W271-Lab1 Spring 2016

Charles Kekeh

Thursday, January 14, 2016

Question 1

 $\begin{aligned} &\mathrm{ML} = 36 \\ &\mathrm{Stat} = 28 \\ &\mathrm{Awesome} = 18 \\ &\mathrm{ML} \cap \mathrm{Stat} = 22 \\ &\mathrm{ML} \cap \mathrm{Awesome} = 12 \end{aligned}$

 $Stat \cap Awesome = 9$ $ML \cup Stat \cup Awesome = 48$

1)

$$ML \cup Stat = ML + Stat - ML \cap Stat = 42$$

$$Awe some. Other = (ML \cup Stat \cup Awe some) - (ML \cup Stat) = 6$$

 $Awe some = Awe some. Other \cup (Stat \cap Awe some) \cup (ML \cap Awe some) - (ML \cap Stat \cap Awe some)$

$$18 = 6 + 9 + 12 - (ML \cap Stat \cap Awesome)$$

 $ML \cap Stat \cap Awesome = 9$

$$\mathbf{Pr}(\mathbf{ML} \cap \mathbf{Stat} \cap \mathbf{Awesome}) = \frac{\mathbf{ML} \cap \mathbf{Stat} \cap \mathbf{Awesome}}{\mathbf{ML} \cup \mathbf{Stat} \cup \mathbf{Awesome}} = \frac{9}{48}$$

2)

$$Pr(Awe some | ML) = \frac{Pr(Awe some \cap ML)}{Pr(ML)}$$

$$Pr(Awe some | ML) = \frac{12}{36} = \frac{1}{3}$$

$$\mathbf{Pr}(!\mathbf{Awesome}|\mathbf{ML}) = 1 - \mathbf{Pr}(\mathbf{Awesome}|\mathbf{ML}) = 1 - \frac{12}{36} = 1 - \frac{1}{3} = \frac{2}{3}$$

3)

$$Pr(ML \cup Stat | Awesome) = \frac{Pr((ML \cup Stat) \cap Awesome)}{Pr(Awesome)}$$

$$Pr(ML \cup Stat | Awesome) = \frac{Pr(ML \cup Awesome) + Pr(Stat \cup Awesome) - Pr(Stat \cap ML \cap Awesome)}{Pr(Awesome)}$$

$$\mathbf{Pr}(\mathbf{ML} \cup \mathbf{Stat} | \mathbf{Awesome}) = \frac{\mathbf{12} + \mathbf{9} - \mathbf{9}}{\mathbf{48}} = \frac{\mathbf{12}}{\mathbf{48}} = \frac{\mathbf{1}}{\mathbf{4}}$$

$$Pr(A) = p \le \frac{1}{2}, Pr(B) = qwhere \frac{1}{4} < q < \frac{1}{2}$$

1)

We know that:

$$Pr(A \cup B) = Pr(A) + Pr(B) - Pr(A \cap B)$$

 $Pr(A \cup B)$ is maximized when $Pr(A \cap B)$ is minimized (A and B are independent and $Pr(A \cap B) = 0$). The maximum value is in the range:

 $\frac{1}{4} < \mathbf{Max}(\mathbf{Pr}(\mathbf{A} \cup \mathbf{B})) < 1$

From there, we also know that $Pr(A \cup B)$ is minimized when $Pr(A \cap B)$ is maximized and A and B are completely overlapping random events and $Pr(A \cap B) = Min(Pr(A), Pr(B))$. In these conditions

$$\frac{1}{4}<\mathbf{Min}(\mathbf{Pr}(\mathbf{A}\cup\mathbf{B})<\frac{1}{2}$$

2

We know that:

$$Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}$$

Thus Pr(A|B) is minimized when $Pr(A \cap B) = 0$. And

$$\mathbf{Min}(\mathbf{Pr}(\mathbf{A} \cup \mathbf{B})) = \mathbf{0}$$

Similarly, Pr(A|B) is maximized when the random event B is completely overlapped by the random event A. In such cases

$$Max(Pr(A|B)) = 1$$

Question 3

1) Given that the server's lifespan is a randon uniform distribution over the range [0,k], the probability of every additional year of operation is independent of the time elapsed and is equal to

$$\mathbf{Pr}(\mathbf{1yearofoperation}) = \frac{1}{k}$$

2)

