

Solution exercise set 5

Exercise 1:

a)

$$L(\lambda) = \prod_{i=1}^n (\lambda e^{-\lambda t_i}) = \lambda^n e^{-\lambda \sum_{i=1}^n t_i}$$

$$l(\lambda) = \ln L(\lambda; t_1, \dots, t_n) = \ln(\lambda)^n + \ln(e^{-\lambda \sum_{i=1}^n t_i}) = n \ln(\lambda) - \lambda \sum_{i=1}^n t_i$$

$$\frac{dl(\lambda)}{d\lambda} = \frac{n}{\lambda} - \sum_{i=1}^n t_i = 0 \quad \Rightarrow \quad \lambda = \frac{n}{\sum_{i=1}^n t_i}$$

I.e. the MLE is given as: $\hat{\lambda} = \frac{n}{\sum_{i=1}^n T_i}$. Estimate: $\hat{\lambda} = \frac{12}{108.5} = \underline{\underline{0.11}}$.

b) We start by considering the distribution of $Y = 2\lambda T_i$. From the result on transformations (see collection of formulas) we have for the exponential distribution that $2X/\beta$ has a χ^2_2 -distribution if X is exponentially distributed with parameter β . In the current setting we have that T_i is exponentially distributed with expectation $1/\lambda$, i.e. $\beta = 1/\lambda$, and it thus follow that $Y = 2T_i/\beta = 2\lambda T_i$ is having a χ^2_2 -distribution.

Further we have from results of linear combinations (collection of formulas) that since a sum of independent χ^2 -distributed variables is χ^2 -distributed with parameter ("degrees of freedom") equal to the sum of the parameters in the distribution of each variable, we will have that $Z = 2\lambda \sum_{i=1}^n T_i = \sum_{i=1}^n 2\lambda T_i$ is having a χ^2_{2n} -distribution (by being a sum of n indep. χ^2_2 -distributed variables).

c)

$$E(\hat{\lambda}) = nE\left(\frac{1}{\sum_{i=1}^n T_i}\right) = nE\left(\frac{2\lambda}{2\lambda \sum_{i=1}^n T_i}\right) = 2n\lambda E\left(\frac{1}{Z}\right) = 2n\lambda \cdot \left(\frac{1}{2(n-1)}\right) = \lambda \frac{n}{n-1}$$

I.e. $\hat{\lambda}$ is biased.

We try the slightly modified estimator $\lambda^* = \frac{n-1}{n} \hat{\lambda} = \frac{n-1}{\sum_{i=1}^n T_i}$.

$$E(\lambda^*) = \frac{n-1}{n} E(\hat{\lambda}) = \frac{n-1}{n} \frac{n}{n-1} \lambda = \lambda$$

I.e. $\lambda^* = \frac{n-1}{\sum_{i=1}^n T_i}$ is an unbiased estimator for λ .

Using this estimator gives the estimate: $\lambda^* = \frac{11}{108.5} = 0.10$.

Generally we know that maximum likelihood estimators can be biased, but asymptotically (as $n \rightarrow \infty$) they are unbiased. We have found the MLE $\hat{\lambda}$ to be biased, but we see that

$$E(\hat{\lambda}) = \lambda \frac{n}{n-1} \rightarrow \lambda \text{ when } n \rightarrow \infty \text{ (since } \frac{n}{n-1} \rightarrow 1)$$

i.e. asymptotically the estimator is unbiased as it should be.

d)

Since

$$Z = 2\lambda \sum_{i=1}^n T_i = 2\lambda n \frac{\sum_{i=1}^n T_i}{n} = 2n \frac{\lambda}{\hat{\lambda}} \sim \chi_{2n}^2$$

we get

$$\begin{aligned} P(\chi_{1-\frac{\alpha}{2}, 2n}^2 < Z < \chi_{\frac{\alpha}{2}, 2n}^2) &= 1 - \alpha \\ P(\chi_{1-\frac{\alpha}{2}, 2n}^2 < 2n \frac{\lambda}{\hat{\lambda}} < \chi_{\frac{\alpha}{2}, 2n}^2) &= 1 - \alpha \\ P\left(\frac{\hat{\lambda}}{2n} \chi_{1-\frac{\alpha}{2}, 2n}^2 < \lambda < \frac{\hat{\lambda}}{2n} \chi_{\frac{\alpha}{2}, 2n}^2\right) &= 1 - \alpha \end{aligned}$$

I.e. a $(1 - \alpha)100\%$ confidence interval for λ becomes:

$$\left[\frac{\hat{\lambda}}{2n} \chi_{1-\frac{\alpha}{2}, 2n}^2, \frac{\hat{\lambda}}{2n} \chi_{\frac{\alpha}{2}, 2n}^2 \right]$$

By inserting $\alpha = 0.05$ which gives $\chi_{1-\frac{\alpha}{2}, 2n}^2 = \chi_{0.975, 24}^2 = 12.401$, $\chi_{\frac{\alpha}{2}, 2n}^2 = \chi_{0.025, 24}^2 = 39.364$ and $\hat{\lambda} = \frac{\sum_{i=1}^n T_i}{n} = \frac{12}{108.5} = 0.111$ we get the 95% confidence interval:

$$\left[\frac{0.111}{2 \cdot 12} \cdot 12.401, \frac{0.111}{2 \cdot 12} \cdot 39.364 \right] = \underline{\underline{[0.06, 0.18]}}$$

Exercise 2:

a) If we first look at $Y_i = 2X_i/\beta$ we have from the overview of results on transformations in the collection of formulas that Y has a χ_2^2 -distribution.

