408 Final Exam Solutions¹

1. QUESTION 1

True/False

(a) The negation of the statement

"There exists an integer j such that $j^2 - j < 3$ " is:

"For every integer j, we have $j^2 - j \ge 3$."

TRUE, by the rules of negation, "There exists" is negated to "For every," and the inequality < is negated to \geq .

(b) Let **P** be the uniform probability law on [0, 1]. Let $x_1, x_2, \ldots \in [0, 1]$ be a countable set of distinct points. Then

$$\mathbf{P}\left(\cup_{n=1}^{\infty}\{x_n\}\right) = 0.$$

TRUE. By the definition of \mathbf{P} , $\mathbf{P}(\{x_n\}) = 0$ for all $n \ge 1$. So, from Axiom (ii) for probability laws,

(c) Let X_1, \ldots, X_n be i.i.d random variables drawn from a family of probability density functions $\{f_{\theta} \colon \theta \in \mathbf{R}\}$ where $f_{\theta} \colon \mathbf{R} \to [0, \infty)$ for all $\theta \in \mathbf{R}$. Then there must exist some integer $k \ge 1, \exists$ some function $t \colon \mathbf{R}^n \to \mathbf{R}^k$ and there exists some statistic $Y = t(X_1, \ldots, X_n)$ such that Y is a sufficient statistic for θ .

TRUE. The statistic (X_1, \ldots, X_n) is always sufficient for θ .

(d) Suppose t(X) defined in the definition of *p*-value is a continuous random variable. Then the *p*-value satisfies

$$\mathbf{P}_{\theta}(p(X) \le c) \le c, \qquad \forall c \in (0, 1).$$

TRUE by Remark 5.19 in the notes.

(e) Let X_1, \ldots, X_n be positive random variables. Then Pearson's chi-squared statistic

$$S := \sum_{j=1}^{n} \frac{\left(X_j - \mathbf{E}X_j\right)^2}{\mathbf{E}X_j}$$

has a chi-squared distribution.

FALSE. Just let n = 1 and let X_1 be any non-Gaussian random variable.

2. Question 2

Let X_1, \ldots, X_n be a random sample of size *n* from a Poisson distribution with unknown parameter $\lambda > 0$. (So, $\mathbf{P}(X_1 = k) = e^{-\lambda} \lambda^k / k!$ for all integers $k \ge 0$.)

- Find an MLE for λ . As usual, justify your answer.
- Is the MLE you found unique? That is, could there be more than one MLE for this problem? Justify your answer.

Solution. Denote $k = (k_1, \ldots, k_n) \in \mathbb{Z}_{>0}^n$. Then

$$f_{\lambda}(k) = \prod_{i=1}^{n} e^{-\lambda} \lambda^{k_i} / k_i! = e^{-\lambda n} \lambda^{\sum_{i=1}^{n} k_i} / \prod_{i=1}^{n} k_i!.$$

¹December 15, 2021, © 2021 Steven Heilman, All Rights Reserved.

$$\log f_{\lambda}(k) = -\lambda n + \log \lambda \cdot \sum_{i=1}^{n} k_i - \sum_{i=1}^{n} \log(k_i!).$$

Differentiating in λ , we get

$$\frac{d}{d\lambda}\log f_{\lambda}(k) = -n + \frac{1}{\lambda}\sum_{i=1}^{n}k_{i}$$

We get a single critical point for $\log f_{\lambda}$, when

$$\lambda = \frac{1}{n} \sum_{i=1}^{n} k_i.$$

Moreover, $\log f_{\lambda}$ is (possibly increasing) then decreasing, as λ increases. We conclude that the single critical point is then in fact a global maximum. So, the MLE is

$$\frac{1}{n}\sum_{i=1}^{n}X_{i}.$$

3. QUESTION 3

Let X_1, \ldots, X_n be a random sample of size n from the uniform distribution on $[\theta - 1/2, \theta + 1/2]$ where $\theta \in \mathbf{R}$ is unknown.

Show that

 $(X_{(1)}, X_{(n)})$

is a sufficient statistic for θ .

