

# Markov Chain Simulations

**Moti Ben-Ari**

<http://www.weizmann.ac.il/sci-tea/benari/>

April 10, 2023

© Moti Ben-Ari 2023

This work is licensed under Attribution-ShareAlike 4.0 International. To view a copy of this license, visit <http://creativecommons.org/licenses/by-sa/4.0/>.

## Contents

<b>1</b>	<b>Introduction</b>	<b>3</b>
<b>2</b>	<b>Gambler's ruin</b>	<b>3</b>
<b>3</b>	<b>Random walk</b>	<b>4</b>
3.1	One-dimensional random walk . . . . .	4
3.2	Two-dimensional random walk . . . . .	7
3.3	Three-dimensional random walk . . . . .	9
3.4	Random walk in a circle . . . . .	9
<b>4</b>	<b>The Ehrenfest model</b>	<b>10</b>
<b>5</b>	<b>The two-state process</b>	<b>12</b>
<b>6</b>	<b>A maze</b>	<b>13</b>
	<b>References</b>	<b>14</b>

# 1 Introduction

Simulations are an excellent way of understanding probability, especially the behavior of processes of long duration. Simulation programs enable the user to perform experiments by varying the parameters of problems and analyzing. The simulations in this archive are of processes known as *Markov chains*, where the next state of the system depends only on the current state and not on the history of how the process got to the current state.

The following problems are simulated: the *gambler's ruin*, one-, two- and three-dimensional *random walk* and random walk in a circle, the *Ehrenfest model*, the *two-state process* and *transversing a maze*.

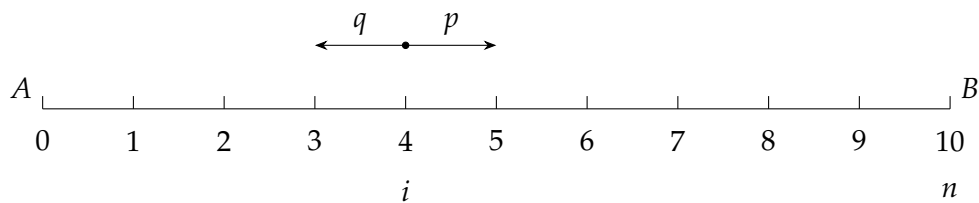
A knowledge of probability is assumed at the level of the first few chapters of [2, 7]. The problems and their theoretical solutions are from the works cited in the references.

The programs are written in the Python 3 language and use the `matplotlib` library to generate the graphs. You need to install Python (<https://www.python.org/downloads/>) although a knowledge of Python programming is not necessary to run the simulations.

Parameters directly related to the problems, such as the probability of success, can be modified interactively. Others, related to the simulation, such as the number of steps in a simulation, are defined in a file `configuration.py`. The code that uses `matplotlib` also appears in a separate file.

## 2 Gambler's ruin

Two players  $A$  and  $B$  compete in a contest. There is an initial finite capital of  $n$  units:  $A$  has  $i$  and  $B$  has  $n - i$ . They repeatedly play a game where the probability that  $A$  wins is  $p$  and the probability that  $B$  wins is  $q = 1 - p$ . The loser gives one unit to the winner. When one player has all  $n$  units the contest is terminated and that player is declared the winner.



- Given initial parameters  $(p, n, i)$ , what is the probability that  $A$  wins?
- What is the expected duration of the game?

Given  $(p, n, i)$  the probability that  $A$  wins the contest is:

$$P_A(p, n, i) = \left( \frac{1 - r^i}{1 - r^n} \right),$$

where  $r = q/p$ . By symmetry, the probability that  $B$  wins is:

$$P_B(p, n, i) = \left( \frac{1 - (1/r)^{n-i}}{1 - (1/r)^n} \right).$$

For  $p \neq 1/2$  the expected duration of the contest is:

$$E_{duration}(p, n, i) = \frac{1}{q - p} \left( i - n \frac{1 - r^k}{1 - r^n} \right),$$

while for  $p = 1/2$  the expected duration is:

$$E_{duration}(p, n, i) = i(n - 1).$$

Of course the duration does not depend on which player wins. If  $A$  wins, the contest terminates for  $B$  and conversely.