Further, among the result on linear combinations we have one result which says that a sum of independent χ^2 -distributed variables is χ^2 -distributed with parameter (“degrees of freedom”) equal to the sum of the parameters in the distribution of each single variable. I.e. in our case will $Z = \sum_{i=1}^n Y_i = \sum_{i=1}^n 2X_i/\beta$ be χ^2 -distributed with parameter $\sum_{i=1}^n 2 = 2n$, i.e. Z is χ_{2n}^2 -distributed.

b) We have from the results on transformations that if X is gamma(α, β)-distributed then $Y = 2X/\beta$ is $\chi_{2\alpha}^2$ -distributed. Turned the other way around this means that if Y has a $\chi_{2\alpha}^2$ -distribution then $X = Y\beta/2$ has a gamma(α, β)-distribution.

Now, in our specific case we showed in a) that $Z = \sum_{i=1}^n 2X_i/\beta = 2(\sum_{i=1}^n X_i)/\beta = 2V/\beta$ has a χ_{2n}^2 -distribution. It then follows that $V = Z\beta/2$ has a gamma-distribution with $\alpha = n$ and $\beta = \beta$.

We have here shown the result that a sum of independent identically exponentially distributed variables is gamma distributed with $\alpha = n$ and $\beta = \beta$.

Exercise 3:

a) The exact distribution of X will be a hypergeometric distributions with parameters N, k and n where N is the number of voters, k is the number of voters voting on Ap and $n = 1000$ is the number of voters which is asked in the opinion poll. Since $n \ll N$ we have that X will be approximately binomially distributed with parameters $n = 1000$ and $p = k/N$.

b) Since $np(1-p) > 5$ we can use the approximation to the normal distribution:

$$\begin{aligned} P(X > 300) &= 1 - P(X \leq 300) = 1 - P(Z \leq \frac{300 + 0.5 - 1000 \cdot 0.275}{\sqrt{1000 \cdot 0.275 \cdot (1 - 0.275)}}) \\ &= 1 - P(Z \leq 1.81) = 1 - 0.9649 = \underline{\underline{0.0351}} \end{aligned}$$

I.e. there is approximately a probability of 3.5% that the opinion poll will indicate that more than 30% would vote for Ap when the reality is that only 27.5% would vote for Ap.

c) In the binomial distribution we have $f(x; p) = \binom{n}{x} p^x (1-p)^{n-x}$, and since we have only made on binomial experiment (only one X , one poll) we get $L(p; x) = f(x; p)$, i.e.

$$\begin{aligned} L(p; x) &= \binom{n}{x} p^x (1-p)^{n-x} \\ l(p; x) &= \ln L(p; x) = \ln \binom{n}{x} + x \ln p + (n-x) \ln(1-p) \\ \frac{\partial l(p; x)}{\partial p} &= \frac{x}{p} - \frac{n-x}{1-p} = 0 \\ &\Rightarrow (1-p)x - p(n-x) = 0 \\ &\quad x - px - pn + px = 0 \quad \Rightarrow \quad \underline{\underline{\hat{p} = \frac{X}{n}}} \end{aligned}$$

Check that we have found a maximum:

$$\frac{\partial^2 l(p; x_1, \dots, x_n)}{\partial p^2} = -\frac{1}{p^2}x - \frac{1}{(1-p)^2}(n-x) < 0 \quad \text{i.e. maximum!}$$

$$\begin{aligned} E(\hat{p}) &= E\left(\frac{X}{n}\right) = \frac{1}{n}E(X) = \frac{1}{n}np = \underline{\underline{p}} \\ \text{Var}(\hat{p}) &= \frac{1}{n^2}\text{Var}(X) = \frac{1}{n^2}np(1-p) = \underline{\underline{\frac{p(1-p)}{n}}} \end{aligned}$$

d) $X \sim \text{bin}(n, p)$. Confidence interval for p :

$$\hat{p} = \frac{X}{n}$$

$$\frac{\hat{p} - E(\hat{p})}{\sqrt{\text{Var}(\hat{p})}} = \frac{\hat{p} - p}{\sqrt{\frac{p(1-p)}{n}}} \stackrel{CLT}{\approx} N(0, 1)$$

To simplify the calculations of the confidence interval we further use the approximation that when n is large $p(1-p) \approx \hat{p}(1-\hat{p})$, i.e. we use as starting point:

$$Z = \frac{\hat{p} - p}{\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}} \approx N(0, 1)$$

$$P(-z_{\alpha/2} \leq Z \leq z_{\alpha/2}) \approx 1 - \alpha$$

$$P(-z_{\alpha/2} \leq \frac{\hat{p} - p}{\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}} \leq z_{\alpha/2}) \approx 1 - \alpha$$

⋮

$$P(\hat{p} - z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \leq p \leq \hat{p} + z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}) \approx 1 - \alpha$$

Observed: $n = 1000$ and $x = 297$ gives $\hat{p} = \frac{297}{1000} = 0.297$.

$\alpha = 0.05 \Rightarrow z_{\alpha/2} = z_{0.025} = 1.96$.

Inserted this give the approximate 95% conf. int. for p :

$$\left[0.297 - 1.96 \sqrt{\frac{0.297 \cdot 0.703}{1000}}, 0.297 + 1.96 \sqrt{\frac{0.297 \cdot 0.703}{1000}} \right] = \underline{\underline{[0.269, 0.325]}}$$