Math Statistics Weekly HW 6

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Question 1

Problem: Consider the distribution $Ber(\theta)$. For a sample of n i.i.d. variables $X_i \sim Ber(\theta)$, show that the following is a sufficient statistic of θ :

$$\hat{\theta} = \sum_{i=1}^{n} X_i$$

Solution: Note the following:

$$p_{X}(\mathbf{x};\theta) = \prod_{i=1}^{n} p_{X_{i}}(x_{i};\theta)$$
 (independent sample)
$$= \prod_{i=1}^{n} p^{x_{i}} (1-p)^{1-x_{i}}$$
 ($X_{i} \sim \operatorname{Ber}(\theta)$)
$$= p^{\sum_{i=1}^{n} x_{i}} (1-p)^{\sum_{i=1}^{n} (1-x_{i})}$$
 (sum of exponents)
$$= p^{\sum_{i=1}^{n} x_{i}} (1-p)^{n-\sum_{i=1}^{n} x_{i}}$$
 (linearity of summation)
$$= p^{\hat{\theta}(\mathbf{x})} (1-p)^{n-\hat{\theta}(\mathbf{x})}$$
 (def. of $\hat{\theta}$)
$$= \underbrace{1}_{h(\mathbf{x})} \underbrace{p^{\hat{\theta}(\mathbf{x})} (1-p)^{n-\hat{\theta}(\mathbf{x})}}_{g(\hat{\theta}(\mathbf{x});\theta)}$$

And so by the factorization theorem, we have that $\hat{\theta}$ is a sufficient statistic of θ .

Question 2

Consider two distributions with the same mean μ but with different variances σ_1^2 , σ_2^2 . Suppose we take independent samples from each distribution of sizes n_1 , n_2 , and that these samples have sample means \bar{X}_1 , \bar{X}_2 .

Part a: Show that for any $\omega \in \mathbb{R}$, the statistic $\hat{\theta}_{\omega} = \omega \bar{X}_1 + (1 - \omega)\bar{X}_2$ is an unbiased estimator of μ .

Solution: Let us compute the expected value of $\hat{\theta} - \omega$:

$$E[\hat{\theta}_{\omega}] = E[\omega \bar{X}_1 + (1 - \omega)\bar{X}_2]$$
 (def. of $\hat{\theta}_{\omega}$)

$$= \omega E[\bar{X}_1] + (1 - \omega)E[\bar{X}_2]$$
 (linearity of expectation)

$$= \omega \mu + (1 - \omega)\mu$$
 (mean of sample mean)

$$= \omega \mu + \mu - \omega \mu$$

$$= \mu$$

And so we have that, for any real ω , the mean of our estimator $\hat{\theta}_{\omega}$ is the mean of the population. Thus our estimator is unbiased.

Part b: Give the variance of the estimator $\hat{\theta}_{\omega}$.

Solution: The variance of $\hat{\theta}_{\omega}$ is given by:

$$\begin{aligned} \operatorname{Var}(\hat{\theta}_{\omega}) &= \operatorname{Var}(\omega \bar{X}_1 + (1 - \omega) \bar{X}_2) & (\operatorname{def. of } \hat{\theta}_{\omega}) \\ &= \operatorname{Var}(\omega \bar{X}_1) + \operatorname{Var}((1 - \omega) \bar{X}_2) & (\operatorname{variance of independent RVs)} \\ &= \omega^2 \operatorname{Var}(\bar{X}_1) + (1 - \omega)^2 \operatorname{Var}(\bar{X}_2) & (\operatorname{variance of multiple of RV}) \\ &= \omega^2 \frac{\sigma_1^2}{n_1} + (1 - \omega)^2 \frac{\sigma_2^2}{n_2} & (\operatorname{variance of sample mean}) \end{aligned}$$

Part c: Show that $Var(\hat{\theta}_{\omega})$ is minimized when:

$$\omega = \frac{n_1 \sigma_2^2}{n_2 \sigma_1^2 + n_1 \sigma_2^2}$$

Solution: Our goal is to compute the following:

$$\underset{\omega \in \mathbb{R}}{\operatorname{arg\,min}} \operatorname{Var}(\hat{\theta}_{\omega}) = \underset{\omega \in \mathbb{R}}{\operatorname{arg\,min}} \ \omega^{2} \frac{\sigma_{1}^{2}}{n_{1}} + (1 - \omega)^{2} \frac{\sigma_{2}^{2}}{n_{2}}$$

$$= \underset{\omega \in \mathbb{R}}{\operatorname{arg\,min}} \underbrace{\left(\frac{\sigma_{1}^{2}}{n_{1}} + \frac{\sigma_{2}^{2}}{n_{2}}\right)}_{a} \omega^{2} + \underbrace{\left(-\frac{2\sigma_{2}^{2}}{n_{2}}\right)}_{b} \omega + \underbrace{\frac{\sigma^{2}}{n_{2}}}_{c}$$
(part b)

Note that the expression we are trying to minimize is a quadratic polynomial in ω . Recall that all quadratics in one variable have a single extremum, and that extremum is a minimum if a > 0 and a maximum if a < 0.

In our case, $a = \left(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}\right)$ is always positive, unless both σ_1^2 and σ_2^2 were zero (i.e. both RVs the distributions correspond to are just constants). And so the ω that minimizes estimator's variance is given by the zero of the above quadratic:

$$\underset{\omega \in \mathbb{R}}{\operatorname{arg\,min}} \operatorname{Var}(\hat{\theta}_{\omega}) = \underset{\omega \in \mathbb{R}}{\operatorname{arg\,min}} \underbrace{\left(\frac{\sigma_{1}^{2}}{n_{1}} + \frac{\sigma_{2}^{2}}{n_{2}}\right)}_{a} \omega^{2} + \underbrace{\left(-\frac{2\sigma_{2}^{2}}{n_{2}}\right)}_{b} \omega + \underbrace{\frac{\sigma^{2}}{n_{2}}}_{c}$$

$$= -\frac{b}{2a} \qquad (zero \text{ of a quadratic})$$

$$= -\frac{-\frac{2\sigma_{2}^{2}}{n_{2}}}{2\left(\frac{\sigma_{1}^{2}}{n_{1}} + \frac{\sigma_{2}^{2}}{n_{2}}\right)}$$

$$= \frac{\sigma_{2}^{2}}{n_{2}\left(\frac{\sigma_{1}^{2}}{n_{1}} + \frac{\sigma_{2}^{2}}{n_{2}}\right)}$$

$$= \frac{\sigma_{2}^{2}}{\frac{n_{2}\sigma_{1}^{2}}{n_{1}} + \sigma_{2}^{2}}$$

$$= \frac{n_{1}\sigma_{2}^{2}}{n_{2}\sigma_{1}^{2} + n_{1}\sigma_{2}^{2}}$$

And so we are done.