(Here $X_{(1)} = \min_{1 \le i \le n} X_i$ and $X_{(n)} = \max_{1 \le i \le n} X_i$.)

Solution. Let $x = (x_1, \ldots, x_n) \in \mathbf{R}^n$. Using independence, we write the joint distribution of X_1, \ldots, X_n as

$$f(x) = \prod_{i=1}^{n} 1_{x_i \in [\theta - 1/2, \theta + 1/2]}.$$

The quantity $\prod_{i=1}^{n} 1_{x_i \in [\theta-1/2, \theta+1/2]}$ is zero, except when $x_{(1)} \ge \theta - 1/2$ and $x_{(n)} \le \theta + 1/2$. That is,

$$f(x) = 1_{x_{(1)} \ge \theta - 1/2} 1_{x_{(n)} \le \theta + 1/2}$$

So, defining $g_{\theta}(a,b) := 1_{a \ge \theta - 1/2} 1_{b \le \theta + 1/2}$, h(x) := 1, $t(x) := (x_{(1)}, x_{(n)})$, we have written $f(x) = g_{\theta}(t(x)) \cdot h(x), \quad \forall x \in \mathbf{R}^n.$

So, by the factorization theorem, $t(X) = (X_{(1)}, X_{(n)})$ is sufficient for θ .

4. QUESTION 4

Suppose X is a binomial distributed random variable with parameters 2 and $\theta \in \{1/2, 3/4\}$. (So, X has the distribution of the number of heads that appears from flipping a coin twice, where θ is the probability that a heads appears in a single coin flip.)

We want to test the hypothesis H_0 that $\theta = 1/2$ versus the hypothesis H_1 that $\theta = 3/4$.

- Explicitly describe the rejection region C of the UMP (uniformly most powerful) test among all hypothesis tests with significance level at most 1/4.
- Suppose we observe that X = 2. Report a *p*-value for this observation, for the UMP test you found.

Solution. The Neyman-Pearson Lemma says that the UMP test for the class of tests with an upper bound on the significance level must be a likelihood ratio test. The likelihood ratio test has rejection region

$$C = \{ x \in \mathbf{R} \colon f_{\theta_1}(x) \ge k f_{\theta_0}(x) \} = \{ x \in \mathbf{R} \colon f_{3/4}(x) \ge k f_{1/2}(x) \}.$$

There are only three values that X can take, so we examine the likelihood ratios explicitly:

$$\frac{f_{3/4}(0)}{f_{1/2}(0)} = \frac{(1-3/4)^2}{(1-1/2)^2} = \frac{1}{4}, \qquad \frac{f_{3/4}(1)}{f_{1/2}(1)} = \frac{2(1-3/4)(3/4)}{2(1-1/2)(1/2)} = \frac{3}{4}, \qquad \frac{f_{3/4}(2)}{f_{1/2}(2)} = \frac{(3/4)^2}{(1/2)^2} = \frac{9}{4}.$$

We then get different likelihood ratio tests according to the choice of k > 0.

- If $3/4 < k \le 9/4$, then H_0 is rejected if and only if X = 2, and this test is the unique UMP for tests with significance level at most $\mathbf{P}_{1/2}(X = 2) = 1/4$.
- If $1/4 < k \leq 3/4$, then H_0 is rejected if and only if X = 1 or 2, and this test is the unique UMP for tests with significance level at most $\mathbf{P}_{1/2}(X \in \{1, 2\}) = 3/4$.

In the case k = 2, we get (using the table of values of $f_{3/4}(X)/f_{1/2}(X)$),

$$p(2) = \mathbf{P}_{1/2} \left(\frac{f_{3/4}(X)}{f_{1/2}(X)} \ge \frac{f_{3/4}(2)}{f_{1/2}(2)} \right) = \mathbf{P}_{1/2} \left(\frac{f_{3/4}(X)}{f_{1/2}(X)} \ge \frac{9}{4} \right) = \mathbf{P}_{1/2} (X = 2) = (1/2)^2 = 1/4.$$

5. Question 5

Let X_1, \ldots, X_n be a random sample of size *n* from a Poisson distribution with unknown parameter $\lambda > 0$. (So, $\mathbf{P}(X_1 = k) = e^{-\lambda} \lambda^k / k!$ for all integers $k \ge 0$.)

