

## Homework 04 - STAT416

Joseph Sepich (jps6444)

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### Chapter 3 Problem 36

**Find**  $E[X|X \neq 0]$

We know that if  $X$  is not ever equal to zero, then the mass given to zero would be redistributed over the rest of the support of  $X$ . This mass as defined in the problem is  $p_0$ . Therefore we can divide the rescale the remaining probability values to correspond with the samples space of  $1 - p_0$ . This gives us:

$$E[X|X \neq 0] = \frac{\sum_{x \neq 0} x_i p(x_i)}{1 - p_0} = \frac{1}{1 - p_0} \sum x_i p(x_i) = \frac{\mu}{1 - p_0}$$

**Find**  $Var(X|X \neq 0)$

$$Var(X|X \neq 0) = \frac{E(X^2)}{1 - p_0} - \frac{\mu^2}{(1 - p_0)^2} = \frac{(1 - p_0)E(X^2) - \mu^2}{(1 - p_0)^2}$$
$$Var(X|X \neq 0) = \frac{\sigma^2 - p_0 E(X^2)}{(1 - p_0)^2}$$

### Chapter 3 Problem 38

In this problem  $X$  is distributed uniformly along  $(0, y)$  with  $y$  being selected from  $Y$  with a uniform distribution  $(0, 1)$ . This makes the uniform distribution of  $X$  to be  $f(x|Y = y) = \frac{1}{y}$

$E[X]$

We can calculate this with the law of iterated expectation

$$E[X] = E[E[X|Y = y]]$$
$$E[X|Y = y] = \int_0^y x f(x|Y = y) dx = \int_0^y \frac{x}{y} dx = \frac{x^2}{2y} \Big|_0^y = \frac{y}{2}$$
$$E[X] = E\left[\frac{y}{2}\right] = \int_0^1 \frac{y}{2} dy = \frac{y^2}{4} \Big|_0^1 = \frac{1}{4}$$

The expected value of  $X$  is  $\frac{1}{4}$ .

$Var(X)$

$$\begin{aligned}Var(X) &= E(X^2) - E(X)^2 = E(E(X^2|Y = y)) - \frac{1}{16} \\E(X^2|Y = y) &= \int_0^y x^2 f(x|Y = y) dx = \int_0^y \frac{x^2}{y} dx = \frac{x^3}{3y} \Big|_0^y = \frac{y^2}{3} \\E(E(X^2|Y = y)) &= \int_0^1 \frac{y^2}{3} dy = \frac{y^3}{9} \Big|_0^1 = \frac{1}{9} \\Var(X) &= \frac{1}{9} - \frac{1}{16} \approx 0.04861\end{aligned}$$

### Chapter 3 Problem 44

In this problem we are looking at a compound random variables  $Y = \sum_{i=1}^N X_i$ .

$$E[Y] = E[N]E[X]$$

We know the mean of  $N$  is  $\lambda = 10$  and the mean of  $X$  is  $\frac{100+0}{2} = 50$ .

$$E[Y] = 10 * 50 = 500$$

$$Var(Y) = Var(X)E[N] + (E[X])^2Var(N)$$

Again we know  $Var(X) = \frac{100^2}{12} = 833.33$  from its distribution and  $Var(N) = \lambda = 10$ .

$$Var(Y) = 833.33 * 10 + 50^2 * 10 = 33,333.33$$

### Chapter 3 Problem 49

#### Part a

To find the probability that A is the overall winner, let us first consider the winning condition. The overall winner must have won net 2 games over the other player. There are three options for what could happen after the first game: A wins two, B wins two, or they split. The probability of A winning two is  $p^2$ , the probability of B winning two is  $(1-p)^2$  and there are two ways they can split, so the probability of them splitting is  $2p(1-p)$ . The games will keep going until one of them attains net 2 games, so this implies an infinite series where they keep splitting until A or B wins. This gives us the probability of A winning to be:

$$P(W = A) = \sum_{k=0}^{\infty} (2p(1-p))^k p^2$$

This summation is a geometric series, so we get:

$$P(W = A) = p^2 \frac{1}{1 - (2p - 2p^2)} = \frac{p^2}{2p^2 - 2p + 1}$$

## Part b

Expected number of games played follows a similar logic to the first part:

$$\begin{aligned}E[N] &= 2 + 0p + 0(1-p) + E[N|split](2p(1-p)) \\ E[N|split] &= 2 + 0p + 0(1-p) + E[N|split](2p(1-p))\end{aligned}$$