You can run a simulation more than once with the saved parameters, enter new parameters, or run a sequence of simulations for a range of probabilities or initial values. Here is one output:

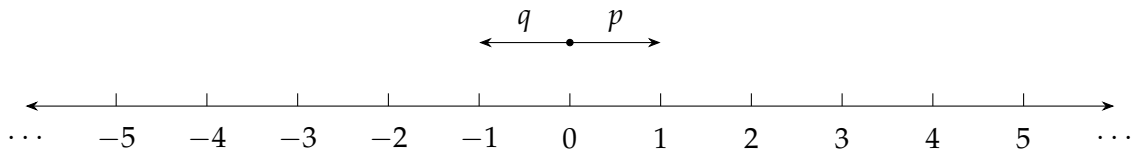
```
Probability = 0.45, capital = 20, initial = 8
Wins = 789, losses = 9211, limits exceeded = 0
Proportion of wins      = 0.0789
Probability of winning = 0.0732
Average duration  = 65
Expected duration = 65
```

A graph of the proportion of wins and the histogram of the durations are shown in Figures 1, 2. The vertical lines in the histograms are the average durations.

### 3 Random walk

#### 3.1 One-dimensional random walk

A particle is placed at the origin of the  $x$ -axis. It repeatedly takes steps: right with probability  $p$  and left with probability  $q = 1 - p$ .



- What is the probability that the particle will return to the origin?

Gambler's ruin for  $n = 20, i = 10$

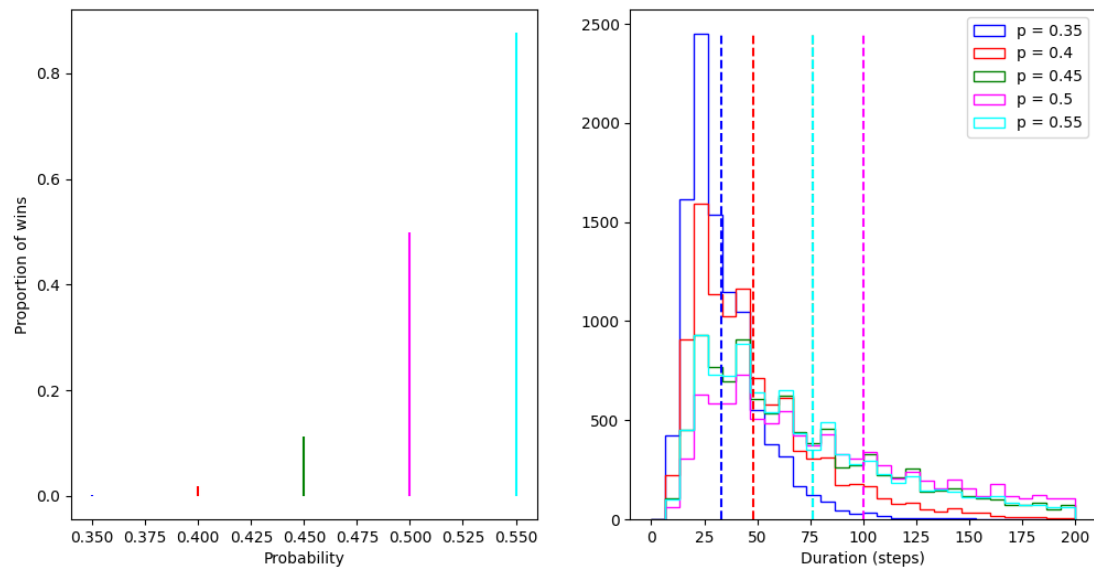


Figure 1: Proportion of wins and histogram for  $n = 20, i = 10$  and multiple probabilities