We know that:

$$E(g(x)) = \int_{x=0}^{k} g(x) f_x(x) dx$$

Considering g to be our refund function over time t:

$$\begin{split} E(g(t)) &= \int_{t=0}^{1} \frac{\theta}{k} dt + \int_{t=1}^{k/2} \frac{A(k-t)^{\frac{1}{2}}}{k} dt + \int_{t=k/2}^{\frac{3k}{4}} \frac{\theta}{10k} dt \\ E(g(t)) &= \frac{\theta}{k} [t]_{0}^{1} + [\frac{-2}{3} (k-t)^{\frac{3}{2}}]_{1}^{k/2} + [\frac{\theta}{10k} t]_{\frac{k}{2}}^{\frac{3k}{4}} \\ \mathbf{E}(\mathbf{g}(\mathbf{t})) &= \frac{\theta}{\mathbf{k}} + \frac{\theta}{40} + \frac{2}{3} (\mathbf{k} - \mathbf{1})^{\frac{3}{2}} - \frac{\mathbf{k}}{2}^{\frac{3}{2}} \end{split}$$

We know that $Var(X) = E[X^2] - \mu^2$ Thus $Var(g(x)) = E[(g(x)^2] - [E[g(X)]^2]$ We previously computed E(g(x)). We now compute $E[(g(x)^2]$

$$E[(g(x)^{2})] = \int_{0}^{1} \frac{\theta^{2}}{k} dt + \int_{1}^{k/2} \frac{A^{2}(k-t)}{k} dt + \int_{\frac{k}{2}}^{\frac{3k}{2}} \frac{Q^{2}}{100k} dt$$
$$\mathbf{E}[(\mathbf{g}(\mathbf{x})^{2})] = \frac{\theta^{2}}{k} - \frac{\theta^{2}}{400} - \frac{\mathbf{A}^{2}(3\mathbf{k}^{2} - 8\mathbf{k} + 4)}{8\mathbf{k}}$$

We substract $E(g(x))^2$ as previously computed to obtain the variance

Question 4

 $f(x,y) = 2e^{-x}e^{-2y}$ for $0 < x < \infty$, $0 < y < \infty$, 0 otherwise 1)

$$\begin{split} Pr(x>a,ya,ya,ya,ya,ya,y$$

2)

$$\begin{split} Pr(x < y) &= \int_{y=0}^{infty} \int_{x=0}^{y} 2e^{-x}e^{-2y} dx dy \\ Pr(x < y) &= 2 \int_{y=0}^{\infty} e^{-2y} dy \int_{x=0}^{y} e^{-x} dx \\ Pr(x < y) &= 2 \int_{y=0}^{\infty} e^{-2y} dy [-e^{-x}]_{0}^{y} \\ Pr(x < y) &= 2 \int_{y=0}^{\infty} e^{-2y} (1 - e^{-y}) dy \\ Pr(x < y) &= 2 \int_{y=0}^{\infty} e^{-2y} - e^{-3y} dy \\ Pr(x < y) &= 2 \left[\frac{1}{6} e^{-3y} (2 - 3e^{y}) \right]_{0}^{\infty} \\ Pr(x < y) &= \frac{1}{2} \end{split}$$

3)

$$\begin{split} Pr(X < a) &= \int_{x=0}^{a} \int_{y=0}^{\infty} 2e^{-x}e^{-2y} dx dy \\ Pr(X < a) &= 2 \int_{x=0}^{a} e^{-x} dx \int_{y=0}^{\infty} e^{-2y} dy \\ Pr(X < a) &= 2 \int_{x=0}^{a} e^{-x} dx [-\frac{1}{2}e^{-2y}]_{0}^{\infty} \\ Pr(X < a) &= \int_{x=0}^{a} e^{-x} dx \\ Pr(X < a) &= 1 - e^{-a} \end{split}$$

Question 5

X random variable, x a real number.

$$Y = a + b (X - x^2)$$

1)

$$E(Y) = a + bE[(x - x^{2})]$$

$$E(Y) = a + bE[X^{2} - 2Xx - x^{2}]$$

$$E(Y) = a + b[E[X^{2} - 2xE[X] + x^{2}]]$$

E(Y) is minimized when $\frac{d}{dx}E(Y) = 0$

$$\frac{d}{dx}E(Y) = -2bE(X) + 2bx$$
$$\frac{d}{dx}E(Y) = 0 \Rightarrow \mathbf{x} = \mathbf{E}(\mathbf{X})$$

