

## Discretionary Note

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**IF YOU USE THIS FILE TO CHEAT, YOU ARE NOT ONLY STUPID BUT YOU ARE CHEATING YOURSELF OUT OF THE ABILITY TO FALL IN LOVE WITH MATH.** Furthermore, I am not smarter than you and my solutions did not always get a perfect score.

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# STATS 242 HW 1

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Number of late days: 0; Collaborators: None.

1.

- a) For  $i = 1 \dots \frac{n}{2}$ , let the Bernoulli variables  $F_i \sim \text{Bern}(\theta + \delta)$  and  $M_i \sim \text{Bern}(\theta - \delta)$  represent whether the  $i$ th female or male (respectively) voter supports Harris. Therefore,  $\hat{\theta}$  is given by:

$$\hat{\theta} = \frac{\sum_{i=1}^{\frac{n}{2}} F_i + M_i}{n}$$

and so we have that  $\mathbb{E}[\hat{\theta}]$  is given by:

$$\begin{aligned}\mathbb{E}[\hat{\theta}] &= \mathbb{E}\left[\frac{\sum_{i=1}^{\frac{n}{2}} F_i + M_i}{n}\right] = \frac{1}{n} \sum_{i=1}^{\frac{n}{2}} \mathbb{E}[F_i + M_i] = \frac{1}{n} \sum_{i=1}^{\frac{n}{2}} \mathbb{E}[F_i] + \mathbb{E}[M_i] = \frac{1}{n} \left[ \frac{n}{2} (\theta + \delta + \theta - \delta) \right] \\ &= \frac{1}{n} \left[ \frac{n}{2} (2\theta) \right] = \frac{n\theta}{n} = \theta\end{aligned}$$

Because  $\mathbb{E}[\hat{\theta}] = \theta$ , the bias of  $\hat{\theta}$  is zero.

b)

$$\text{Var}(\hat{\theta}) = \mathbb{E}[\hat{\theta}^2] - \mathbb{E}[\theta]^2$$

Let random variables  $\hat{\theta}_F = \frac{1}{0.5n} \sum_{i=1}^{\frac{n}{2}} F_i$  and  $\hat{\theta}_M = \frac{1}{0.5n} \sum_{i=1}^{\frac{n}{2}} M_i$  define the sampling parameters from the female and male independent simple random samples, respectively. Thus, we have that  $\hat{\theta} = \frac{(\hat{\theta}_F + \hat{\theta}_M)}{2}$ . Note  $\hat{\theta}_F$  and  $\hat{\theta}_M$  are independent as their respective simple random samples are independent. Thus, we can compute  $\text{Var}(\hat{\theta}) = \text{Var}\left(\frac{\hat{\theta}_F + \hat{\theta}_M}{2}\right) = \frac{1}{4} [\text{Var}(\hat{\theta}_F) + \text{Var}(\hat{\theta}_M)]$ . Because both sampling parameters  $\hat{\theta}_F$  and  $\hat{\theta}_M$  are drawn from simple random samples, their respective variances can be given by  $\frac{(\theta + \delta)(1 - \theta - \delta)}{0.5n} \left(1 - \frac{0.5n - 1}{0.5N - 1}\right)$  and  $\frac{(\theta - \delta)(1 - \theta + \delta)}{0.5n} \left(1 - \frac{0.5n - 1}{0.5N - 1}\right)$ . Thus, putting it all together:

$$\begin{aligned} \text{Var}(\hat{\theta}) &= \frac{1}{4}[\text{Var}(\hat{\theta}_F) + \text{Var}(\hat{\theta}_M)] = \frac{1}{4} \frac{(\theta + \delta)(1 - \theta - \delta) + (\theta - \delta)(1 - \theta + \delta)}{0.5n} \left(1 - \frac{0.5n - 1}{0.5N - 1}\right) = \\ &= \frac{(\theta - \theta^2 - \delta^2)}{n} \frac{0.5N - 0.5n}{0.5N - 1} = \frac{(\theta - \theta^2 - \delta^2)}{n} \frac{N - n}{N - 2} \end{aligned}$$

c) We first simplify the given quantity in this question to:

$$\text{Var}[\hat{\theta}] = \frac{\theta - \theta^2}{n} \left(1 - \frac{n - 1}{N - 1}\right) = \frac{\theta - \theta^2}{n} \left(\frac{N - n}{N - 1}\right)$$

Given  $N$  is significantly larger than  $n$ , both  $\frac{N-n}{n-1}$  and  $\frac{N-n}{N-2}$  are approximately equal to one. This means the variance computed in part (b) is approximately  $\frac{\delta^2}{n}$  smaller than the quantity given in this question.