Gambler's ruin for  $p = 0.45, n = 20$

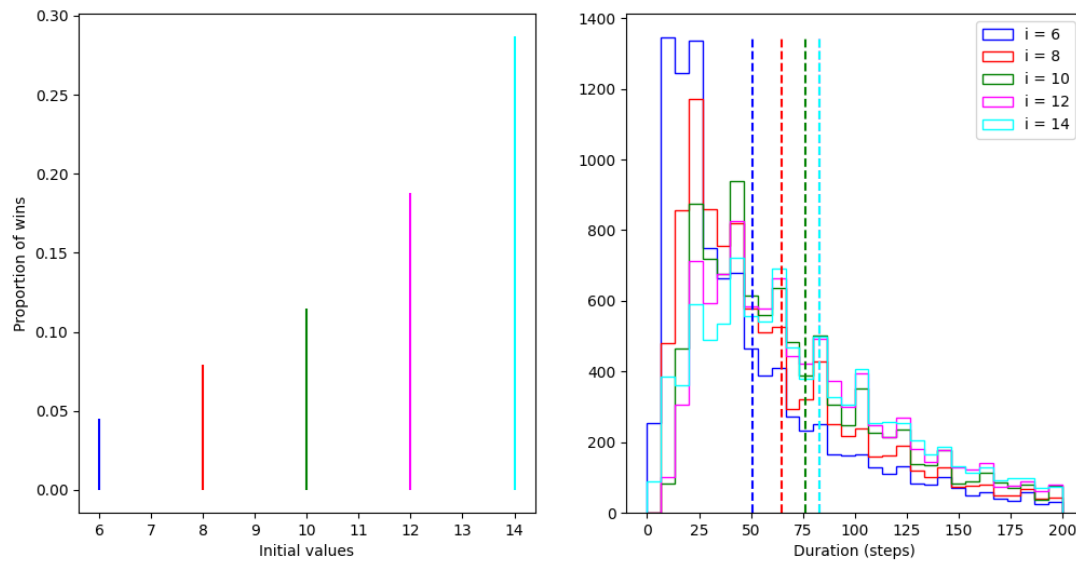


Figure 2: Proportion of wins and histogram for  $p = 0.45, n = 20$  and multiple initial values

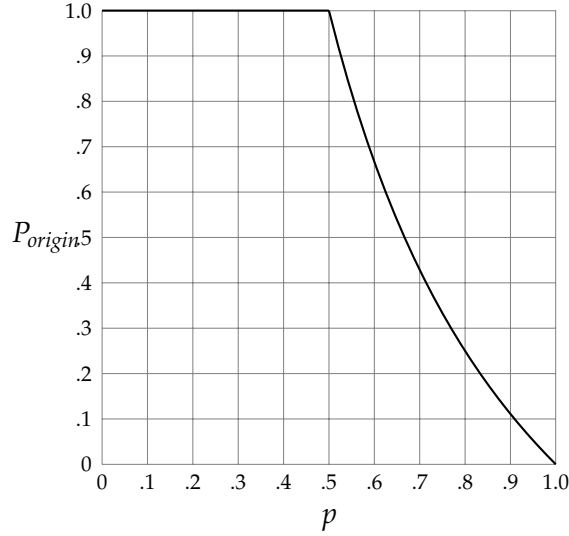


Figure 3: Graph of  $P_{origin}$

- What is the expected duration until the particle returns to the origin?

By symmetry let the first step be to the right. The particle can only return to the origin after an even number of steps. Assume that  $p = 1/2$ . Let  $S_{2m}$  be the position of the particle after  $2m$  steps. Then:

$$P(S_{2m} = 0) = \binom{2m}{m} \frac{1}{2^{2m}},$$

which by Stirling's formula is approximately equal to  $1/\sqrt{\pi m}$ . It can now be proved that the probability of a return to the origin is 1.

For  $p \leq 1/2$ ,  $P_{origin}$ , the probability of a return to the origin, is 1 and for  $p \geq 1/2$  the probability is (Figure 3):

$$P_{origin} = \frac{q}{p} = \frac{1-p}{p}.$$

$E_{origin}$ , the expected duration until the first return to the origin, is infinite for  $p \geq 1/2$  while for  $p < 1/2$  it is:

$$E_{origin} = \frac{1}{q-p} = \frac{1}{1-2p}.$$

You can run a simulation more than once with the saved parameters, enter new parameters, or run a sequence of simulations for a range of probabilities or limits. Here is one output:

```

Probability = 0.50, step limit    = 1000
Proportion returning to origin   = 0.977
Probability of return to origin  = 1.000
Proportion reaching limit        = 0.023