2)

$$\begin{split} When x &= E(X) : E(Y) = a + b[E[X^2] - 2(E[X])^2 + (E[X])^2] \\ E(Y) &= a + b[E[X^2] - (E[X])^2] \\ \mathbf{E}(\mathbf{Y}) &= \mathbf{a} + \mathbf{bVar}[\mathbf{X}] \end{split}$$

3)

$$Y = ax + b(X - x^{2})$$

$$E(Y) = ax + bE[(x - x^{2})]$$

$$E(Y) = ax + bE[X^{2} - 2Xx - x^{2}]$$

$$E(Y) = ax + b[E[X^{2} - 2xE[X] + x^{2}]]$$

E(Y) is minimized when $\frac{d}{dx}E(Y) = 0$

$$\frac{d}{dx}E(Y) = a - 2bE(X) + 2bx$$
$$\frac{d}{dx}E(Y) = 0 \Rightarrow \mathbf{x} = \mathbf{E}(\mathbf{X}) - \frac{\mathbf{a}}{2\mathbf{b}}$$

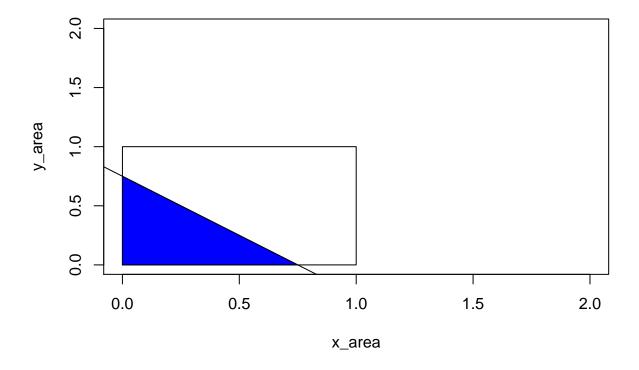
```
X, Y independent continuous variables, uniform over [0..1] Z = X + Y 1)
```

```
x_area = c(0:2)
y_area = c(0:2)

plot(x_area, y_area, type = "n")

xx = c(0, 1, 1, 0)
yy = c(0, 0, 1, 1)
polygon(xx, yy, density = 0, border = "black")

abline(.75, -1)
xz = c(0, .75, 0)
yz = c(0, 0, .75)
polygon(xz, yz, col = "blue", border = "black")
```

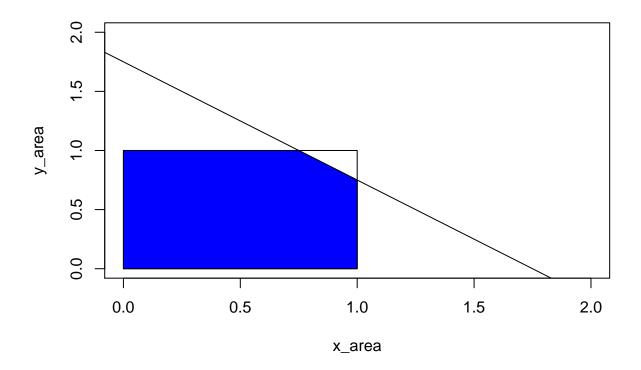


```
plot(x_area, y_area, type = "n")

xx = c(0, 1, 1, 0)

yy = c(0, 0, 1, 1)
```

```
polygon(xx, yy, density = 0, border = "black")
abline(1.75, -1)
xz = c (0, 1, 1, .75, 0, 0)
yz = c(0, 0, .75, 1, 1, 0)
polygon(xz, yz, col = "blue", border = "black")
```



2) From the areas above, we derive that:

For $0 \le z \le 1$:

$$\mathbf{Pr}(\mathbf{Z} < \mathbf{z}) = \frac{\mathbf{z^2}}{2}$$

For 1 < z <= 2:

$$\mathbf{Pr}(\mathbf{Z} < \mathbf{z}) = 1 - \frac{(2-\mathbf{z})^2}{2}$$

Hence:

For $0 \le z \le 1$:

$$\mathbf{f}(\mathbf{z}) = \frac{\mathbf{d}}{\mathbf{d}\mathbf{z}} \frac{\mathbf{z^2}}{2} = \mathbf{z}$$

