dynamics consists in choosing randomly one spin and flipping it with probability  $p$ .

We should now define the **transition matrix**.

Let us first compute  $P_{12}$ , i.e. the, probability of going from  $(+1, +1)$  to  $(+1, -1)$ . We obtain  $(+1, -1)$  if: (i) we choose the second spin (this occurs with probability  $1/2$ ), (ii) we flip it (this occurs with probability  $p$ ). It follows

$$P_{12} = 1/2 \times p = p/2.$$

Let us compute  $P_{13}$ , i.e. the, probability of going from  $(+1, +1)$  to  $(-1, +1)$ . We obtain  $(-1, +1)$  if: (i) we choose the first spin (this occurs with probability  $1/2$ ), (ii) we flip it (this occurs with probability  $p$ ). It follows

$$P_{13} = 1/2 \times p = p/2.$$

Let us compute  $P_{14}$ , i.e. the, probability of going from  $(+1, +1)$  to  $(-1, -1)$ . This can never occur as we only change the direction of one spin at each time.

$$P_{14} = 0.$$

Finally, we compute  $P_{11}$ , which is defined by the condition that  $\sum_y P_{1y} = 1$ . Therefore:

$$P_{11} + p/2 + p/2 + 0 = 1 \quad P_{11} = 1 - p$$

We do the same calculation for all other three points. We obtain

$$P = \begin{pmatrix} 1-p & p/2 & p/2 & 0 \\ p/2 & 1-p & 0 & p/2 \\ p/2 & 0 & 1-p & p/2 \\ 0 & p/2 & p/2 & 1-p \end{pmatrix}$$

## A numerical implementation.

The configurations are stored in the vectors  $s1[N+1], s2[N+1]$ , where  $N$  is the number of iterations

```
s1[0] = 1; s2[0] = 1; /* starting point */
REPEAT N times (i in [1,N])
  x = RAN()
  y = RAN()
  IF (x < 0.5)           /* first spin selected */
    if (y < p) s1[i] = -s1[i-1] /* spin 1 changes with prob p */
    else   s1[i] = s1[i-1]
  fi
  s2[i] = s2[i-1]          /* spin 2 does not change */
  ELSE
    if (y < p) s2[i] = -s2[i-1] /* spin 2 changes with prob p */
    else   s2[i] = s2[i-1]
  fi
  s1[i] = s1[i-1]          /* spin 1 does not change */
  FI
END REPEAT
```

Given  $P_{xy}$ , we can define the probability of a given **history**.

The probability that the system is in  $x_0$  at time 0, in  $x_1$  at time 1, in  $x_2$  at time 2, ..., in  $x_N$  at time  $N$  is simply the product of the probabilities of each transition

$$P_{x_0,x_1} P_{x_1,x_2} \dots P_{x_{N-1},x_N}$$

We can also determine the probability of being in  $x_N$  at time  $N$ , **irrespective of the position at intermediate times**.

To compute this probability we should sum over all histories that start in  $x_0$  and end in  $x_N$ .

## Example

Let us go back to the example of the dynamics of two spins. In this system there are four states  $S_i$ . At time 0 the system is  $S_1$  and want to determine the probability of being in  $S_4$  at time  $t = 2$ .

There are four possible histories:

$$\begin{aligned} S_1 \rightarrow S_1 \rightarrow S_4 & \quad \text{probability} = P_{11}P_{14} \\ S_1 \rightarrow S_2 \rightarrow S_4 & \quad \text{probability} = P_{12}P_{24} \\ S_1 \rightarrow S_3 \rightarrow S_4 & \quad \text{probability} = P_{13}P_{34} \\ S_1 \rightarrow S_4 \rightarrow S_4 & \quad \text{probability} = P_{14}P_{44} \end{aligned} \tag{1}$$

The required probability is obtained by summing over all histories:

$$P_{11}P_{14} + P_{12}P_{24} + P_{13}P_{34} + P_{14}P_{44} = \sum_x P_{1x}P_{x4}$$

We sum over the all state points. If we consider  $P$  as a matrix, the probability is  $(P \cdot P)_{14} = P_{1,4}^2$ , i.e., it is the element  $(1, 4)$  of the matrix  $P^2$ .

