Stat 8003, Homework 4

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Question 4.1. Suppose X is a discrete random variables with $P(X = 1) = \theta$ and $P(X = 2) = 1 - \theta$. Three independent observations of X are made: $x_1 = 1,\ x_2 = 2,\ x_3 = 2$.

(a) Find the method of moments estimate of θ;

(b) What is the likelihood function?

(c) What is the MLE of θ?:

Answer: X is Bernoulli with parameter θ:

$$X = \begin{cases} 1 & \text{with probability } \theta \\ 2 & \text{with probability } 1 - \theta \end{cases}$$

We write its `pdf` compactly as:

$$f(x \mid \theta) = \theta^{2-x}(1-\theta)^{x-1}$$

(This function evaluates to θ when $X = 1$ and to $1-\theta$ when $X = 2$. The likelihood function is the product of `pdf`s viewed as a function of θ for the observed data: $L(\theta; \tilde{x}) = \prod_i f(x_i \mid \theta)$. Here the data consist of three independent observations: $x_1 = 1, x_2 = 2, x_3 = 2$.)

(a) The method of moments (MOM) estimate of θ:

$$m_1 = E(X) = (1)(\theta) + (2)(1-\theta) = \theta + 2 - 2\theta = 2 - \theta$$

So,

$$\hat{\theta} = 2 - m_1$$

From our data,

$$m_1 = \bar{x} = \frac{1+2+2}{3} = \frac{5}{3}$$

so our method of moment estimate for $\hat{\theta}$ is

$$\hat{\theta} = 2 - \frac{5}{3} = \frac{1}{3}$$

(b) The likelihood function for this data is:

$$\begin{aligned} L(\theta; x) &= \theta^{2-1}(1-\theta)^{1-1}\theta^{2-2}(1-\theta)^{x-2}\theta^{2-2}(1-\theta)^{x-2} \\ &= \theta(1-\theta)^2 \end{aligned}$$

(c) To get the maximum likelihood estimate (MLE) for θ, we can differentiate the likelihood function with respect to θ, set it to zero, and solve for θ. Alternatively, we can take the $\log$ of the likelihood function and set that to zero to solve for θ:

$$\frac{d}{d\theta}\log(\theta(1-\theta)^2) = \frac{d}{d\theta}\left(\log\theta + 2\log(1-\theta)\right) = 0$$

Or

$$\frac{1}{\theta} = \frac{2}{1-\theta}$$

$$1-\theta = 2\theta$$

From where we get:

$$\boxed{\hat{\theta} = \frac{1}{3}}$$

We now check whether this extremum is indeed a *maximum*. We take the second derivative of $L(\theta; x)$, evaluate it at $\frac{1}{3}$ and see if it's negative. Indeed:

$$\begin{aligned} \frac{d^2}{d\theta^2}L(\theta; x) &= \frac{d}{d\theta}\left(\frac{1}{\theta} + \frac{2}{1-\theta}\right) \\ &= -\frac{1}{\theta^2} + \frac{2}{(1-\theta)^2} \\ &= -\frac{1}{(\frac{1}{3})^2} + \frac{2}{(1-(\frac{1}{3}))^2} \\ &= -9 + \frac{9}{2} \\ &< 0 \end{aligned}$$

So we indeed have a *maximum* at $\hat{\theta} = \frac{1}{3}$.

Question 4.2. Consider an `i.i.d.` sample of random variables with density function

$$f(x \mid \sigma) = \frac{1}{2\sigma} exp(-\frac{|x|}{\sigma})$$

(a) Find the MOM estimate of σ;

(b) Find the MLE estimate of σ;

Answer:

(a)

$$m_1 = E(X) = \int_{-\infty}^{+\infty} \frac{x}{2\sigma} exp(-\frac{|x|}{\sigma}) dx$$