For 1 < z <= 2:

$$\mathbf{f}(\mathbf{z}) = \frac{\mathbf{d}}{\mathbf{d}\mathbf{z}}\mathbf{1} - \frac{(\mathbf{2} - \mathbf{z})^2}{2} = \mathbf{2} - \mathbf{z}$$

1)

Event Class	Sum of Dices	Events in Class	Pr(Sum of Dices)
House wins	2	(1,1)	$\frac{1}{36}$
	3	(1,2)(2,1)	$\frac{1}{18}$
	12	(6,6)	$\frac{1}{36}$
You win	7	(3,4)(4,3)(5,2)(2,5)(1,6)(6,1)	$\frac{1}{6}$
	11	(5,6)(6,5)	$\frac{1}{18}$
X	4	(2,2)(3,1)(1,3)	$\frac{1}{12}$
	5	(2,3)(3,2)(1,4)(4,1)	$\frac{1}{9}$
	6	(3,3)(4,2)(2,4)(5,1)(1,5)	$\frac{5}{36}$
	8	(4,4)(6,2)(2,6)(3,5)(5,3)	12 14 5 36 36
	9	(3,6)(6,3)(5,4)(4,5)	$\frac{1}{9}$
	10	(5,5)(6,4)(4,6)	$\frac{1}{12}$

We can now define

$$\begin{split} &E(Y_{Playerwins}) = Pr(Playerwinsinone) * 1 + \\ &\sum_{n=0}^{\infty} (Pr(4))^2 (1 - (Pr(4) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(5))^2 (1 - (Pr(5) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(6))^2 (1 - (Pr(6) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(8))^2 (1 - (Pr(8) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(9))^2 (1 - (Pr(9) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (1 - (Pr(10) + Pr(7)))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (Pr(10) + Pr(10))^n (n+2) + \\ &\sum_{n=0}^{\infty} (Pr(10))^2 (Pr(10) + Pr(10))^n (Pr(10) + Pr(10))$$

$$E(Y_{Housewins}) = Pr(Housewinsinone) * 1 + \sum_{n=0}^{\infty} Pr(X)Pr(7)(1 - Pr(7))^{n}(n+2)$$

We know:

$$\frac{1}{(1-x)^2} = 1 + 2x + 3x^2 + 4x^3 + \cdots$$

$$\frac{1}{(1-x)^2} - 1 = 2x + 3x^2 + 4x^3 + \cdots$$

$$\frac{1}{x(1-x)^2} - \frac{1}{x} = 2 + 3x + 4x^2 + 5x^3 + \cdots$$

$$\frac{1 - (1-x)^2}{x(1-x)^2} = 2 + 3x + 4x^2 + 5x^3 + \cdots$$

Thus:

$$\begin{split} E(Y_{PlayerWins}) &= Pr(Playerwin) * 1 + \Pr(4)^2 \frac{1 - (Pr(4) + Pr(7))^2}{(Pr(4) + Pr(7))^2 (1 - (Pr(4) + Pr(7)))} + \\ &\qquad \qquad \qquad \qquad \qquad \\ \Pr(5)^2 \frac{1 - (Pr(5) + Pr(7))^2}{(Pr(5) + Pr(7))^2 (1 - (Pr(5) + Pr(7)))} + \\ &\qquad \qquad \qquad \qquad \\ \Pr(6)^2 \frac{1 - (Pr(6) + Pr(7))^2}{(Pr(6) + Pr(7))^2 (1 - (Pr(6) + Pr(7)))} + \\ &\qquad \qquad \qquad \qquad \\ \Pr(8)^2 \frac{1 - (Pr(8) + Pr(7))^2}{(Pr(8) + Pr(7))^2 (1 - (Pr(8) + Pr(7)))} + \\ &\qquad \qquad \qquad \\ \Pr(9)^2 \frac{1 - (Pr(9) + Pr(7))^2}{(Pr(9) + Pr(7))^2 (1 - (Pr(9) + Pr(7)))} + \\ &\qquad \qquad \\ \Pr(10)^2 \frac{1 - (Pr(10) + Pr(7))^2}{(Pr(10) + Pr(7))^2 (1 - (Pr(10) + Pr(7)))} + \end{split}$$