It is thus clear how to generalize the expression in the generic case:

$$\sum_{x_1, x_2, \dots, x_{N-1}} P_{x_0, x_1} P_{x_1, x_2} \dots P_{x_{N-1}, x_N} = P_{x_0, x_N}^N$$

# The relevant family of Markov chains

Among all Markov chains we will consider processes which satisfy two conditions:

- 1) **Ergodicity** (in the mathematical literature it is called irreducibility). We can go from any state to any state:  
**For any  $x, y$ , there is  $n > 0$  such that  $P_{xy}^n > 0$**
- 2) **Aperiodicity** (technical, not very interesting condition): **the greatest common divisor of the set of integers  $n$  such that  $P_{xx}^n > 0$  is 1.**

## The fundamental theorem

If  $P$  is irreducible and aperiodic:

a)

$$\lim_{n \rightarrow \infty} P_{xy}^n = \pi_y$$

with  $\pi_y$  nonnegative.

b) If  $\pi_x$  is not identically zero, it satisfies

$$\sum_x \pi_x = 1.$$

Hence  $\pi_x$  is a probability distribution on the state space.

c) If  $\pi_x$  is not identically zero, it satisfies the **stationarity condition**

$$\sum_x \pi_x P_{xy} = \pi_y.$$

Hence  $\pi_x$  is the **equilibrium distribution**.

## The fundamental theorem

- d) (**Uniqueness**)  $\pi_x$  is the unique probability distribution satisfying the stationarity condition.
- e) (**Ergodic theorem**) Consider the process  $X_0 \rightarrow X_1 \rightarrow X_2 \dots \rightarrow X_N$  generated by  $P$ . Then

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=1}^N f(X_n) = \sum_x f(x) \pi_x$$

for any function  $f(x)$  defined on the state space, irrespective of  $X_0$ .

## Example

Again, we consider our example with two spins, in which the transition matrix is (we set  $p = 1/2$ )

$$P = \begin{pmatrix} 0.5 & 0.25 & 0.25 & 0 \\ 0.25 & 0.5 & 0 & 0.25 \\ 0.25 & 0 & 0.5 & 0.25 \\ 0 & 0.25 & 0.25 & 0.5 \end{pmatrix}$$

Now, we take products

$$P^2 = P \cdot P = \begin{pmatrix} 0.375 & 0.25 & 0.25 & 0.125 \\ 0.25 & 0.375 & 0.125 & 0.25 \\ 0.25 & 0.125 & 0.375 & 0.25 \\ 0.125 & 0.25 & 0.25 & 0.375 \end{pmatrix} \quad P^4 = P^2 \cdot P^2 = \begin{pmatrix} 0.281 & 0.25 & 0.25 & 0.219 \\ 0.25 & 0.281 & 0.219 & 0.25 \\ 0.25 & 0.219 & 0.281 & 0.25 \\ 0.219 & 0.25 & 0.25 & 0.281 \end{pmatrix}$$

$$P^8 = P^4 \cdot P^4 = \begin{pmatrix} 0.252 & 0.25 & 0.25 & 0.248 \\ 0.25 & 0.252 & 0.248 & 0.25 \\ 0.25 & 0.248 & 0.252 & 0.25 \\ 0.248 & 0.25 & 0.25 & 0.252 \end{pmatrix}$$

## Example

Iterating the procedure we find that  $P^n$  converges to

$$\begin{pmatrix} 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.25 & 0.25 & 0.25 & 0.25 \end{pmatrix}$$

As expected, each row is the same we can estimate  $\pi_1 = \pi_2 = \pi_3 = \pi_4 = 0.25$ .

$\pi_x$  is the equilibrium distribution of the Markov chain.

The stationarity condition states that  $\pi_x$  is a left-eigenvalue of  $P_{xy}$ . We find

$$\sum_x \pi_x P_{xy} = 1/4(P_{1x} + P_{2x} + P_{3x} + P_{4x}).$$

The quantity in parentheses is the sum of the elements of each column, which is 1:

$$\sum_x \pi_x P_{xy} = 1/4 = \pi_y$$

## Static algorithms

The algorithms that generate **uncorrelated** data can be considered as trivial Markov chains. The transition matrix is defined as

$$P_{xy} = \pi_y$$

Note that

$$P_{xy}^2 = \sum_z P_{xz} P_{zy} = \sum_z \pi_z \pi_y = (\sum_z \pi_z) \pi_y = \pi_y$$

and in general  $P_{xy}^N = \pi_y$ .

All Markov chain theorems are trivial for these distributions.