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Generalized linear models III

Peter McCullagh

*Department of Statistics
University of Chicago
Chicago IL 60637, USA*

Binary response models
Example: Titanic survival rates
Nuisance parameters

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Department of Statistics
University of Chicago

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Outline

1 Binary response models

2 Example: Titanic survival rates

3 Nuisance parameters



Binary response models

Model:

Y_1, \dots, Y_n independent Bernoulli variables

$E(Y_i) = \pi(x_i)$ is the mean

Need a model for the response function $\pi(x)$

Constraint: $0 \leq \pi(x) \leq 1$

Standard response functions: $\pi(x) = F(\beta'x)$

F is a cumulative distribution function

$f = F'$ is a density function on \mathcal{R}

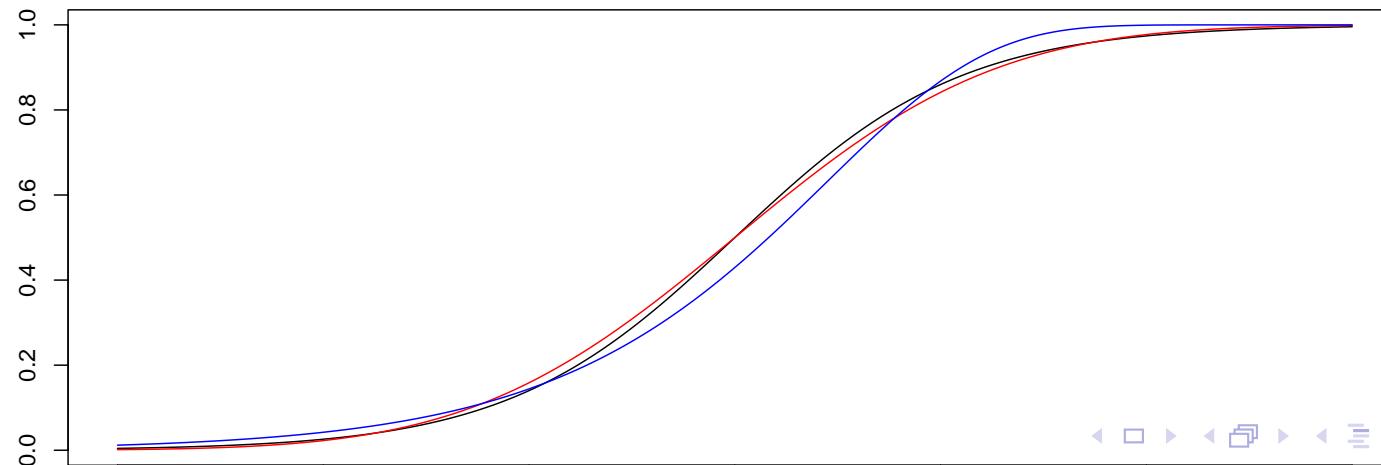
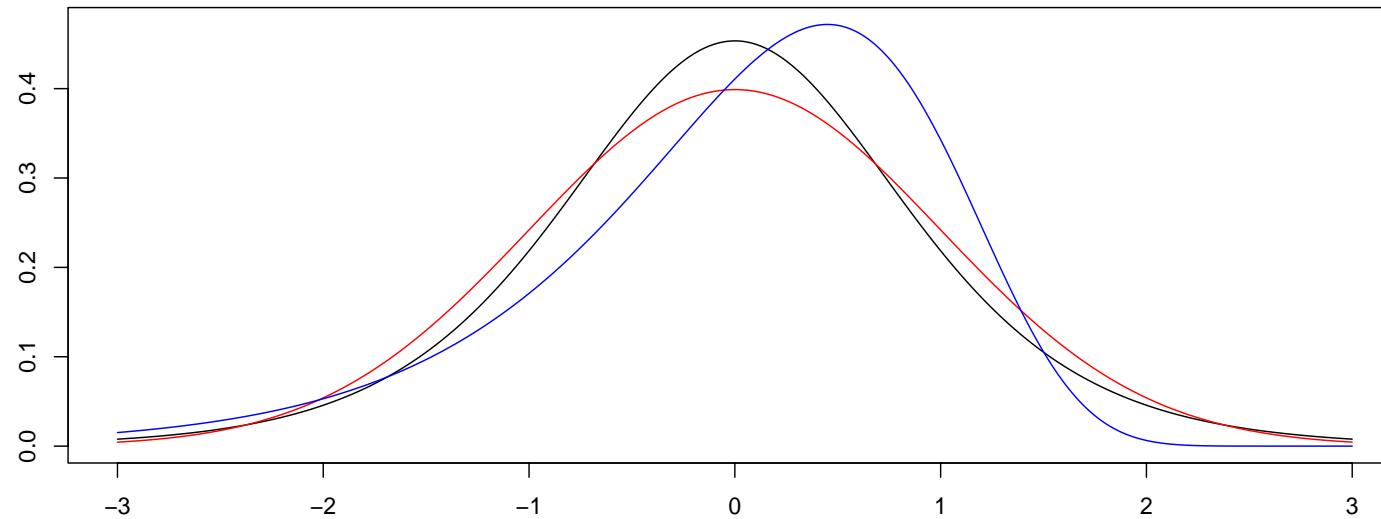
logit: $F(\eta) = e^\eta / (1 + e^\eta); \quad \eta = \log(\pi/(1 - \pi))$