$$E(Y_{HouseWins}) = Pr(Housewin) * 1 + Pr(X)Pr(7) \frac{1 - (Pr(7) + Pr(X))^2}{(1 - (Pr(7) + Pr(X)))(Pr(7) + Pr(X))^2}$$

```
pr.house.wins.in.one <- 4/36
pr.player.wins.in.one <- 8/36
pr.seven < - 6/36
pr.x.events <- c(3/36, 4/36, 5/36/ 5/36, 4/36, 3/36)
pr.x.plus.seven.events <- pr.x.events + pr.seven</pre>
exp.y.player.wins <- pr.player.wins.in.one +</pre>
    sum((pr.x.events)^2 * (1 - pr.x.plus.seven.events^2)/((1- pr.x.plus.seven.events)*pr.x.plus.seven.e
exp.y.house.wins <- pr.house.wins.in.one +
    pr.seven*sum(pr.x.events)*(1 - (pr.seven + sum(pr.x.events))^2)/
    ((1 - (pr.seven + sum(pr.x.events)))*(pr.seven + sum(pr.x.events))^2)
print(sprintf("E(Y_Player_Wins) = %f", exp.y.player.wins))
## [1] "E(Y_Player_Wins) = 0.908914"
print(sprintf("E(Y_House_Wins) = %f", exp.y.house.wins))
## [1] "E(Y House Wins) = 0.437681"
2)
  E(Payoff) = 100 * Pr(Y = 1) + 80 * Pr(Y = 2) + 60 * Pr(Y = 3) + 40 * Pr(Y = 4) + 0 * Pr(Y = 5)
                              Pr(Y = 1) = Pr(Playerwinsinone)
```

Question 8

$$E(Y_1) = E(Y_2) = \dots = E(Y_n) = \mu$$

 $Var(Y_1) = Var(Y_2) = \dots = Var(Y_n) = \sigma^2$

1)

For W to be un unbiased estimator of μ :

$$E(W) = \mu$$

$$\Rightarrow E(\sum_{i=1}^{n} a_i Y_i) = \mu$$

$$\Rightarrow \sum_{i=1}^{n} a_i E(Y_i) = \mu$$

$$\Rightarrow \sum_{i=1}^{n} a_i \mu = \mu$$

$$\Rightarrow \mu \sum_{i=1}^{n} a_i = \mu$$

$$\Rightarrow \sum_{i=1}^{n} a_i = 1$$

2)

$$Var(W) = Var(\sum_{i=1}^{n} a_i Y_i)$$

$$Var(W) = \sum_{i=1}^{n} a_i^2 Var(Y_i)$$

$$\mathbf{Var}(\mathbf{W}) = \sigma^2 \sum_{i=1}^{n} \mathbf{a}_i^2$$

3)

We know that:

$$\frac{1}{n}(\sum_{i=1} na_i)^2 \le \sum_{i=1}^n a_i^2$$

Knowing also that:

$$Var(W) = \sigma^2 \sum_{i=1}^{n} a_i^2$$

We conclude:

$$Var(W) \ge \sigma^2 \frac{1}{n} (\sum_{i=1}^n a_i)^2$$

When W is unbiased, we know that:

$$\sum_{i=1}^{n} a_i = 1$$

Thus:

$$Var(W) \ge \frac{\sigma^2}{n}$$

and

$$\mathbf{Var}(\mathbf{W}) \geq \mathbf{\bar{Y}}$$

$$W_1 = \left(\frac{n-1}{n}\right)\bar{Y}$$

$$W_2 = k\bar{Y}$$
1)

$$bias(W_1) = E((\frac{n-1}{n})\bar{Y})$$

$$bias(W_1) = \frac{n-1}{n}E(\bar{Y}) - \mu$$

$$bias(W_1) = \frac{n-1}{n}\mu - \mu$$

$$bias(\mathbf{W_1}) = \frac{\mu}{n}$$

Similarly:

$$\begin{aligned} bias(W2) &= E(k\bar{Y}) - \mu \\ bias(W2) &= kE(\bar{Y}) - \mu \\ bias(W2) &= k\mu - \mu \\ \mathbf{bias(W2)} &= \mu(\mathbf{k-1}) \end{aligned}$$

