

TMA4265 - Stochastic Processes

Semester Project

Candidate number
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Problem One

a.

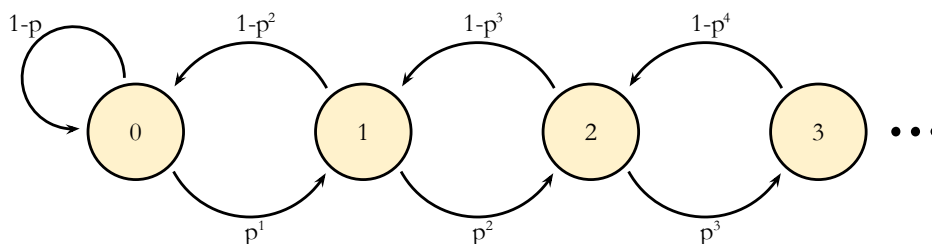


Figure 1: The Markov chain P_{ij} illustrated as a digraph.

The Markov chain P_{ij} in fig. 1 describes a random walk. Starting in any state, you can reach any other state - i.e. all states communicate. Thus, P_{ij} is **strongly connected**, has **one equivalence class** and is **irreducible**. Let X_n and X_{n+s} be two states such that there are $s - 1$ intermediate states between them. To get from state i to $j = i + s$ you have to visit all intermediate states at least once¹. Another trait of P_{ij} is that with growing i , the probability of moving from state i to $j = i + 1$ diminishes exponentially, while the probability of moving back to $j' = i - 1$ grows exponentially. Starting in state i , it is therefore reasonable to claim that it is always possible to return to state i in a finite number of steps. State i

¹Equivalently, s is the minimum number of steps you must perform to make the transition from state i to $i + s$

is then said to be positive recurrent, and since positive recurrence is a class property, the whole chain is **positive recurrent**.

Starting in state i , let n be the number that allows you to end up in state i after n transitions with the probability $P_{ii}^n > 0$. Let N_i be the set of all such numbers for our chain. The greatest common divisor of the elements in N_i is called the period d of state i . Since $P_{00}^n > 0$ for any n , $N_0 = 0, 1, 2, \dots$ and so P_{00} has a period of $d = 1$. Since periodicity is a class property, the chain as a whole has period one. A Markov chain with $d = 1$ is called **aperiodic**.

A positive recurrent aperiodic chain is called **ergodic**. Theorem 4.1 in [Ross 2010] states that for an irreducible ergodic Markov chain the limit $\pi_j = \lim_{n \rightarrow \infty} P_{ij}^n$, $j \geq 0$ exists,

$$\pi_j = \sum_{i=0}^{\infty} \pi_i P_{ij} \quad (1)$$

and

$$\sum_{j=0}^{\infty} \pi_j = 1. \quad (2)$$

In this case eq. (1) becomes

$$\pi_i = \begin{cases} \pi_{i-1}P_{i-1,i} + \pi_{i+1}P_{i+1,i} & = \pi_{i-1}p^i + \pi_{i+1}(1-p^{i+2}) & i > 0 \\ \pi_i P_{i,i} + \pi_{i+1}P_{i+1,i} & = \pi_0(1-p) + \pi_1(1-p) & i = 0 \end{cases} \quad (3)$$

The π 's are called the limiting probabilities that the process will be in state i at time n , and it can be shown that π_i also equals the long-run proportion of time that the process will be in state i . Below the limiting probabilities are calculated for the first 3 states.

$$\pi_1 = \frac{p}{1-p^2}\pi_0; \quad \pi_2 = \frac{p^2}{1-p^3}\pi_1; \quad \pi_3 = \frac{p^3}{1-p^4}\pi_2$$

By induction this yields the general formula (recurrence relation)

$$\begin{aligned}\pi_{i+1} &= \frac{p^{i+1}}{1-p^{i+2}}\pi_i = \frac{p^{i+1}p^i p^{i-1} \dots p^2 p^1}{(1-p^{i+2})(1-p^{i+1})(1-p^i) \dots (1-p^3)(1-p^2)}\pi_0 \\ &= \frac{p^{1+2+\dots+(i-1)+i+(i+1)}}{\prod_{k=2}^{k=i+2}(1-p^k)}\pi_0 = \frac{p^{\frac{1}{2}(i+1)(i+2)}}{\prod_{k=2}^{k=i+2}(1-p^k)}\pi_0\end{aligned}$$

or, equivalently,

$$\pi_i = \pi_0 \cdot \prod_{k=1}^{k=i+1} \frac{p^k}{1-p^{k+1}} \quad (4)$$

Now eq. (2) becomes

$$\begin{aligned}\sum_i \pi_i &= \pi_0 \left(1 + \sum_i \cdot \prod_{k=1}^{k=i+1} \frac{p^k}{1-p^{k+1}} \right) = 1 \\ \Rightarrow \pi_0 &= \left(1 + \sum_i \cdot \prod_{k=1}^{k=i+1} \frac{p^k}{1-p^{k+1}} \right)^{-1}\end{aligned} \quad (5)$$

Substituting eq. (5) into eq. (4) gives an expression for the limiting probabilities

$$\pi_i = \frac{\prod_{k=1}^{k=i+1} \frac{p^k}{1-p^{k+1}}}{1 + \sum_i \cdot \prod_{k=1}^{k=i+1} \frac{p^k}{1-p^{k+1}}} \quad (6)$$

The distribution is positive so the limiting probabilities exist and the states are indeed positive recurrent.

b.