Let Y be the estimator $Y = 1_{\{X_1=0\}}$.

(That is, Y = 1 when $X_1 = 0$, and otherwise Y = 0.)

- Explicitly compute $W_n := \mathbf{E}_{\lambda}(Y \mid \sum_{i=1}^n X_i).$
- State an inequality comparing $\operatorname{Var}_{\lambda}(Y)$ and $\operatorname{Var}_{\lambda}(W_n)$.
- What happens to W_n as $n \to \infty$? Does it converge to something? Justify your answer.

(Hint: a sum of n independent Poissons with parameter λ is a Poisson with parameter $n\lambda$.)

Solution. A sum of n independent Poisson random variables, each with parameter $\lambda > 0$, is a Poisson random variable with parameter $n\lambda$. That is,

$$\mathbf{P}(\sum_{i=1}^{n} X_i = x) = e^{-\lambda n} (\lambda n)^x / x!, \qquad \forall x \in \mathbf{Z}_{\geq 0}.$$

So, the conditional PMF satisfies

$$\mathbf{P}\left(1_{\{X_{1}=0\}}=1 \mid \sum_{i=1}^{n} X_{i}=x\right) = \frac{\mathbf{P}(1_{\{X_{1}=0\}}=1, \sum_{i=1}^{n} X_{i}=x)}{\mathbf{P}(\sum_{i=1}^{n} X_{i}=x)}$$
$$= \frac{\mathbf{P}(X_{1}=0, \sum_{i=2}^{n} X_{i}=x)}{e^{-\lambda n} (\lambda n)^{x} / x!} = \frac{e^{-\lambda} e^{-\lambda (n-1)} (\lambda (n-1))^{x} / x!}{e^{-\lambda n} (\lambda n)^{x} / x!} = \left(1-\frac{1}{n}\right)^{x}.$$

Then, since $1_{\{X_1=0\}}$ only takes values 0 and 1, the conditional expectation is

$$\mathbf{E}\Big(\mathbf{1}_{\{X_1=0\}} \mid \sum_{i=1}^n X_i = x\Big) = \mathbf{P}\Big(\mathbf{1}_{\{X_1=0\}} = 1 \mid \sum_{i=1}^n X_i = x\Big) = \Big(1 - \frac{1}{n}\Big)^x.$$

That is,

$$\mathbf{E}\Big(\mathbf{1}_{\{X_1=0\}} \mid \sum_{i=1}^n X_i\Big) = \Big(1 - \frac{1}{n}\Big)^{\sum_{i=1}^n X_i}.$$

That is,

$$W_n = \left(1 - \frac{1}{n}\right)^{n\frac{1}{n}\sum_{i=1}^n X_i}$$

As $n \to \infty$, $\left(1 - \frac{1}{n}\right)^n$ converges to e^{-1} , and $\frac{1}{n} \sum_{i=1}^n X_i$ converges in probability to the constant $\mathbf{E}X_1 = \lambda$, by the weak law of large numbers. So, as $n \to \infty$, W_n converges in probability to the constant $e^{-\lambda}$. That is, W_1, W_2, \ldots is consistent.

Finally, $\operatorname{Var}_{\lambda}(Y) \geq \operatorname{Var}_{\lambda}(W_n)$ by Rao-Blackwell, since Y is unbiased, as $\mathbf{E}Y = \mathbf{P}(X_1 = 0) = \lambda$.

6. QUESTION 6

Suppose X_1, X_2 is a random sample from a Gaussian random variable X with unknown mean $\mu_X \in \mathbf{R}$ and unknown variance $\sigma^2 > 0$. Suppose Y_1, Y_2 is a random sample from a Gaussian random variable Y with unknown mean $\mu_Y \in \mathbf{R}$ and unknown variance $\sigma^2 > 0$. Assume that X_1, X_2 is independent of Y_1, Y_2 , i.e. assume that X, Y are independent.

Suppose you find that $X_1 = 1$, $X_2 = 3$, $Y_1 = 2$ and $Y_2 = 4$.