2.

- a) For  $i = 1 \dots n$ , let  $X_i$  be a Bernoulli variable that models whether the  $i$ th person in the survey support Harris. This probability is equivalent to the expected percentage of the sample that supports Harris, or the expected number of people in the survey who support Harris divided by the total number of people in the survey.

**The number of people who support Harris in the survey** can be given by  $\theta N$ , the number of people who support Harris in the population, times  $\frac{p}{N}$  (probability each person who support Harris in the population was chosen.)

**The number of people who support other candidates in the survey** can be given by  $(1 - \theta)N$ , the number of people who support other candidates in the population, times  $\frac{q}{N}$  (probability each person who supports another candidate in the population was chosen.)

Thus,  $\mathbb{E}[X_i]$  is given by:

$$\mathbb{E}[X_i] = P(X_i = 1) = \frac{\theta N \cdot \frac{p}{N}}{\theta N \cdot \frac{p}{N} + (1 - \theta)N \cdot \frac{q}{N}} = \frac{p\theta}{p\theta + (1 - \theta)q}$$

Given  $p\theta + (1 - \theta)q = 1$ , we have that:

$$\mathbb{E}[X_i] = p\theta$$

Given this, we can compute the bias of  $\hat{\theta}$  as:

$$\mathbb{E}[\hat{\theta}] - \theta = \mathbb{E}\left[\frac{1}{n} \sum_{i=1}^n X_i\right] - \theta = \frac{1}{n} \cdot n \cdot \mathbb{E}[X_1] - \theta = p\theta - \theta$$

For  $\hat{\theta}$  to be unbiased,  $p\theta - \theta = 0$ , or  $p$  (and  $q$ ) has to equal to one.

b) Given  $Var(X_i) = \mathbb{E}[X_i^2] - \mathbb{E}[X_i]^2 = p\theta(1 - p\theta)$ , we can use the Central Limit Theorem to approximate  $\hat{\theta} \sim \mathcal{N}(\mathbb{E}[X_i], \frac{Var(X_i)}{n})$  or  $\hat{\theta} \sim \mathcal{N}(p\theta, \frac{p\theta - p^2\theta^2}{n})$ . Plugging in  $\theta = 0.5, p = 1.02, q = 0.98$ , we have:

- i.  $P(\hat{\theta} > 0.5) = 0.5793$  for  $n = 100$
- ii.  $P(\hat{\theta} > 0.5) = 0.7365$  for  $n = 1000$
- iii.  $P(\hat{\theta} > 0.5) = 0.97727$  for  $n = 10000$

As  $n$  increases,  $P(\hat{\theta} > 0.5)$  increases.

3.

22 We first compute the joint distribution  $f_{X,Y}(x, y)$ . Because  $(X, Y)$  is uniformly distributed over the region  $R$  where  $x^2 + y^2 \leq 1$ , we have  $\iint_R f_{X,Y}(x, y) = 1$ . Note that  $R$  forms a circle with radius one, and so its area is  $\pi$ . Because  $f_{X,Y}(x, y)$  is constant over region  $R$  as  $(X, Y)$  is uniformly distributed,  $\iint_R f_{X,Y}(x, y) = Area_R \cdot f_{X,Y} = 1$ , or that for  $(x, y) \in R$ ,  $f_{X,Y}(x, y) = \frac{1}{\pi}$ . Putting it all together, we have:

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{\pi} & \text{for } x^2 + y^2 \leq 1 \\ 0 & \text{else} \end{cases}$$