This makes  $E[N]$  a geometric series with  $a = 2$  and  $r = p(1-p)$ :

$$E[N] = \frac{2}{1 - p(1-p)} = \frac{2}{p^2 + (1-p)}$$

## Chapter 3 Problem 62

A, B, and C are all evenly matched tennis players and play until someone wins twice in a row. We want to find  $P(W = A)$ . We must consider the result after the first two games: A wins twice, B wins twice, A wins once, or B wins once. Each of these events occur with probability of  $\frac{1}{4}$ . Since we are looking for when A wins, we are looking for a pattern where A loses and then another game is played until A wins twice in a row. We already stated that the pattern where A loses, then another game is played occurs 1 in four times. This gives us:

$$P(W = A) = \sum_{k=0}^{\infty} \left(\frac{1}{4}\right)^k \left(\frac{1}{4}\right)$$

This is a geometric series that yields:

$$P(W = A) = \frac{\frac{1}{4}}{\frac{3}{4}} = \frac{1}{3}$$

This makes sense, since each of them are evenly matched.

## Chapter 4 Problem 2

The proposed Markov Chain is a Markov Chain, since the state (population of gen n) is only dependent on the size of the previous population (gen n-1). We determined that the number of offspring of an individual follows Poisson distribution with mean of  $\lambda$ . The total offspring of a generation would be the sum of all the individuals. We know that the sum of i.i.d. Poisson random variables is a Poisson distribution whose mean is the sum of means. This gives us the transition probability:

$$P_{i,j} = \frac{\lambda_i^j e^{-\lambda_i}}{j!}$$

## Chapter 4 Problem 3

### Part a

The Markov chain we can use to analyze this model follows states that are a list of players 1 through k order the following way: (prev\_winner, next\_up, next\_next\_up, ..., prev\_loser). Basically the state tells us the ordered line and the two who are playing a game in the given period.

## Part b

This Markov chain has  $k!$  states, since it includes all possible permutations of the orderings of players 1 through  $k$ .

## Part c

For the transition probability  $P_{i,j}$  there are only two cases with a probability greater than zero. The first two players in line play each other and one of them wins. This gives us the two probabilities. Considering the transition from state  $(i,j,\dots,k)$  to  $(i,\dots,k,j)$  the probability is  $\frac{v_i}{v_i+v_j}$ . The transition from state  $(i,j,\dots,k)$  to  $(j,\dots,k,i)$  the probability is  $\frac{v_j}{v_i+v_j}$ . Note that flipping  $i$  and  $j$  in the initial state in the transition is merely changing the notation for the same state representation of any two given players playing a game.

## Chapter 4 Problem 6

Base Case:

$$P^1 = \begin{bmatrix} \frac{1}{2} + \frac{1}{2}(2p-1)^1 & \frac{1}{2} - \frac{1}{2}(2p-1)^1 \\ \frac{1}{2} - \frac{1}{2}(2p-1)^1 & \frac{1}{2} + \frac{1}{2}(2p-1)^1 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} + p - \frac{1}{2} & \frac{1}{2} - p + \frac{1}{2} \\ \frac{1}{2} - p + \frac{1}{2} & \frac{1}{2} + p - \frac{1}{2} \end{bmatrix} = \begin{bmatrix} p & 1-p \\ 1-p & p \end{bmatrix}$$

Hypothesis:

$$P^k = \begin{bmatrix} \frac{1}{2} + \frac{1}{2}(2p-1)^k & \frac{1}{2} - \frac{1}{2}(2p-1)^k \\ \frac{1}{2} - \frac{1}{2}(2p-1)^k & \frac{1}{2} + \frac{1}{2}(2p-1)^k \end{bmatrix}$$

Inductive Step:

$$P^{k+1} = P^k P^1 = \begin{bmatrix} \frac{1}{2} + \frac{1}{2}(2p-1)^k & \frac{1}{2} - \frac{1}{2}(2p-1)^k \\ \frac{1}{2} - \frac{1}{2}(2p-1)^k & \frac{1}{2} + \frac{1}{2}(2p-1)^k \end{bmatrix} * \begin{bmatrix} p & 1-p \\ 1-p & p \end{bmatrix}$$