```

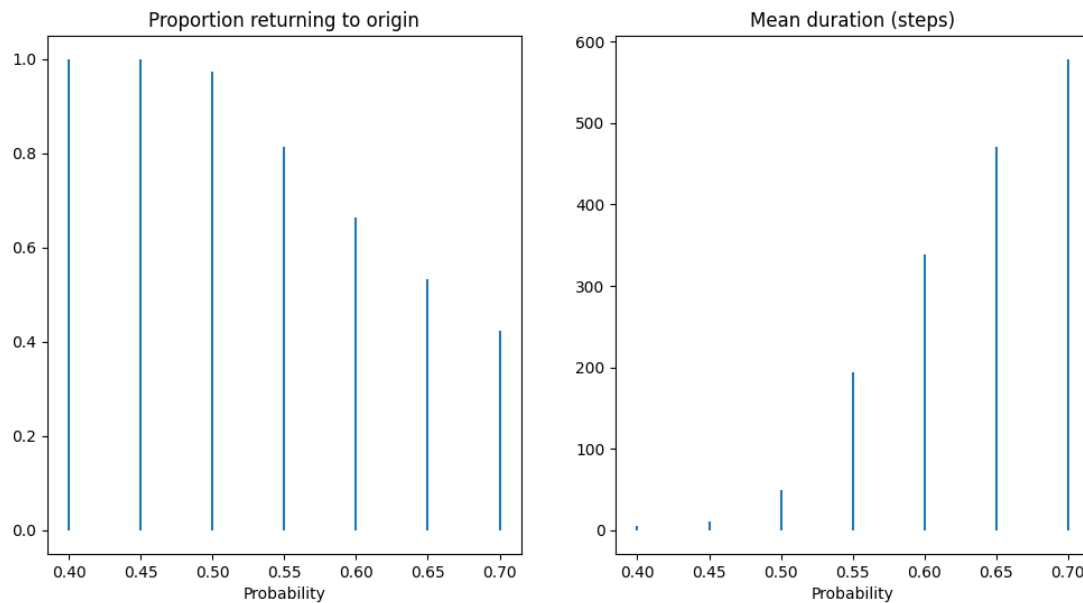


Figure 4: Proportion of returns to origin and and mean durations for multiple probabilities

```

Mean duration (steps)           = 49
Expected duration (steps)      = infinity

```

The proportion of wins in the simulation are very close to the theoretical probability, but the mean duration is far from infinite because the step limit was too small. The proportion of wins and the mean durations are shown in Figures 4 and 5.

### 3.2 Two-dimensional random walk

In a two-dimensional random walk a step of the particle consists of one step left or right on the  $x$ -axis with probability  $1/2$  and simultaneously one step up or down on the  $y$ -axis also with probability  $1/2$  (Figure 6).

The probability 1 the particle will return to the origin but the expected duration is infinite! Therefore, when you run the simulation with any reasonable limit on the number of steps, the proportion of returns to the origin will be much less than 1 and the mean duration will be quite large:

```

Limit                           = 100000
Proportion returning to origin   = 0.777
Proportion reaching limit       = 0.223
Mean duration (steps)           = 24133

