## ESE 402/542: Statistics for Data Science Instructor: Hamed Hassani Fall 2021

## **Midterm Examination**

NAME |

## **Additional Information:**

- The pdf of a Gaussian,  $\mathcal{N}(\mu, \sigma^2)$ , is  $f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ .
- $\int_{-\infty}^{\infty} \frac{x^2}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx = \mu^2 + \sigma^2, \int_{-\infty}^{\infty} \frac{x}{\sqrt{2\pi\sigma}}, e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx = \mu,$  $\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma}}, e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx = 1$
- Linearity of expectation is your friend.
- $\operatorname{Var}(X) = \mathbb{E}\left[X^2\right] \mathbb{E}\left[X\right]^2$ , i.e.  $\sigma^2 = \mathbb{E}\left[X^2\right] \mu^2$ .
- If X continuous  $(p(x) \text{ is its pdf}), \mathbb{E}[g(X)] = \int g(x)p(x)dx$
- If X discrete  $(p(x) \text{ is its pmf}), \mathbb{E}[g(X)] = \sum_{x} g(x)p(x)$

	Grade (y/n)	Score	Max. Score
Problem 1			50
Problem 2			50
TOTAL			100

**Problem 1.** [50 pts] We have access to a data set  $X_1, X_2, \dots, X_n$  where  $X_i$ 's are generated i.i.d. according to a distribution with the following pdf:

$$f(x|a,p) = p \times \frac{1}{\sqrt{2\pi}} e^{-\frac{(x+a)^2}{2}} + (1-p) \times \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-a)^2}{2}}.$$

where the parameters p is known to be between 0 and 1.

In the following, for parts (a)-(f) we assume that a=1 is given, but the value of p is to be estimated from data.

(a) Draw the pdf f(x|a, p) as a function of x for the case p = 1/4.

(b) Find the variance of  $X_i$  in terms of p.

(c) Use the method of moments to estimate the parameter p from data. Let's denote this estimator by  $\hat{p}$ .

(d) Is  $\hat{p}$  an unbiased estimator?

(e) Let  $\mu = \mathbb{E}[X_1]$  and also let  $\hat{\mu}$  be the empirical mean of the data (i.e.  $\hat{\mu} = (X_1 + \cdots + X_n)/n$ ). For any  $\beta > 0$ , find  $\beta'$  such that the following holds:

$$\Pr(\mu \in [\hat{\mu} - \beta, \hat{\mu} + \beta]) = \Pr(p \in [\hat{p} - \beta', \hat{p} + \beta']).$$

(f) Use part (e) to find the  $1-\alpha$  confidence interval for p using the estimate  $\hat{p}$ .

(g) Let us now assume that the value of a is also unknown (in addition to p). Use the method of moments to estimate both a and p from data. Assume  $a \ge 0$ . (Hint: treat this as solving a system of equations with two variables.)

**Problem 2.** [50 pts] We have access to a data set  $X_1, X_2, \dots, X_n$  where  $X_i$ 's are generated i.i.d. according to a distribution with the following pdf:

$$f(x|\sigma) = \frac{1}{2\sigma} e^{-\frac{|x|}{\sigma}}. (1)$$

We are given that  $\mathbb{E}[X_i] = 0$ ,  $\mathbb{E}[|X_i|] = \sigma$ , and  $\text{Var}(X_i) = 2\sigma^2$ .

We consider a hypothesis testing problem with  $H_0: \sigma = \sigma_0$  and  $H_a: \sigma = \sigma_1$ . For this setting, we consider the following test statistic:

$$T(X_1, X_2, \cdots, X_n) = \frac{1}{n} \log f(X_1, X_2, \cdots, X_n | \sigma_0) - \frac{1}{n} \log f(X_1, X_2, \cdots, X_n | \sigma_1),$$

where  $f(X_1, X_2 \cdots, X_n | \sigma_0)$  is the joint density of  $X_1, \cdots, X_n$  given  $\sigma = \sigma_0$  (and the other term is defined similarly). You may assume that  $\sigma_0 < \sigma_1$ .

(a) Explain why

$$f(X_1, X_2 \cdots, X_n | \sigma_0) = f(X_1 | \sigma_0) \times f(X_2 | \sigma_0) \times \cdots \times f(X_n | \sigma_0).$$

(b) Using part (a) and (1) expand and simplify the term  $\frac{1}{n} \log f(X_1, X_2 \cdots, X_n | \sigma_0)$  as much as you can.

(c) Derive an approximate formula for the distribution of  $T(X_1, \dots, X_n)$  in the case that  $H_0$  is the true hypothesis.

(d) Given a significance level  $\alpha$ , design the acceptance/rejection regions for the above hypothesis testing problem and test statistic T. (Remember:  $\sigma_0 < \sigma_1$ ).