

HOMEWORK 4

p.1

1. $\pi_{ij} = P(\text{competitor } i \text{ beats } j)$
 $\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \theta_i - \theta_j, \quad i \neq j, \quad i, j = 1, \dots, K$
 say $K=7$ teams
 $m_{ij} = \# \text{ games } i \text{ \& } j \text{ play together}$
 $Y_{ij} = \# \text{ games } i \text{ beats } j$

ⓐ what is the distribution of Y_{ij} in terms of m_{ij} & π_{ij} ?

$$\pi_{ij} = P(Y_{ij}=1)$$

Y_{ij} has binomial distribution, with $n = m_{ij}$

and $p = \pi_{ij}$

Binomial dist. takes the form:

$$f(x|n, p) = \binom{n}{x} p^x (1-p)^{n-x}$$

here, $n = m_{ij}, \quad p = \pi_{ij} = Pr(Y_{ij}=1)$

ⓑ Let $lij(\theta_i, \theta_j; Y_{ij})$ be log-likelihood for ⓐ.

Show that

$$lij(\theta_i, \theta_j; Y_{ij}) = Y_{ij}(\theta_i - \theta_j) - m_{ij}K(\theta_i - \theta_j) + h(Y_{ij})$$

for some functions $K(t), h(t)$.

Find an expression for $K(t)$.

If $i \& j$ teams play n games (m_{ij}), say

$Y_{ij} = 1$ if i wins & $Y_{ij} = 0$ if i loses

$$\begin{aligned} L f(Y_{ij} | m_{ij}, \pi_{ij}) &= \log \left[\binom{m_{ij}}{Y_{ij}} \pi_{ij}^{Y_{ij}} (1-\pi_{ij})^{m_{ij}-Y_{ij}} \right] \\ &= \log \left(\binom{m_{ij}}{Y_{ij}} \right) + Y_{ij} \log(\pi_{ij}) + (m_{ij} - Y_{ij}) \log(1-\pi_{ij}) \\ &= \log \left(\binom{m_{ij}}{Y_{ij}} \right) + Y_{ij} \log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) + m_{ij} \log(1-\pi_{ij}) \\ &= \log \left(\binom{m_{ij}}{Y_{ij}} \right) + Y_{ij}(\theta_i - \theta_j) + m_{ij} \log \left[(1 + e^{\theta_i - \theta_j})^{-1} \right] \\ &= \underbrace{\log \left(\binom{m_{ij}}{Y_{ij}} \right)}_{h(Y_{ij})} + \underbrace{Y_{ij}(\theta_i - \theta_j)}_{Y_{ij}(\theta_i - \theta_j)} - \underbrace{m_{ij} \log[1 + \exp(\theta_i - \theta_j)]}_{m_{ij} K(\theta_i - \theta_j)} \end{aligned}$$

$$h(Y_{ij}) \quad Y_{ij}(\theta_i - \theta_j) \quad m_{ij} K(\theta_i - \theta_j)$$

$$K(t) = \log(1 + e^t)$$

1, continued

p.2

① write 21×7 design matrix X for BT model.

7 teams $i=1, \dots, 7$, $j=1, \dots, 7$

for team i winning, $y=1$

for team i winning, j loses, $y=-1$

(see next page for matrix)

② Now suppose we have home field advantage taken into account. what is new X ?

If team i is the home team, our model now has an intercept, say α , so that the model becomes

$$\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \alpha + \theta_i - \theta_j$$

The new design matrix has a column of 1 at the first column.

match	team	1	2	3	4	5	6	7
1	2	1	-1	0	0	0	0	0
1	3	1	0	-1	0	0	0	0
1	4	1	0	0	-1	0	0	0
1	5	1	0	0	0	-1	0	0
1	6	1	0	0	0	0	-1	0
1	7	1	0	0	0	0	0	-1
2	3	0	1	-1	0	0	0	0
2	4	0	1	0	-1	0	0	0
2	5	0	1	0	0	-1	0	0
2	6	0	1	0	0	0	-1	0
2	7	0	1	0	0	0	0	-1
3	4	0	0	1	-1	0	0	0
3	5	0	0	1	0	-1	0	0
3	6	0	0	1	0	0	-1	0
3	7	0	0	1	0	0	0	-1
4	5	0	0	0	1	-1	0	0
4	6	0	0	0	1	0	-1	0
4	7	0	0	0	1	0	0	-1
5	6	0	0	0	0	1	-1	0
5	7	0	0	0	0	1	0	-1
6	7	0	0	0	0	0	1	-1

this matrix is actually 42×7
 but there is a pattern based
 on who plays who

2. consider

$$f(y; \theta, \phi) = \exp \left\{ \frac{y\theta - K(\theta)}{\phi} \right\} h(y, \phi)$$

 $\phi \rightarrow$ dispersion parameter $\theta \rightarrow$ canonical parameter

@ what are θ , ϕ , and $K(\theta)$ if $Y \sim \text{Poisson}(\mu)$, $\mu > 0$?
 what about if $Y \sim N(\mu, \sigma^2)$?