2)

$$Var(W_1) = Var((\frac{n-1}{n})\bar{Y})$$

$$Var(W_1) = \frac{(n-1)^2}{n^2}Var(\bar{Y})$$

$$Var(W_1) = \frac{(n-1)^2}{n^2}\frac{\sigma^2}{n}$$

$$Var(\mathbf{W_1}) = \frac{(\mathbf{n}-1)^2\sigma^2}{\mathbf{n}^3}$$

Similarly:

$$Var(W_2) = Var(k\bar{Y})$$

$$Var(W_2) = k^2 Var(\bar{Y})$$

$$Var(W_2) = k^2 \frac{\sigma^2}{n}$$

$$Var(\mathbf{W_2}) = \mathbf{k^2} \frac{\sigma^2}{n}$$

$$\widehat{\sigma^2} = \frac{1}{n} \sum_{i=1}^{n} (Y_{i} \{i\} - \bar{Y})^2$$
1)

$$E(\bar{Y}) = E\left[\frac{\sum_{i=1}^{n} Y_i}{n}\right]$$

We know that E(X) is a linear function, thus:

$$E(\bar{Y}) = \frac{1}{n} \sum_{i=1}^{n} E[Y_i]$$
$$E(\bar{Y}) = \frac{1}{n} (n\mu)$$
$$\Rightarrow \mathbf{E}(\bar{\mathbf{Y}}) = \mu = \mathbf{E}[\mathbf{Y}_i], \mathbf{y} = \mathbf{1}, \dots, \mathbf{n}$$

2)

$$Var(\bar{Y}) = Var[\frac{\sum_{i=1}^{n} Y_i}{n}]]$$

We know that $\operatorname{Var}\left[\sum_{i=1}^{n} \mathbf{a}_{i} X_{i}\right] = \sum_{i=1}^{n} a_{i}^{2} \operatorname{Var}(X_{i})$, thus:

$$Var(\bar{Y}) = \frac{1}{n^2} \sum_{i=1} n(Var[Y_i])$$

$$\Rightarrow Var(\bar{Y}) = \frac{1}{n^2} n\sigma^2 = \frac{1}{n} Var[Y_i], y = 1, \dots, n$$

3)

$$\widehat{\sigma^2} = E\left[\frac{1}{n}\sum_{i=1}^n (Y_i - \bar{Y})^2\right]$$

$$\widehat{\sigma^2} = \frac{1}{n}\sum_{i=1}^n E[(Y_i - \bar{Y})^2]$$

$$\widehat{\sigma^2} = \frac{1}{n}\sum_{i=1}^n E(Y_i^2 - 2Y_i\bar{Y} + \bar{Y}^2)$$

$$\widehat{\sigma^2} = \frac{1}{n}\sum_{i=1}^n E(Y_i^2) - 2E(Y_i)E(\bar{Y}) + \bar{Y}^2)$$

$$\widehat{\sigma^2} = \frac{1}{n}\sum_{i=1}^n E(Y_i^2) - E(\bar{Y}_i)^2 + E(\bar{Y}^2) - E(\bar{Y}^2)$$

$$\widehat{\sigma^2} = \frac{1}{n}\sum_{i=1}^n Var(Y_i) + Var(\bar{Y})$$

$$\widehat{\sigma^2} = \frac{1}{n}(n\sigma^2 + n\frac{\sigma^2}{n})$$

$$\widehat{\sigma^2} = \frac{\mathbf{n} + \mathbf{1}}{n}\sigma^2$$

We have shown that $E(\widehat{\sigma^2}) := \sigma^2$ and we conclude that $\widehat{\sigma^2}$ is a biased estimator for σ^2 .

5)

We know that:

$$\widehat{\sigma^2} = \frac{n+1}{n}\sigma^2$$

is a biased estimator. Thus:

$$\frac{n}{n+1}\widehat{\sigma^2}$$

is an unbiased estimator of σ^2

Question 11

X, Y positive random variables. $E(Y|X) = \theta X$

i)

We know that $Z = \frac{Y}{X}$ We first compute E(Z|X)

$$E(Z|X) = E(\frac{X}{V}|X)$$

Using E(a(X) Y + b(X))|X) = a(X)E(Y|X) + bX, we derive:

$$E(Z|X) == \frac{1}{X}E(Y|X) = \frac{\theta X}{X} = \theta$$

Then, we knwo that E[E(Z|X)] = E(Z). Thus:

$$E(\theta) = E(Z)$$

 Θ being a constant:

$$E(\theta) = \theta$$

and

$$\mathbf{E}(\mathbf{Z}) = \theta$$

ii) $W_1 = n^{-1} \sum_{i=1}^n \frac{Y_i}{X_i}(X_i, Y_i) : i = 1, 2, \dots, n$ is the estimator. We compute $E(W_{1}):$

$$E(W_1) = n^{-1} E[\sum_{i=1}^{n} (\frac{Y_i}{X_i})]$$

$$E(W_1) = n^{-1} \sum_{i=1}^{n} E(Y_i/X_i)$$

$$\mathbf{E}(\mathbf{W_1}) = \mathbf{n^{-1}}[\mathbf{n}\mathbf{E}(\mathbf{Z})] = \mathbf{E}(\mathbf{Z}) = \theta$$