Explicitly construct a confidence interval of the form [a, b] for $\mu_X - \mu_Y$, so that

$$\mathbf{P}(a \le \mu_X - \mu_Y \le b) = \frac{1}{2\sqrt{2}} \int_{-3}^{3} \left(1 + \frac{s^2}{2}\right)^{-3/2} ds$$

Hint: $\Gamma(1/2) = \sqrt{\pi}$, $\Gamma(1) = 1$, $\Gamma(3/2) = \sqrt{\pi}/2$, $\Gamma(2) = 1$, $\Gamma(5/2) = 3\sqrt{\pi}/4$, $\Gamma(3) = 2$. Hint: Recall that Student's *t*-distribution with *p* degrees of freedom has density

$$f_T(s) := \frac{\Gamma(\frac{p+1}{2})}{\sqrt{p}\sqrt{\pi}\Gamma(p/2)} \left(1 + \frac{s^2}{p}\right)^{-(p+1)/2}, \qquad \forall s \in \mathbf{R}.$$

Solution. We have n = m = 2,

$$\overline{X} := \frac{1}{n} \sum_{i=1}^{n} X_i = 2, \qquad \overline{Y} := \frac{1}{m} \sum_{i=1}^{m} Y_i = 3,$$

$$S_X^2 := \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \overline{X})^2 = [(1-2)^2 + (3-2)^2] = 2,$$

$$S_Y^2 := \frac{1}{m-1} \sum_{i=1}^{m} (Y_i - \overline{Y})^2 = [(2-3)^2 + (4-3)^2] = 2,$$

$$S^2 := \frac{(n-1)S_X^2 + (m-1)S_Y^2}{n+m-2} = \frac{2+2}{2} = 2.$$

Then

$$\frac{\overline{X} - \overline{Y} - \mu_X + \mu_Y}{S\sqrt{\frac{1}{n} + \frac{1}{m}}}$$

has Student's t-distribution with p = n + m - 2 = 2 degrees of freedom. Therefore,

$$\mathbf{P}\left(\overline{X} - \overline{Y} - tS\sqrt{\frac{1}{n} + \frac{1}{m}} < \mu_X - \mu_Y < \overline{X} - \overline{Y} + tS\sqrt{\frac{1}{n} + \frac{1}{m}}\right) \\ = \frac{\Gamma(\frac{p+1}{2})}{\sqrt{p}\sqrt{\pi}\Gamma(p/2)} \int_{-t}^t \left(1 + \frac{s^2}{p}\right)^{-(p+1)/2} ds,$$

Choosing t = 3, we get

$$\mathbf{P}\Big(-1 - 3\sqrt{2} < \mu_X - \mu_Y < -1 + 3\sqrt{2}\Big) = \frac{\Gamma(\frac{3}{2})}{\sqrt{2}\sqrt{\pi}\Gamma(1)} \int_{-3}^3 \Big(1 + \frac{s^2}{p}\Big)^{-(2+1)/2} ds$$
$$= \frac{\sqrt{\pi}/2}{\sqrt{2}\sqrt{\pi}} \int_{-3}^3 \Big(1 + \frac{s^2}{p}\Big)^{-3/2} ds$$
$$= \frac{1}{2\sqrt{2}} \int_{-3}^3 \Big(1 + \frac{s^2}{2}\Big)^{-3/2} ds$$

That is, we choose $[a, b] = [-1 - 3\sqrt{2}, -1 + 3\sqrt{2}].$

7. QUESTION 7

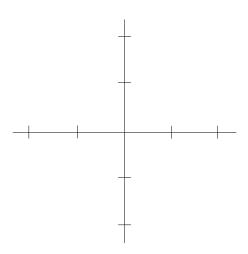
Suppose you are given the following three data points in (x, y) coordinates:

 $(x_1, y_1) = (-1, 0),$ $(x_2, y_2) = (0, 0),$ $(x_3, y_3) = (0, 1).$

• Find the parabola of the form $y = mx^2 + b$ that best fits these three points. That is, find $m, b \in \mathbf{R}$ that minimizes the quantity.

$$h(m,b) := \frac{1}{2} \sum_{i=1}^{3} \left(y_i - (mx_i^2 + b) \right)^2.$$

- Make sure to prove that the minimal m, b that you find actually minimizes h(m, b).
- Finally, plot the points (x_1, y_1) , (x_2, y_2) , (x_3, y_3) along with the parabola $y = mx^2 + b$ that best fits the points.