We now are ready to compute  $Cov[X, Y] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$ . We compute  $\mathbb{E}[XY]$ ,  $\mathbb{E}[X]$ , and  $\mathbb{E}[Y]$  below:

①  $\mathbb{E}[XY]$

$$\begin{aligned} \mathbb{E}[XY] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{X,Y}(x, y) dx dy = \int_{-1}^1 \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} \frac{xy}{\pi} dx dy = \int_{-1}^1 \frac{x^2 y}{2\pi} \Big|_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} dx dy \\ &= \int_{-1}^1 0 dx dy = 0 \end{aligned}$$

②  $\mathbb{E}[X]$

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{X,Y}(x, y) dx dy = \int_{-1}^1 \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} \frac{x}{\pi} dx dy = \int_{-1}^1 \frac{x^2}{2\pi} \Big|_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} dx dy = \int_{-1}^1 0 dx = 0$$

③  $\mathbb{E}[Y]$

$$\begin{aligned} \mathbb{E}[Y] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f_{X,Y}(x, y) dx dy = \int_{-1}^1 \int_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} \frac{y}{\pi} dx dy = \int_{-1}^1 \frac{xy}{\pi} \Big|_{-\sqrt{1-y^2}}^{\sqrt{1-y^2}} dx dy = \\ &= \int_{-1}^1 \frac{2y\sqrt{1-y^2}}{\pi} dy = \frac{2}{\pi} \int_{-1}^1 y\sqrt{1-y^2} dy \end{aligned}$$

Because  $y\sqrt{1-y^2}$  is an odd function, its integral from  $-1$  to  $1$  will be  $0$ . Thus:

$$\mathbb{E}[Y] = \frac{2}{\pi} \int_{-1}^1 y\sqrt{1-y^2} dy = 0$$

Thus,  $Cov[X, Y] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] = 0 - 0 \cdot 0 = 0$ .  $X$  and  $Y$  are not independent because their joint distribution  $(X, Y)$  is not defined over a rectangular region, but instead a circle. As a simple demonstration of this idea, let us assume that  $X$  and  $Y$  are independent. If so, then:

$$P(X > 0.5 | Y > 0.9) = P(X > 0.5)$$

Note that  $P(X > 0.5)$  is obviously nonzero. However,  $P(X > 0.5 | Y > 0.9) = 0$  as if  $Y > 0.9$ , then in order for  $x^2 + y^2 \leq 1$ ,  $x$  must be in the range  $[-\sqrt{1 - 0.9^2}, \sqrt{1 - 0.9^2}]$  and so  $x$  cannot be greater than 0.5. Thus, we have shown  $P(X > 0.5 | Y > 0.9) = 0 \neq P(X > 0.5)$  and so  $X$  and  $Y$  are demonstrated to not be independent.

4.

Note that because  $X$  is a normal distribution, it is symmetric and so  $P(X > 0) = 0.5$ .

$$P(X + Y > 0 | X > 0) = \frac{P(X + Y > 0 \cap X > 0)}{P(X > 0)} = 2P(X + Y > 0 \cap X > 0)$$

The event  $X + Y > 0 \cap X > 0$  can be given by  $(X > 0 \cap Y > 0) \cup (X > -Y \cap Y < 0)$ . Thus, we have that:

$$\begin{aligned} P(X + Y > 0 | X > 0) &= 2P((X > 0 \cap Y > 0) \cup (X > -Y \cap Y < 0)) \\ &= 2[P(X > 0 \cap Y > 0) + P(X > -Y \cap Y < 0)] = 2[P(X > 0)P(Y > 0) + P(X > -Y \cap Y < 0)] \\ &= 2[0.5(0.5) + P(X > -Y \cap Y < 0)] \end{aligned}$$

$P(X > -Y \cap Y < 0)$  takes up half of the space in the third quadrant, and because the joint PDF of  $(X, Y)$  is rotationally symmetric about the origin, we know that  $P(X > -Y \cap Y < 0) = 0.125$ . Thus:

$$P(X + Y > 0 | X > 0) = 2[0.25 + 0.125] = 2[0.375] = 0.75$$