MAST30027 Modern Applied Statistics Assignment 1

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Tutorial: Wed 1-2PM, Yidi Deng

Question 1

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(a)  > \mathbf{library}(\mathbf{faraway}) \\ > \mathbf{data}(\mathbf{orings}) \\ > \\ > \log \mathbf{L} = \mathbf{function}(\mathbf{betas}, \mathbf{orings}) \\ + \quad \mathbf{eta} = \mathbf{cbind}(\mathbf{1}, \mathbf{orings\$temp}) \% \% \mathbf{betas} \\ + \quad \mathbf{return} \ (\mathbf{sum}(\mathbf{orings\$damage} * \mathbf{log}(\mathbf{pnorm}(\mathbf{eta})) + (6 - \mathbf{orings\$damage}) \\ & \quad * \mathbf{log}(\mathbf{1} - \mathbf{pnorm}(\mathbf{eta})))) \\ + \\ > \\ > (\mathbf{betahat} = \mathbf{optim}(\mathbf{c}(\mathbf{10}, -.1), \mathbf{logL}, \mathbf{orings=orings}, \\ & \quad \mathbf{control=list}(\mathbf{fnscale} = -1))\$\mathbf{par}) \\ [1] \quad 5.5917242 \quad -0.1058008 \\ \\ \hat{\beta_0} = 5.5917 \\ \\ \hat{\beta_1} = -0.1058
```

$$\begin{split} &= \left\{ \sum_{i=1}^{N} \left[\frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \right\} \\ &= \left\{ \sum_{i=1}^{N} \left[\frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \right\} \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \sum_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\ &= \int_{i=1}^{N} \left[f_{i}(x_{i}) + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} + \frac{f_{i}(x_{i})}{f_{i}(x_{i})} \right] \\$$

= $\left[\left(\frac{\partial^2 L(R,R)}{\partial R} \right) \right]$ as both partial derivatives are continuous

$$\frac{\partial L(\beta_{0},\beta_{1})}{\partial \beta_{1}} = \sum_{i} \left[\gamma_{i} \frac{f(\gamma_{i})k_{i}}{F(\gamma_{i})} + (\gamma_{i} - 6) \frac{1}{1 - F(\gamma_{i})} - f(\gamma_{i}) \frac{1}{k_{i}^{2}} \right]$$

$$= \sum_{i} \left[\gamma_{i} \frac{f(\gamma_{i})k_{i}}{F(\gamma_{i})} + (\gamma_{i} - 6) \frac{f(\gamma_{i})k_{i}}{1 - F(\gamma_{i})} - f(\gamma_{i}) \frac{1}{k_{i}^{2}} + (\gamma_{i} - 6) \frac{(1 - F(\gamma_{i}))^{2} + (\gamma_{i})k_{i} + (\gamma_{i} - 6) \frac{1}{k_{i}^{2}} - f(\gamma_{i})k_{i}^{2} + (\gamma_{i} - 6) \frac{1}{k_{i}^{2}} - f(\gamma_{i})k_{i}^{2} + f(\gamma_{i})k_{i}^{2}$$

```
> iprobit = function(x) pnorm(x)
> phat = iprobit(betahat[1] + orings$temp*betahat[2])
> I11 = 3/pi * sum(dexp(qnorm(phat)^2) / (phat*(1-phat)))
> I12 = 3/pi * sum(orings$temp * dexp(qnorm(phat)^2) / (phat*(1-phat)))
> I22 = 3/pi * sum(orings$temp^2 * dexp(qnorm(phat)^2) / (phat*(1-phat)))
>
> Iinv = solve(matrix(c(I11, I12, I12, I22), 2, 2))
> betahat[1] + c(-1,1)*qnorm(0.975)*sqrt(Iinv[1,1])
[1] 2.239762 8.943686
> betahat[2] + c(-1,1)*qnorm(0.975)*sqrt(Iinv[2,2])
[1] -0.15784670 -0.05375481
```

95% Confidence Interval for $\hat{\beta}_0$: (2.2398, 8.9437)

95% Confidence Interval for $\hat{\beta}_1$: (-0.1578, -0.0538)

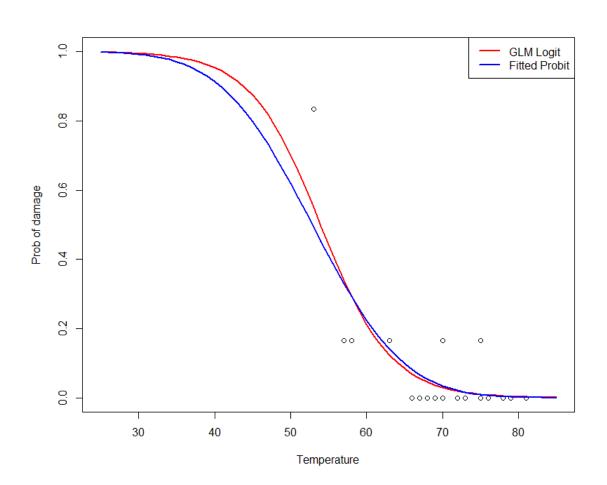
```
(c)
> logL.F = function(betas, orings) {
       eta = cbind(1, orings$temp) %*% betas
       return (sum(orings $damage * log(pnorm(eta)) + (6 - orings $damage)
+
                                                          * log(1 - pnorm(eta)))
+ }
> logL.R = function(beta0, orings) {
       eta = beta0
       return (sum(orings$damage * log(pnorm(eta)) + (6 - orings$damage)
                                                          * log(1 - pnorm(eta)))
+ }
>
> (betahat.F = optim(c(10, -.1), logL.F, orings=orings,
                                      control=list (fnscale=-1))$par)
[1]
     5.5917242\  \  -0.1058008
> (betahat.R = optim(c(5), logL.R, orings=orings, control=list(fnscale=-1))$par)
[1] -1.40625
> (LR = -2*(logL.R(betahat.R, orings) - logL.F(betahat.F, orings)))
[1] 20.76711
> pchisq(LR, df=1, lower=FALSE)
[1] 5.186617e-06
p-value < 0.05, so we reject H_0: \beta_1 = 0
(d)
> si2 = matrix(c(1, 31), 1, 2) \% \% Iinv \% \% matrix(c(1, 31), 2, 1)
> etahat = betahat [1] + betahat [2] *31
> \text{eta_l} = \text{etahat} - \text{qnorm}(0.975)*\text{sqrt}(\text{si}2)
> \text{eta_r} = \text{etahat} + \text{qnorm}(0.975)*\text{sqrt}(\text{si}2)
> \mathbf{c}(\text{eta\_l}, \text{eta\_r})
[1] 0.5557902 4.0680114
> iprobit (etahat)
[1] 0.9896084
> c(iprobit(eta_l), iprobit(eta_r))
[1] 0.7108229 0.9999763
\hat{p} = 0.9896
95% Confidence Interval for \hat{p}: (0.7108, 0.9999)
```

(e)

 $lty = \mathbf{c}(1),$

lwd = 2)

 $\mathbf{col} = \mathbf{c}("red", "blue"),$



Question 2