Let's just take  $P_{0,0}^{k+1}$

$$P_{0,0}^{k+1} = \frac{p}{2} + \frac{p}{2}(2p-1)^k + \frac{1}{2} - \frac{1}{2}(2p-1)^k - \frac{p}{2} + \frac{p}{2}(2p-1)^k$$

$$P_{0,0}^{k+1} = \frac{1}{2} - \frac{1}{2}(2p-1)^k + p(2p-1)^k$$

$$P_{0,0}^{k+1} = \frac{1}{2} + (p - \frac{1}{2})(2p-1)^k$$

$$P_{0,0}^{k+1} = \frac{1}{2} + \frac{1}{2}(2p-1)(2p-1)^k$$

$$P_{0,0}^{k+1} = \frac{1}{2} + \frac{1}{2}(2p-1)^{k+1}$$

Note that the value at  $P_{1,1}^{k+1}$  is the same due to the symmetric square matrix.

$$P_{1,0}^{k+1} = \frac{p}{2} - \frac{p}{2}(2p-1)^k + \frac{1}{2} + \frac{1}{2}(2p-1)^k - \frac{p}{2} - \frac{p}{2}(2p-1)^k$$

$$P_{1,0}^{k+1} = \frac{1}{2} + \frac{1}{2}(2p-1)^k - p(2p-1)^k$$

$$\begin{aligned}
P_{1,0}^{k+1} &= \frac{1}{2} + (\frac{1}{2} - p)(2p - 1)^k \\
P_{1,0}^{k+1} &= \frac{1}{2} + \frac{-1}{2}(2p - 1)(2p - 1)^k \\
P_{1,0}^{k+1} &= \frac{1}{2} - \frac{1}{2}(2p - 1)^{k+1}
\end{aligned}$$

Note that the value at  $P_{0,1}^{k+1}$  is the same due to the symmetric square matrix.

This gives us that

$$P^{k+1} = P^k P^1 = \begin{bmatrix} \frac{1}{2} + \frac{1}{2}(2p - 1)^{k+1} & \frac{1}{2} - \frac{1}{2}(2p - 1)^{k+1} \\ \frac{1}{2} - \frac{1}{2}(2p - 1)^{k+1} & \frac{1}{2} + \frac{1}{2}(2p - 1)^{k+1} \end{bmatrix}$$

which satisfies our inductive hypothesis.

## Chapter 4 Problem 8

### Part a

The proposed Markov chain is in fact not a Markov chain. The  $n^{th}$  ball selected depends on more than just the  $(n-1)^{th}$  ball selected. For example say the urn contained two red balls at time  $n$ . We get the probability that a red ball is selected at  $n+1$  is the probability that the red ball that was selected (since two red balls would guarantee a red) plus the random choice between red and blue times the probability of the ball being replaced with the blue. The same logic follows for drawing a blue ball at time  $n+1$ .

$$\begin{aligned}
P_{1,1}^n &= 0.5 * 0.3 + 0.7 \\
P_{1,0}^n &= 0.5 * 0.3
\end{aligned}$$

However if the urn contains one red balls at time  $n$  we could still have drawn a red ball, but our transition probabilities would change:

$$\begin{aligned}
P_{1,1}^n &= 0.5 * 0.7 \\
P_{1,0}^n &= 0.5 * 0.7 + 0.3
\end{aligned}$$

### Part b

The proposed Markov chain is in fact a Markov chain with three states: zero red balls, one red ball, or two red balls. This gives us the probability matrix:

$$P = \begin{bmatrix} 0.5 & 0.5 & 0 \\ 0.15 & 0.6 & 0.25 \\ 0 & 0.3 & 0.7 \end{bmatrix}$$

The first and third rows are trivial. The urn either has 2 red or 2 blues, so the new states depend on the replacement balls. The middle row is a different case. Transition from 1 to no red balls requires that red is selected and replaced by blue  $0.5 * 0.3 = 0.15$ . Transition from 1 to 2 red balls requires the blue selected and replaced by red  $0.5 * 0.5 = 0.25$ . Transition from 1 to 1 could have either red or blue selected, but then replaced with their same color  $0.5 * 0.7 + 0.5 * 0.5 = 0.6$