```

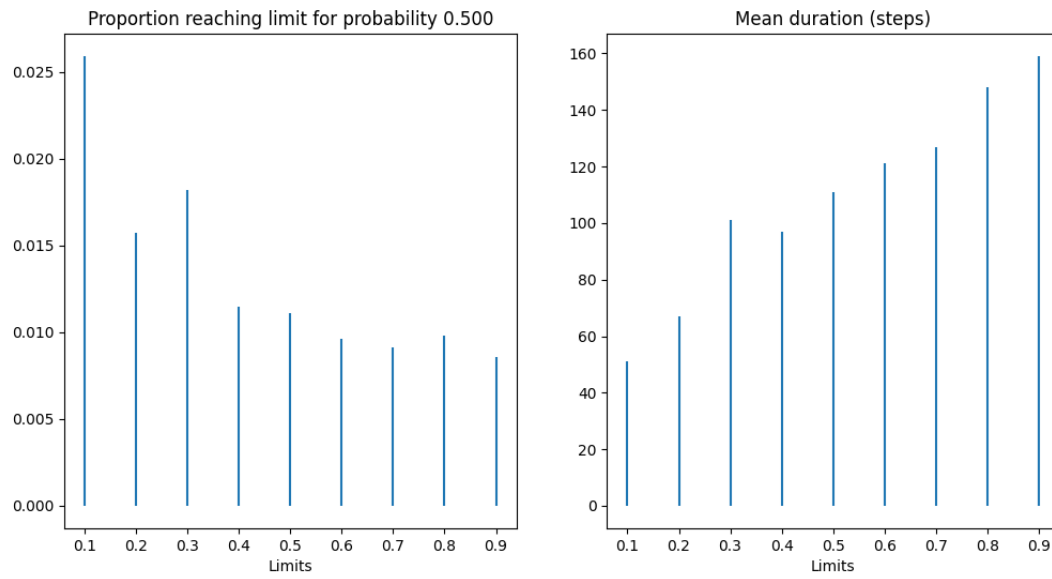


Figure 5: Proportion of returns to origin and mean durations for multiple limits

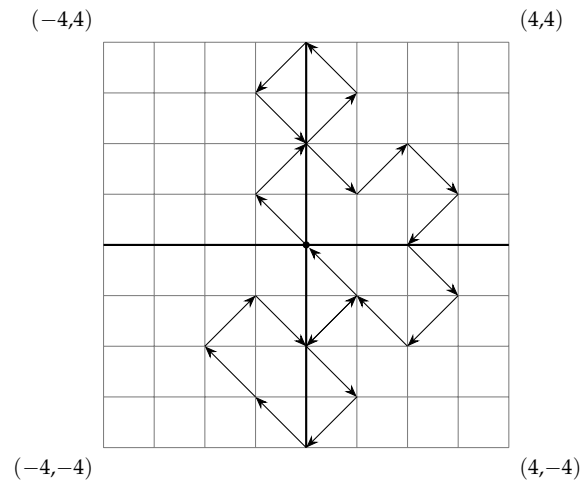


Figure 6: A 22-step two-dimensional random walk



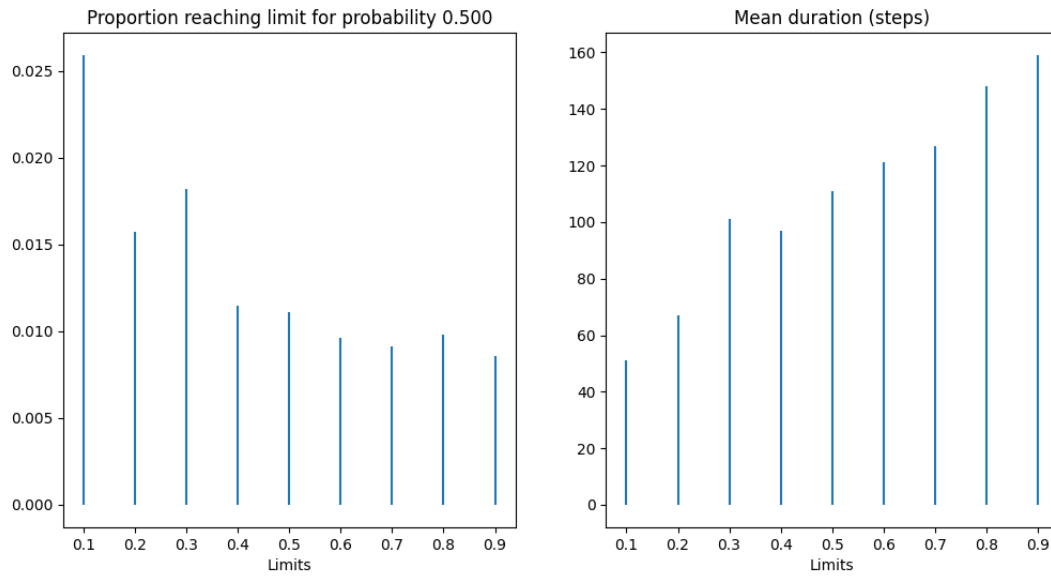


Figure 7: Proportion of returns to origin and and mean durations for multiple limits

Figure 7 shows the proportion of returns to the origin and the mean durations for a range of fractions of the limit.