Let the set ξ contain the first 10 states, and let T_i be the time spent to reach state 10, starting in state $X_0 = i \in \xi$.

$$\begin{aligned}\mu_i &= E[T_i] \\ &= E[T_i|X_1 = i-1]P(X_1 = i-1) + E[T_i|X_1 = i+1]P(X_1 = i+1) \\ &= (1 + E[T_{i-1}])(1-p^{i+1}) + (1 + E[T_{i+1}])p^{i+1} \\ &= 1 + \mu_{i-1} + (\mu_{i+1} - \mu_{i-1})p^{i+1}\end{aligned} \quad (7)$$

Note the special cases for $\mu_0 = 1 + \mu_0 + (\mu_1 - \mu_0)p$, and $\mu_9 = 1 + \mu_8(1 - p^{10})$

eq. (7) constitutes a set of 10 equations that can be solved with MATLAB. In table 1 the solutions are listed for $p = 0.75$ and $p = 0.90$.

The exponential decay for the probabilities for moving on to the next state clearly manifests itself for the case of $p = 0.75$; no matter what state you start in, you'll have to wait for a very long time to reach state 10. The transition from state 9 to 10 is taking very long time compared to the other one-step transitions.

c.

The probability for ever reaching state 100 is 1, no matter what state you start in, since all limiting probabilities are positive. If you start in state $X_0 < 100$, you will have to wait for a very long time to reach state 100, and if $X_0 > 100$ you will only have to wait close to $X_0 - 100$ steps (at least if not $p \approx 1$).

d.

Problem Two

In the following X_n is the number of individuals in the n 'th generation, X_0 is the initial population, $\mu = E[\text{children per individual}]$, $p_j = P\{\text{an individual has } j \text{ offspring}\}$. The distributions that are analyzed are listed in table 3

	p_0	p_1	p_2	p_3
I	0.6	0.05	0.15	0.2
II	0.25	0.60	0.10	0.05

Table 1: The probability distributions given in Problem Two.

Chapter 4.7 in [Ross 2010] presents some results that is used in this problem. Below is some properties of branching processes discussed.

Generally, the mean number, and the variance, off offspring of a single individual is

$$\mu = \sum_{j=0}^{\infty} jP_j \quad ; \quad \sigma^2 = \sum_{j=0}^{\infty} (j - \mu)^2 P_j \quad (8)$$

respectively.

For both our distributions $\mu = 0.95$, and since $\mu < 1$ the population will eventually die out. Defining Z_i to be the number of offspring of the i 'th individual for the $(n - 1)$ st generation, one can find

$$X_n = \sum_{i=1}^{X_{n-1}} Z_i \quad (9)$$

in the edge case where $X_0 = 1$. One can then obtain

$$E[X_n] = E[E[X_n|X_{n-1}]] = E \left[E \left[\sum_{i=1}^{X_{n-1}} Z_i | X_{i-1} \right] \right] = E[X_{n-1}] \mu \quad (10)$$

which leads to the result

$$E[X_1] = \mu, \quad E[X_2] = \mu E[X_1] = \mu^2, \quad \dots, \quad E[X_n] = \mu^n. \quad (11)$$

It can then be shown that the variance is

$$Var(X_n) = \begin{cases} \sigma^2 \mu^{n-1} \cdot \frac{1-\mu^n}{1-\mu}, & \mu \neq 1 \\ n\sigma^2, & \mu = 1 \end{cases} \quad (12)$$

When doing simulations, the estimated mean value and standard deviation is given by

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i, \quad S^2 = \frac{1}{n-1} \sum_{i=1}^n X_i - \bar{X}, \quad (13)$$

respectively.

a.

The mean value and the standard deviation of X_n is found. First analytically, then using simulations, and at last a comparison.

Analytic results

From eq. (8) and eq. (12) the mean and standard deviation is found analytically and presented in eq. (13).

Generation n	Mean		Variance	
	$E_I[X_n]$	$E_{II}[X_n]$	$Var_I[X_n]$	$Var_{II}[X_n]$
10	0.5987		2.7977	2.7692
100	0.0059		0.4379	0.0678
1000	~ 0		~ 0	~ 0

Table 2: Analytical values of μ and σ

n	Generation n		
	10	100	1000
10	0.5987	2.7977	2.7692
100	0.0059	0.4379	0.0678
1000	~ 0	~ 0	~ 0

Table 3: Analytical values of μ and σ

Simulated results

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References

[Ross 2010] Sheldon M. Ross (2010), Introduction to Probability Models.

Problem Two

```
1 function popu = branchsim(init,dist)
2
3 % ----// branchsim.m //--
4 %
5 % Simulates a branching process
6 %
7 %
8 % Input:
9 %   init - int, initial size of the population
10 %   dist - vector, offspring probability
11 %          distribution [p0, ..., pn]
12 %
13 % Output:
14 %   popu - vector, population for each generation.
15 %
16 % -----
17
18
19 % The population of the 1st generation
20 popu(1) = init;
21 % Accumulated probabilities to be used w. rand(1)
22 cumdist = cumsum(dist);
23 % Generation number n
24 n = 1;
25 while popu(n) > 0
26     popu(n+1) = 0;
27     for j=1:popu(n)
28         random = rand(1);
29         for k=0:length(dist)-1
30             if random < cumdist(k+1)
31                 % Update the population of generation n+1
32                 popu(n+1) += k;
33                 break;
34             end
35         end
36     end
37     ++n;
38 end
```