```
(a)
> library (faraway)
> missing = with(pima, missing <- glucose==0 | diastolic==0 | triceps==0
                                                | \text{bmi}==0)
> pima_subset = pima[!missing, c(6,9)]
> str(pima_subset)
'data.frame':
                 532 obs. of 2 variables:
 $ bmi : num 33.6 26.6 28.1 43.1 31 30.5 30.1 25.8 45.8 43.3 ...
 $ test: int 1 0 0 1 1 1 1 1 1 0 ...
> pima_mdl = glm(test ~ bmi, family=binomial(link="logit"),
                    pima_subset)
> phat = ilogit (pima_mdl$coefficients[2]*7)
> log_odds = logit(phat)
> as.numeric(log_odds)
[1] 0.6980179
logit(\hat{p}) = 0.6980
(b)
> phat_l = ilogit ((pima_mdl\$coefficients[2]*7 - qnorm(0.975))
                   * summary(pima_mdl)$coefficients[2, 2] * 7))
> phat_r = ilogit ((pima_mdl$coefficients[2]*7 + qnorm(0.975)
                   * summary(pima_mdl)$coefficients[2, 2] * 7))
> CI_logodds = c(logit(phat_l), logit(phat_r))
> as.numeric(CI_logodds)
[1] 0.4883237 0.9077121
95% Confidence Interval for logit(\hat{p}): (0.4883, 0.9077)
```

Question 3

(a)

$$\int (x; v, \lambda) = \frac{\lambda^{\nu}}{\prod (\nu)} x^{\nu-1} e^{-\lambda x} \qquad x > 0$$

$$\int_{\Gamma(\nu)} x^{\nu-1} e^{-\lambda x}$$

$$= \exp \left[-\lambda x + \left(\nu - 1 \right) \log x + \nu \log \lambda - \log \Gamma(\nu) \right]$$

$$= \exp \left[-\lambda x + \nu \log \lambda + \left(\nu - 1 \right) \log x - \log \Gamma(\nu) \right]$$

$$= \exp \left[\frac{x(-\frac{\lambda}{\nu}) - \log \left(\frac{\nu}{\lambda} \right) - \log \left(\nu \right)}{\frac{1}{\nu}} + \left(\nu - 1 \right) \log x - \log \Gamma(\nu) \right]$$

$$= \exp \left[\frac{x(-\frac{\lambda}{\nu}) - \log \left(\frac{\nu}{\lambda} \right)}{\frac{1}{\nu}} + \frac{-\log \left(\nu \right) + \left(1 - \frac{1}{\nu} \right) \log x - \frac{1}{\nu} \log \Gamma(\nu)}{\frac{1}{\nu}} \right]$$

$$(at \theta = -\frac{\lambda}{\nu}) \quad b(\theta) = \log \left(\frac{\nu}{\lambda} \right) = \log(-\frac{1}{\theta}), \quad \theta < 0$$

$$\phi = \frac{1}{\nu} \quad a(\phi) = \frac{1}{\nu}$$

$$\phi > 0$$

$$c(x, \phi) = -\frac{\log(\frac{1}{\theta}) + \left(1 - \phi \right) \log x - \phi \log \Gamma(\frac{1}{\theta})}{a(\phi)}$$

$$\Rightarrow f(x; \nu, \lambda) = \exp \left[\frac{x \theta - b(\theta)}{a(\phi)} + c(x, \phi) \right]$$

The gamma distribution is an exponential family

$$\theta = -\frac{\lambda}{\nu}$$
 $b(\theta) = \log(-\frac{1}{\theta})$ $a(\phi) = \frac{1}{\nu}$

variance function v (M) = 6" ((b')-1 (M))

$$b'(\theta) = \frac{1}{-\frac{1}{\theta}} \times \frac{1}{\theta^2} = -\frac{1}{\theta}, \quad (b')^{-1}(\mu) = -\frac{1}{\mu}$$

$$b''(\theta) = \frac{1}{\theta^2}$$

$$\Rightarrow v(\mu) = \frac{1}{(-\frac{1}{\mu})^2}$$

$$= \frac{1}{\frac{1}{\mu^2}} = \mu^2$$

$$\Rightarrow$$
 canonical link
 $g(\mu) = -\frac{1}{\mu}$