### 3.3 Three-dimensional random walk

The three-dimensional random walk adds a simultaneous step along the z-axis with probability  $1/2$ . The probability of a return to the origin is only 0.2379 so the simulations will show a large number of simulations reaching the limit:

Limit	= 100000
Proportion returning to origin	= 0.370
Proportion reaching limit	= 0.630
Mean duration (steps)	= 63518

### 3.4 Random walk in a circle

Consider a circle with  $n$  equally-spaced points around its circumference (Figure 8). A random walk starts at point 0 and proceeds to the next point or the previous point both with probability  $1/2$ .

- With probability 1 the all points will be visited.
- With probability  $1/n$  a designated point  $k$  will be the last point visited.

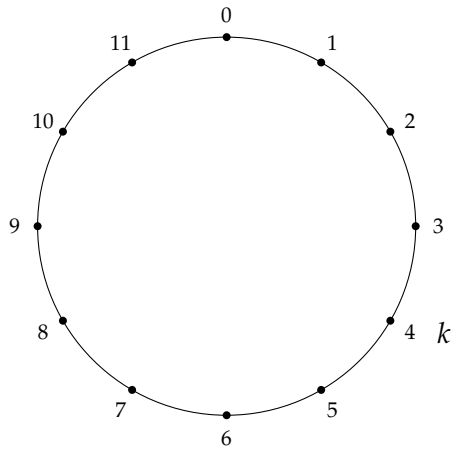


Figure 8: Random walk in a circle

The random walk will eventually visit all points, but it may take a very large number of steps. (Try to run the simulation for 100 points!) Here is an output:

For 50 points, 1000 simulations, at most 3000 steps:

Designated point visited 22 times

Probability = 0.020, proportion = 0.022

Did not visit all points 26 times

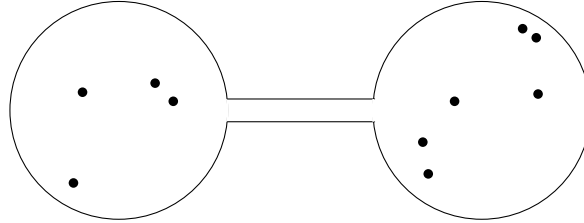
The histogram of steps visited is shown Figure 9.



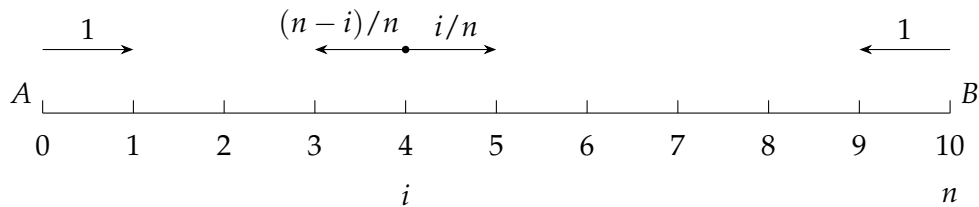
Figure 9: Histogram of steps until all points are visited

## 4 The Ehrenfest model

The Ehrenfest model models the diffusion of particles between two containers. In the following diagram there are 4 particles in the left container and 6 in the right container.



Repeatedly choose a particle at random with uniform distribution and move it to the other container. If there are  $i$  particles in the left container then the probability of choosing a particle from the left container is  $i/n$  and the probability of choosing a particle from the right container is  $(n - i)/n$ . If one container is empty the next particle must be chosen from the other container.



The problem is similar to the gambler's ruin except that the process never ends and the probability of a left or right step changes with each step.

The process is a Markov chain which eventually reaches a *stationary distribution*:

$$s_i = \binom{n}{i} \left(\frac{1}{n}\right)^n,$$

where  $s_i$  is the proportion of time that the particle is at the  $i$ 'th position.

Here is an output of the simulation:

Total particles in urns = 10

Theoretical stationary distribution

[0.001 0.01 0.044 0.117 0.205 0.246 0.205 0.117 0.044 0.01 0.001]

Simulation stationary distribution

[0.001 0.009 0.044 0.12 0.208 0.243 0.205 0.121 0.042 0.008 0.001]

A graph of these distributions is shown in Figure 10; the theoretical distribution and the result of simulation are so close together that the lines are slightly offset.