$$\begin{aligned} \text{If } Y \sim \text{Poisson}(\mu), \quad f(y|\mu) &= \frac{\mu^y e^{-\mu}}{y!} \\ &= \frac{1}{y!} \exp \{ y \log \mu - \mu \} \end{aligned}$$

which gives us

$$\theta = \log \mu$$

$$K(\theta) = \mu = \exp(\theta)$$

$$\phi = \frac{1}{y!}, \quad \mu > 0$$

$$\begin{aligned} \text{If } Y \sim N(\mu, \sigma^2), \quad f(y|\mu, \sigma^2) &= \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2\sigma^2} (y-\mu)^2 \right\} \\ &= \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ \frac{\mu}{\sigma^2} y - \frac{1}{2\sigma^2} y^2 - \frac{1}{2\sigma^2} \mu^2 - \log \sigma \right\} \end{aligned}$$

$$\theta = \mu$$

$$K(\theta) = \frac{\theta^2}{2} = \frac{\mu^2}{2}$$

$$\phi = \sigma^2$$

⑥ $Y \sim f(y; \theta, \phi)$. Find expressions for $E(Y)$, $\text{var}(Y)$
 in terms of $K(\theta)$ and ϕ .

Take derivative:

$$f'(y; \theta, \phi) = \frac{y - K'(\theta)}{\phi} f(y; \theta, \phi)$$

Integrate both sides

$$\int f'(y; \theta, \phi) dy = \frac{\partial}{\partial \theta} \int f(y; \theta, \phi) dy = \frac{\partial}{\partial \theta} (1) = 0$$

(assuming we can interchange der. & integral)

$$\rightarrow \int \frac{y - K'(\theta)}{\phi} f(y; \theta, \phi) dy = \frac{1}{\phi} \left[\int y f(y; \theta, \phi) dy - K'(\theta) \int f(y; \theta, \phi) dy \right]$$

$$= \frac{1}{\phi} [E(Y) - K'(\theta)] = 0$$

$$\text{so, } E(Y) = K'(\theta)$$

2, continued

p. 5

$\text{var}(Y)$:

take the second derivative of both sides

$$f''(y; \theta, \phi) = \left[\left(\frac{y - \kappa'(\theta)}{\phi} \right) - \frac{\kappa''(\theta)}{\phi} \right] f(y; \theta, \phi)$$

Integrate both sides

$$\int f''(y; \theta, \phi) dy = \frac{\partial^2}{\partial \theta^2} \int f(y; \theta, \phi) dy = \frac{\partial^2}{\partial \theta^2} (1) = 0$$

$$\rightarrow \int \left[\left(\frac{y - \kappa'(\theta)}{\phi} \right) - \frac{\kappa''(\theta)}{\phi} \right] f(y; \theta, \phi) dy$$

$$E(Y)^2 - E(Y^2) = \text{var}(Y)$$

$$= \frac{1}{\phi} \left[\frac{\text{var}(Y)}{\phi} - \kappa''(\theta) \right]$$

$$\text{So, } \text{var}(Y) = \phi \kappa''(\theta)$$

© $Y_i \sim f(y; x_i^T \beta, \phi)$, $\beta \in \mathbb{R}^p$, $\phi > 0$ are unknown

If $Y_1, \dots, Y_n \perp$, show that $\hat{\beta}$ satisfies

$$X^T \{Y - E_{\hat{\beta}}(Y)\} = 0_p$$

where $E_{\hat{\beta}}(Y)$ is $E(Y_i)$ for $Y_i \sim f(y; x_i^T \hat{\beta}, 1)$

If $y \sim f(y; x_i^T \beta, 1)$,

$$y \Rightarrow \exp \{y x_i^T \beta - \kappa(x_i^T \beta)\} h(y, 1)$$

from ②

$$E_{\hat{\beta}}(Y_i) = \kappa'(x_i^T \hat{\beta})$$

$$\text{And } f'(y; x_i^T \beta, 1) = y - \kappa'(x_i^T \beta) \exp \{y x_i^T \beta - \kappa(x_i^T \beta)\} h(y, 1)$$

set $f' = 0$, solve for β to find $\hat{\beta}$

when $y_i = \kappa'(x_i^T \hat{\beta})$,

$$E_{\hat{\beta}}(Y) = Y$$

$$\text{So } X^T \{Y - E_{\hat{\beta}}(Y)\} = X^T \{Y - Y\} = 0_p$$

④ what is asymptotic variance of $\hat{\beta}$ (inverse of Fisher information) in terms of κ, β, X, ϕ ?

From ③ and based on what we've done

in class, $\hat{\beta} \rightarrow \beta$ is asymptotically normally dist'd

$$\text{Fisher: } -E \left\{ \nabla_{\beta}^2 \ell(x_i^T \beta, \phi) \right\} = -E_{\hat{\beta}} \left\{ \frac{\phi \kappa''(\theta)}{\beta} \right\}$$

$$\text{so } \text{var}(\hat{\beta}) = \frac{1}{-E_{\hat{\beta}} \left\{ \frac{\phi \kappa''(\theta)}{\beta} \right\}}$$