probit: $F(\eta) = \Phi(\eta); \quad \eta = \Phi^{-1}(\pi)$

c-log log: $F(\eta) = 1 - \exp(-e^\eta); \quad \eta = \log(-\log(1 - \pi))$



Associated standardized densities



Logistic models

$$\text{odds}(E) = \frac{\text{pr}(E)}{\text{pr}(\bar{E})}, \quad \text{pr}(E) = \frac{\text{odds}(E)}{1 + \text{odds}(E)}$$

$$\text{logit}(E) = \log \text{odds}(E)$$

$$\text{logit } \pi(x) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p$$

$$\text{odds}(Y = 1; x) = \exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p)$$

Parameter interpretation:

β_p is the change in the log odds... per unit change in x_p when x_1, \dots, x_{p-1} are held fixed

e^{β_p} is the multiplicative change in the odds per unit change in x_p ...

The change in the probability is approximately

$$d\pi(x) = \pi(x)(1 - \pi(x))\beta_p dx_p < \beta_p dx_p / 4$$



Example: Titanic survival rates

Data for 1316 passengers and 885 crew

Data listed by individual

| Name | class | child/adult | female/male | survived |
|---------------|-------|-------------|-------------|----------|
| Andrews, C | 1 | 0 | 1 | 1 |
| Andrews, T | 1 | 0 | 0 | 0 |
| Rothschild, M | 1 | 0 | 0 | 0 |
| Young, M | 1 | 0 | 1 | 1 |
| Abelson, S | 2 | 0 | 0 | 0 |
| Abbott, E | 3 | 0 | 0 | 0 |
| : | : | : | : | : |

Coding: class 0=crew; 1=first, 2, 3
adult=0, child=1; male=0, female=1; died=0, survived=1



Summary table

Summary data for 1316 passengers and 885 crew

| | crew | class1 | class2 | class3 | child | female | surv | pct |
|--------|------|--------|--------|--------|-------|--------|------|-----|
| crew | 885 | 0 | 0 | 0 | 0 | 23 | 212 | 24 |
| class1 | 0 | 325 | 0 | 0 | 6 | 145 | 203 | 63 |
| class2 | 0 | 0 | 285 | 0 | 24 | 106 | 118 | 41 |
| class3 | 0 | 0 | 0 | 706 | 79 | 196 | 178 | 25 |
| child | 0 | 6 | 24 | 79 | 109 | 45 | 57 | 52 |
| female | 23 | 145 | 106 | 196 | 45 | 470 | 344 | 73 |
| surv | 212 | 203 | 118 | 178 | 57 | 344 | 711 | 32 |



Logistic model

Main effects only:

$$\text{odds(survival)} = \text{class effect} \times \text{sex effect} \times \text{age effect}$$

$$\log \text{odds(survival)} = \text{class effect} + \text{sex effect} + \text{age effect}$$

Class treated as a 4-level factor

model formula used: class+child+female

Parameter estimates and S.E.s

| | class+child+female | | class+child+female-1 | |
|-------------|--------------------|-------|----------------------|-------|
| (Intercept) | -1.23 | 0.08 | — | — |
| crew | — | — | -1.23 | 0.080 |
| class1 | 0.86 | 0.157 | -0.38 | 0.136 |
| class2 | -0.16 | 0.174 | -1.39 | 0.155 |
| class3 | -0.92 | 0.149 | -2.15 | 0.127 |
| child | 1.06 | 0.244 | 1.06 | 0.244 |
| female | 2.42 | 0.140 | 2.42 | 0.140 |



Parameter estimates and S.E.s

| | class+child+female | | class+child+female-1 | |
|-------------|--------------------|-------|----------------------|-------|
| (Intercept) | -1.23 | 0.08 | — | — |
| crew | — | — | -1.23 | 0.080 |
| class1 | 0.86 | 0.157 | -0.38 | 0.136 |
| class2 | -0.16 | 0.174 | -1.39 | 0.155 |
| class3 | -0.92 | 0.149 | -2.15 | 0.127 |
| child | 1.06 | 0.244 | 1.06 | 0.244 |
| female | 2.42 | 0.140 | 2.42 | 0.140 |