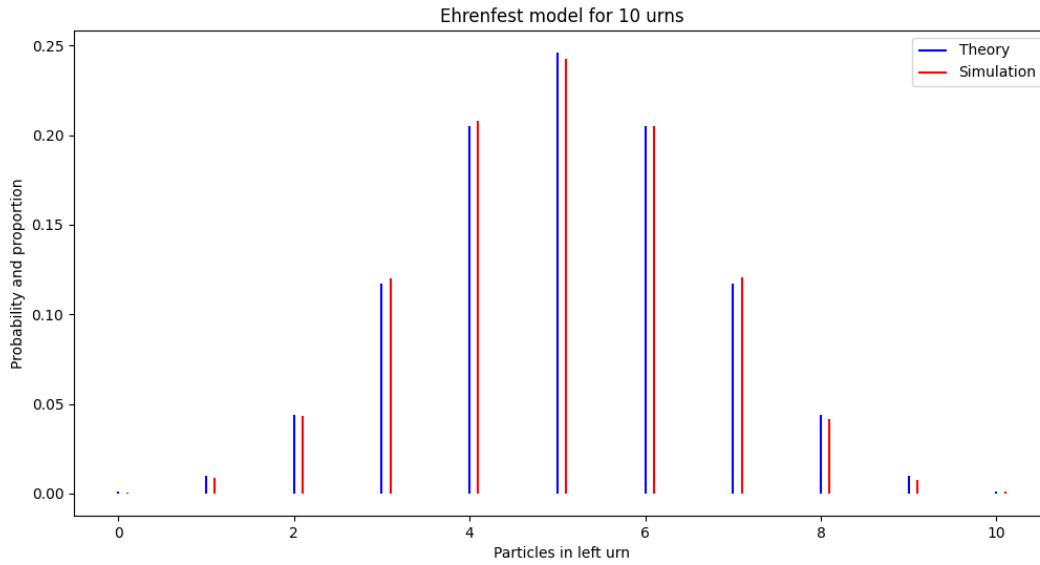
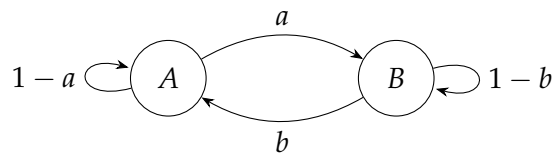


Figure 10: Stationary distribution for the Ehrenfest model

## 5 The two-state process

The two-state process is similar to the Ehrenfest model in that the probabilities at each step are different and we are interested in the stationary probability distribution of the unbounded process. There are two states  $A, B$ . In state  $A$  the process transitions to  $B$  with probability  $a$  and remains in  $A$  with probability  $1 - a$ . Similarly, the probability of a transition from  $B$  to  $A$  is  $b$  and the probability of remaining in  $B$  is  $1 - b$ .



The stationary distribution, that is, the proportion of visits to  $A$  and to  $B$  is:

$$\left[ \frac{b}{a+b}, \frac{a}{a+b} \right].$$

Here is an output of a simulation:

Probabilities:  $a = 0.500$ ,  $b = 0.333$

Theoretical stationary distribution:  $A = 0.400$ ,  $B = 0.600$

Simulation stationary distribution:  $A = 0.402$ ,  $B = 0.598$

When  $a + b = 1$  the probability of being at  $A$  is  $b$  and the probability of being at  $B$  is  $a$ :

Probabilities:  $a = 0.333$ ,  $b = 0.667$

Theoretical stationary distribution:  $A = 0.667$ ,  $B = 0.333$

Simulation stationary distribution:  $A = 0.674$ ,  $B = 0.326$

You can enter a required proportion  $p$  of visits to  $B$  and any probability  $0 < a < p$ . The proportion will be achieved for:

$$b = \frac{a(1-p)}{p},$$

as shown in the following simulation where we entered  $p = 0.8, a = 0.6$ :