This is an integral of an *odd* function, which should evaluate to zero:

$$\begin{aligned} &= \int_{-\infty}^{0} \frac{x}{2\sigma} exp(-\frac{|x|}{\sigma}) dx + \int_{0}^{+\infty} \frac{x}{2\sigma} exp(-\frac{|x|}{\sigma}) dx \\ &= -\int_{0}^{+\infty} \frac{x}{2\sigma} exp(-\frac{|x|}{\sigma}) dx + \int_{0}^{+\infty} \frac{x}{2\sigma} exp(-\frac{|x|}{\sigma}) dx \\ &= 0 \end{aligned}$$

This isn't any help to us. So let us consider m_2.

$$m_2 = E(X^2) = \int_{-\infty}^{+\infty} \frac{x^2}{2\sigma} exp(-\frac{|x|}{\sigma}) dx$$

$$= 2 \int_{0}^{+\infty} \frac{x^2}{2\sigma} exp(-\frac{x}{\sigma}) dx$$

$$= \frac{1}{\sigma} \int_{0}^{+\infty} x^2 exp(-\frac{x}{\sigma}) dx$$

Substitute $(y = \frac{x}{\sigma})$

$$= \sigma^2 \int_{0}^{+\infty} y^2 exp(-y) dy$$

We could recognize this as the Gamma function and write the result.

Or continue:

$$= \sigma^2 \Big(- y^2 e^{-y} \Big|_0^{+\infty} + 2 \int_0^{+\infty} yexp(-y)dy \Big)$$

$$= \sigma^2 \Big(0 + (-2ye^{-y}) \Big|_0^{+\infty} + 2 \int_0^{+\infty} exp(-y)dy \Big)$$

$$= \sigma^2 \Big(0 + 0 - 2exp(-y) \Big|_0^{+\infty} \Big) = 2\sigma^2$$

So $m_2 = 2\sigma^2$.

Therefore

$$\boxed{\hat{\sigma} = \sqrt{\frac{m_2}{2}}}$$

(b) The likelihood function is given by

$$L(\sigma; X) = \prod_{i=1}^{n} \frac{1}{2\sigma} exp(-\frac{|x_i|}{\sigma})$$

Taking the log of this gives

$$l(\sigma; X) = -n\, log(2\sigma) + \sum_{i=1}^{n} \frac{-|x_i|}{\sigma}$$

Then taking the derivative with respect to σ gives

$$\frac{dl}{d\sigma} = -\frac{n}{\sigma} + \frac{1}{\sigma^2} \sum_{i=1}^{n} |x_i|$$

Setting this equal to zero we get

$$\frac{n}{\sigma} = \frac{1}{\sigma^2} \sum_{i=1}^{n} |x_i|$$

i.e.,

$$\boxed{\hat{\sigma} = \frac{1}{n} \sum_{i=1}^{n} |x_i|}$$

Question 4.3. In the shuttle example, let X_i denote the number of damaged o-rings and t_i the temperature, where $i = 1, 2, \ldots, n$. Assume the model as

$$\begin{cases} X_i \mid p_i \sim \text{Binom}(2, p_i) \\ p_i = \mathrm{e}^{(\beta_0+\beta_1 t_i)}/(1+\mathrm{e}^{(\beta_0+\beta_1 t_i)}) \end{cases}$$

(a) Derive the log-likelihood function;

Since

$$\begin{aligned} f(x_i \mid p_i) &= \binom{2}{x_i} \left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right)^{x_i} \left(\frac{1}{(1+exp(\beta_0+\beta_1 t_i)}\right)^{2-x_i} \\ &= \binom{2}{x_i} \frac{exp(\beta_0+\beta_1 t_i)^{x_i}}{(1+exp(\beta_0+\beta_1 t_i))^2} \end{aligned}$$

The likelihood is

$$L(\beta_0, \beta_1; \tilde{x}, \tilde{t}) = \prod_{i=1}^{n} \binom{2}{x_i} \frac{exp(\beta_0+\beta_1 t_i)^{x_i}}{(1+exp(\beta_0+\beta_1 t_i))^2}$$