 $We conclude that W_1 is unbiased for \theta$

iii)

$$W_2 = \frac{\bar{Y}}{\bar{X}}$$

$$W_2 = \frac{n^{-1} \sum_{i=1}^n Y_i}{n^{-1} \sum_{i=1}^n X_i}$$

$$\Rightarrow W_2 = \frac{Y_1 + Y_2 + Y_3 + \dots + Y_n}{X_1 + X_2 + X_3 + \dots + X_n}$$

whereas:

$$W_1 = \frac{Y_1}{X_1} + \frac{Y_2}{X_2} + \frac{Y_3}{X_3} + \dots + \frac{Y_n}{X_n}$$

 W_2 and W_1 are thus different estimators

$$E(W_2) = E[\frac{\bar{Y}}{\bar{X}}]$$

We know that

$$E(Y) = E(\bar{Y}) = E[E(Y|X)] = E[\theta X] = \theta E(X)$$

$$\Rightarrow E(W_2) = E[\frac{\theta E(X)}{E(X)}] = E(\theta)$$

$$\Rightarrow \mathbf{E}(\mathbf{W_2}) = \theta$$

Question 12

i)

The null hypothesis is that $\mu = 0$

ii)

The alternative hypothesis hypothesis is that $\mu < 0$

iii)

$$n = 900$$

$$\bar{Y} = -32.8$$

$$s = 466.4$$

$$t = \frac{\bar{Y}}{\frac{s}{\sqrt{n}}} = -2.150538$$

$$p(z \le t) = 0.0158$$

Thus, we reject the null hypothesis at the 5% significance level as $p(z \le t) \le 0.05$ We cannot reject the null hypothesis at the 1% significance level as $p(z \le t) \ge 0.01$

The effect size is inferior to 10% of the variance of the State Liquor Consumption variable. That's an indication of a small practical effect. We also compute the correlation coefficient as

$$r = \sqrt{\frac{t^2}{t^2 + DF}} = 0.07$$

The value of R also confirms the small practical effect despite the test being statistically significant because of the high sample size.

Question 13

 $Y_i=1$ Shot made. $Y_i=0$ Shot missed. $\theta=Pr(Makinga3ptshot)$ Bernouilli distribution. $\bar{Y}=\frac{FGM}{FGA}$ estimator of θ

i)

$$\theta = \frac{188}{429} = .4382284$$

ii)

Because Y has a Bernouilli distribution: $E(Y) = \theta$ Let $Y_i \in \{1, \dots, n\}$ be an occurance of a free throw. We know that each Y_i is a Bernouilli variable. We can define:

$$\bar{Y} = \frac{\sum_{i=1}^{n} Y_i}{n}$$

Thus:

$$Var(\bar{Y}) = (\frac{1}{n})^2 Var(\sum_{i=1}^n Y_i)$$

$$Var(\bar{Y}) = (\frac{1}{n})^2 \sum_{i=1}^n Var(Y_i)$$

Thus:

$$Var(\bar{Y}) = (\frac{1}{n})^2 n\theta(1-\theta)$$

$$\Rightarrow Var(\bar{Y}) = \frac{\theta(1-\theta)}{n}$$

And:

$$sd(Y) = \sqrt{Var(\bar{Y})}$$

 $\Rightarrow sd(Y) = \sqrt{\frac{\theta(1-\theta)}{n}}$

iii)

We know $se(\bar{\gamma})=\sqrt{\frac{\bar{\gamma}(1-\bar{\gamma})}{n}}$ And $\frac{\bar{\gamma}-\theta}{se(\bar{Y})}\equiv Normal(0,1)$ We compute:

$$z_Y = \frac{\frac{188}{429} - .5}{se(\bar{Y})} = -2.57861$$
$$\Rightarrow p(z) = 0.0058$$

The p-value is significant at the 1% significance level and we reject the null hypothesis.