Solution. We have $h(m, b) = (1/2)[(m+b)^2 + b^2 + (1-b)^2]$. Then $h_m(m, b) = m + b$ and $h_b(m, b) = m + b + b + b - 1 = 3b + m - 1$. Solving for $h_m = h_b = 0$, we get m = -b and 0 = 3b + m - 1 = 2b - 1, so that b = -m = 1/2. So, the parameters b = 1/2, m = -1/2 are the only critical point of h. Since h is strictly convex, its critical point must be a global minimum.

The "best-fit" parabola is

$$y = -(1/2)x^2 + 1/2.$$

Note that y(-1) = 0, y(0) = 1/2. So, the parabola intersects (-1, 0), it lies above (0, 0) and it lies below (0, 1).

8. QUESTION 8

Consider the following table with turkey data. We have 4 (vegetarian) turkeys, with various temperatures x (Fahrenheit), and the status y of each turkey is cooked (corresponding to a value of y = 1) or not cooked (corresponding to a value of y = 0). Using logistic regression, we would like to find $a, b \in \mathbf{R}$, i.e. find a function

$$h(ax+b)$$

that best fits your data, where $h(t) = 1/(1 + e^{-t})$ for all $t \in \mathbf{R}$.

That is, given a temperature x, h(ax + b) should be close to 1 when the turkey is cooked, and h(ax + b) should be close to 0 when the turkey is not cooked.

Turkey	Temperature	Done? Yes or no.
1	150	no
2	155	yes
3	160	no
4	165	yes

Describe in detail how you would find the $a, b \in \mathbf{R}$ that best fit the data using a computer to do logistic regression.

Solution. Let X_1, \ldots, X_4 be i.i.d. real-valued random variables representing the temperatures of the turkeys. Let $g: \mathbb{R} \to \{0, 1\}$ be an unknown function, and let $Y_i := g(X_i)$ for all $1 \le i \le n$, so that $g(X_i) = 0$ if turkey *i* is not cooked, and $g(X_i) = 1$ if turkey *i* is cooked, for all $1 \le i \le 4$.

By our assumptions, Y_1, \ldots, Y_4 are i.i.d. Bernoulli random variables with some unknown probability $0 \le p \le 1$ such that $p = \mathbf{P}(Y_1 = 1)$. Since the logistic function smoothly transitions from value 0 to value 1, we make the heuristic assumption that there are some unknown parameters $a, b \in \mathbf{R}$ such that

$$p \approx h(ax+b) \approx g(x).$$

The likelihood function is then

$$\ell(a,b) := \prod_{i=1}^{4} p^{y_i} (1-p)^{1-y_i} = \prod_{i=1}^{4} [h(ax_i+b)]^{y_i} [1-h(ax_i+b)]^{1-y_i},$$

$$\forall x_1, \dots, x_4 \in \mathbf{R}, \quad \forall y_1, \dots, y_4 \in \{0,1\}.$$

From a homework exercise, the log-likelihood function has at most one global maximum. So, if the MLE exists, it is unique. To find the MLE, we start at some values of a, b (such as a = b = 0), and we perform the following iterative procedure many times

- Randomly perturb a, b. (For example, define $\tilde{a} := a + X/100$, $\tilde{b} := b + Y/100$, where X, Y are independent standard Gaussians.)
- If $\ell(\tilde{a}, \tilde{b}) > \ell(a, b)$, then replace (a, b) with (\tilde{a}, \tilde{b}) , and perform the previous step again. Otherwise, keep the same a, b as before, the perform the previous step again.

Since the log likelihood has at most one global maximum, this stochastic gradient ascent procedure will eventually reach a value of ℓ that is close to its global maximum (if that maximum exists).