And thus the log likelihood is:

$$\begin{aligned} l(\beta_0, \beta_1; \tilde{x}, \tilde{t}) &= \log \prod_{i=1}^{n} \binom{2}{x_i} + \sum_{i=1}^{n} x_i(\beta_0+\beta_1 t_i) - 2\sum_{i=1}^{n} \log(1+exp(\beta_0+\beta_1 t_i)) \\ &= Some\ Constant + \beta_0 \sum_{i=1}^{n} x_i + \beta_1 \sum_{i=1}^{n} x_i t_i - 2\sum_{i=1}^{n} \log(1+exp(\beta_0+\beta_1 t_i)) \end{aligned}$$

(b) Set the equations for the maximum likelihood estimator of β_0, β_1 Since

$$\begin{cases} \frac{\partial l}{\partial \beta_0} = \sum_{i=1}^{n} x_i - 2\sum_{i=1}^{n} \frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} \\ \frac{\partial l}{\partial \beta_1} = \sum_{i=1}^{n} x_i t_i - 2\sum_{i=1}^{n} \frac{t_i exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} \end{cases}$$

We set these partial derivatives to 0 and solve them for β_0 and β_1:

$$\begin{cases} \sum_{i=1}^{n} x_i - 2\sum_{i=1}^{n} \frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} = 0 \\ \sum_{i=1}^{n} x_i t_i - 2\sum_{i=1}^{n} \frac{t_i exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} = 0 \end{cases}$$

(c) Derive the steps for the Newton-Raphson algorithm...

In previous equations, we denote the first one by $f_1(\beta_0, \beta_1)$, the second with $f_2(\beta_0, \beta_1)$ and then apply Newton-Raphson to following two-variable problem:

$$\begin{cases} f_1(\beta_0, \beta_1) = 0 \\ f_2(\beta_0, \beta_1) = 0 \end{cases}$$

The Jacobian matrix is:

$$J = \begin{pmatrix} \frac{\partial f_1(\beta_0,\beta_1)}{\partial \beta_0} & \frac{\partial f_1(\beta_0,\beta_1)}{\partial \beta_1} \\ \frac{\partial f_2(\beta_0,\beta_1)}{\partial \beta_0} & \frac{\partial f_2(\beta_0,\beta_1)}{\partial \beta_1} \end{pmatrix} = \begin{pmatrix} -2\frac{\partial}{\partial \beta_0}\left(\sum_{i=1}^n \frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right) & -2\frac{\partial}{\partial \beta_1}\left(\sum_{i=1}^n \frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right) \\ -2\frac{\partial}{\partial \beta_0}\left(\sum_{i=1}^n \frac{t_i exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right) & -2\frac{\partial}{\partial \beta_1}\left(\sum_{i=1}^n \frac{t_i exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right) \end{pmatrix}$$
$$=$$

$$= -2\sum_i \begin{pmatrix} \frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} - \left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right)^2 & t_i\left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} - \left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right)^2\right) \\ t_i\left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} - \left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right)^2\right) & t_i^2\left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)} - \left(\frac{exp(\beta_0+\beta_1 t_i)}{1+exp(\beta_0+\beta_1 t_i)}\right)^2\right) \end{pmatrix}$$

$$= -2\sum_i \begin{pmatrix} \frac{exp(\beta_0+\beta_1 t_i)}{(1+exp(\beta_0+\beta_1 t_i))^2} & t_i\frac{exp(\beta_0+\beta_1 t_i)}{(1+exp(\beta_0+\beta_1 t_i))^2} \\ t_i\frac{exp(\beta_0+\beta_1 t_i)}{(1+exp(\beta_0+\beta_1 t_i))^2} & t_i^2\frac{exp(\beta_0+\beta_1 t_i)}{(1+exp(\beta_0+\beta_1 t_i))^2} \end{pmatrix}$$

We could invert this Jacobian and use the following Newton-Raphson update rule to find β_0 and β_1:

$$\begin{pmatrix} \beta_0^{i+1} \\ \beta_1^{i+1} \end{pmatrix} = \begin{pmatrix} \beta_0^{i} \\ \beta_1^{i} \end{pmatrix} - J^{-1}\begin{pmatrix} f_1(\beta_0^i, \beta_1^i) \\ f_2(\beta_0^i, \beta_1^i) \end{pmatrix}$$

Before implementing this in `R`, and since these expressions look complicated, we try to simplify life for ourselves by making the following observations.