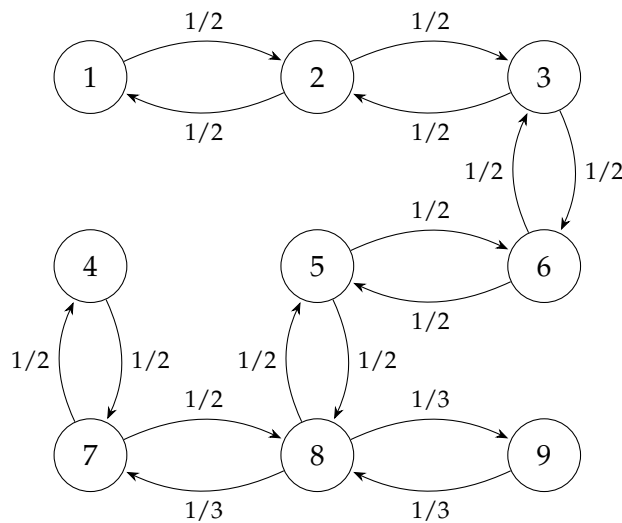
Probabilities:  $a = 0.600$ ,  $b = 0.150$ , proportion = 0.800

Theoretical stationary distribution:  $A = 0.200$ ,  $B = 0.800$

Simulation stationary distribution:  $A = 0.194$ ,  $B = 0.806$

## 6 A maze

Given the Markov chain shown in the following diagram, simulate the average number of steps until the first return to state  $i$  starting in state  $j$ .



Privault [6, Sections 5.3] computes the expected number of returns to state 0 starting in any other state and the average number of steps in the simulation is very close to the expected number of returns:

Expected steps to return to 0 = [16, 15, 28, 59, 48, 39, 58, 55, 56]

Average steps to return to 0 = [14, 15, 28, 59, 46, 39, 59, 55, 54]

The simulation of the average number of returns to any state  $i$  from any state  $j$  gives:

Average steps to return to 0 = [14, 15, 28, 59, 46, 39, 59, 55, 54]  
 Average steps to return to 1 = [ 1, 8, 14, 43, 31, 24, 42, 40, 40]  
 Average steps to return to 2 = [ 3, 2, 8, 31, 20, 10, 29, 27, 30]  
 Average steps to return to 3 = [52, 53, 50, 15, 37, 44, 14, 29, 28]  
 Average steps to return to 5 = [ 8, 8, 5, 20, 8, 7, 18, 15, 16]  
 Average steps to return to 6 = [37, 37, 35, 1, 21, 29, 8, 13, 14]  
 Average steps to return to 7 = [25, 23, 21, 4, 9, 16, 3, 5, 1]  
 Average steps to return to 8 = [38, 37, 37, 19, 25, 30, 18, 14, 16]

Privault [6, Sections 7.2] also computes the expected number of returns to state  $i$  from state  $i$  and the averages (the main diagonal of the above matrix) are very close:

Expected steps to return to  $i$  from  $i$  = [16, 8, 8, 16, 8, 8, 8, 5, 16]  
 Average steps to return to  $i$  from  $i$  = [14, 8, 8, 15, 7, 7, 8, 5, 16]

## References

- [1] Moti Ben-Ari. Mosteller's challenging problems in probability. <https://github.com/motib/probability-mosteller>, 2022.
- [2] Joseph K. Blizstein and Jessica Hwang. *Introduction to Probability (Second Edition)*. CRC Press, 2019.
- [3] K.C. Border. Lecture 16: Simple random walk. <http://www.math.caltech.edu/~2016-17/2term/ma003/Notes/Lecture16.pdf>, 2017.
- [4] Eric Lehman, F. Thomson Leighton, and Albert R. Meyer. *Mathematics for Computer Science*. MIT Open Courseware, 2015. <https://ocw.mit.edu/courses/6-042j-mathematics-for-computer-science-spring-2015/pages/readings/>.
- [5] Frederick Mosteller. *Fifty Challenging Problems in Probability with Solutions*. Dover, 1965.
- [6] Nicolas Privault. *Understanding Markov Chains: Examples and Applications (Second Edition)*. Springer, 2018.
- [7] Sheldon Ross. *A First Course in Probability (Tenth Edition)*. Pearson, 2019.