We can simplify the `R` implementation by noting that the model given in this problem is equivalent to the following:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 t_i$$

We will denote $\log\left(\frac{p_i}{1-p_i}\right) = y_i$ and write

$$y_i = \beta_0 + \beta_1 t_i$$

Once we have estimates for β_0 and β_1, we can then recover p_i from y_i.

(We note that we could use `R`'s linear regression model to get the least squares estimates of β_0 and β_1. However, we will estimate these using Newton-Raphson instead.)

First,

$$L(\beta_0, \beta_1; \tilde{t}) = \prod_{i=1}^{n}(\beta_0 + \beta_1 t_i)$$

and

$$l(\beta_0, \beta_1; \tilde{t}) = \sum_{i=1}^{n} \log(\beta_0 + \beta_1 t_i)$$

And we set the partial derivatives with respect to β_0 and β_1 to zero:

$$\begin{cases} \frac{\partial l}{\partial \beta_0} = \sum_{i=1}^{n} \frac{1}{\beta_0 + \beta_1 t_i} = 0 \\ \frac{\partial l}{\partial \beta_1} = \sum_{i=1}^{n} \frac{t_i}{\beta_0 + \beta_1 t_i} = 0 \end{cases}$$

We then apply Newton-Raphson to these guys.

(d) Use the Newton-Raphson algorithm to calculate the maximum likelihood estimator of β_0 and β_1

The estimates for the parameters are:

$$\begin{aligned} \beta_0 &= 9.0211846741774 \\ \beta_1 &= -0.154296115305373 \end{aligned}$$

(e) On January 28, 1986, the outside temperature was 31 degrees. Based on your estimated β_0 and β_1, what is the probability of an o-ring failure?

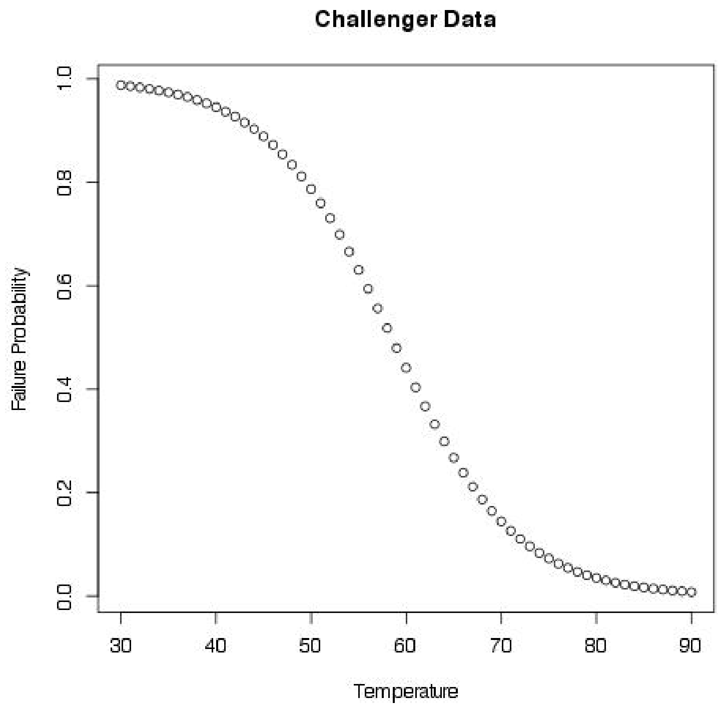
$$y = 9.0211846741774 - 0.154296115305373 * 31$$

$$p = \frac{e^y}{1 + e^y}$$

$$\boxed{p = 0.9857691}$$

(f) Based on your estimator, plot the probability p against the temperature by letting temperature go from 30 degrees to 90 degrees.

The plot of the probability of failure for our estimates of βs looks like this:


Challenger Data
Failure Probability
0.0
0.2
0.4
0.6
0.8
1.0
30
40
50
60
70
80
90
Temperature