Fitted survival odds:

class1 adult female: $\exp(-0.38 + 2.42) = 7.69$, prob=0.89

class1 adult male: $\exp(-0.38) = 0.68$, prob=0.41

class2 adult male: $\exp(-1.39) = 0.25$, prob=0.20

class3 adult male: $\exp(-2.15) = 0.12$, prob=0.10

class3 male child: $\exp(-2.15 + 1.06) = 0.34$, prob=0.25



Does the additive model fit?

Children and females given preferential treatment

Does the degree of preference depend on class?

Model formula: child+class+female+female*class

| Parameter | estimates | S.E. |
|---------------|-----------|-------|
| class0 | -1.25 | 0.082 |
| class1 | -0.68 | 0.158 |
| class2 | -1.91 | 0.219 |
| class3 | -1.70 | 0.124 |
| child | 1.05 | 0.230 |
| female | 3.15 | 0.625 |
| class1:female | 1.09 | 0.820 |
| class2:female | 0.64 | 0.725 |
| class3:female | -1.78 | 0.652 |

Fitted survival odds:

$$\text{class1 adult female: } \exp(-0.68 + 3.15 + 1.09) = 35.16 \text{ pr}=0.97$$

$$\text{class3 adult female: } \exp(-1.70 + 3.15 - 1.78) = 0.72 \text{ pr}=0.41$$



Formal test of significance

Likelihood ratio or deviance test: Deviances:

| Model | Deviance | d.f. | Dev diff |
|--------------------|----------|------|----------|
| child+class+female | 2210 | 2195 | |
| child+class*female | 2143 | 2192 | 67 (3) |
| class+child*female | 2192 | 2194 | 18 (1) |
| class*child+female | 2174 | 2193 | 36 (2) |
| all 2-factors | 2097 | 2187 | 113 (8) |

All 2-factor interactions strongly significant.

Some findings:

Preferential treatment given to females;

Degree of preference higher in 1st class than 3rd



Effects of nuisance parameters

Binary matched pairs problem:

Subjects come in matched pairs (blocks of size 2)

Pair effects $\lambda_1, \dots, \lambda_n$

Common treatment effect Δ

$$\text{pr}(Y_{i1} = 1) = \frac{e^{\lambda_i}}{1 + e^{\lambda_i}}, \quad \text{pr}(Y_{i2} = 1) = \frac{e^{\lambda_i + \Delta}}{1 + e^{\lambda_i + \Delta}}$$

Likelihood

$$\prod_i \frac{e^{\lambda_i y_{i1}}}{1 + e^{\lambda_i}} \frac{e^{\lambda_i y_{i2} + \Delta y_{i2}}}{1 + e^{\lambda_i + \Delta}} = \prod_i \frac{e^{\lambda_i y_{i.}}}{(1 + e^{\lambda_i})(1 + e^{\lambda_i + \Delta})} \times e^{\Delta y_{.2}}$$

So $(\{y_{i.}\}, y_{.2})$ is sufficient
and $(\{y_{i.}\})$ is sufficient for fixed Δ .



Binary matched pairs (contd)

Maximum likelihood estimation: Sufficient statistic $(\{y_{i.}\}, y_{.2})$

$$E(Y_{i.}; \lambda, \Delta) = \frac{e^{\lambda_i}}{1 + e^{\lambda_i}} + \frac{e^{\lambda_i + \Delta}}{1 + e^{\lambda_i + \Delta}}$$
$$E(Y_{.2}; \lambda, \Delta) = \sum \frac{e^{\lambda_i + \Delta}}{1 + e^{\lambda_i + \Delta}}$$

Maximum likelihood equations for fixed Δ

$$\hat{\lambda}_i(\Delta) = \begin{cases} -\infty & y_{i.} = 0 \\ -\Delta/2 & y_{i.} = 1 \\ \infty & y_{i.} = 2 \end{cases}$$

Profile likelihood is a product over the mixed-response pairs

$$\text{pr}(0, 1; \hat{\lambda}, \Delta) = \frac{e^{\Delta/2}}{\sqrt{(2\pi)^2 + (\Delta/2)^2}}$$



Conditional likelihood

$$\begin{aligned}\text{pr}(Y_{i1}, Y_{i2} = (0, 1)) &= \frac{e^{\lambda_i + \Delta}}{(1 + e^{\lambda_i})(1 + e^{\lambda_i + \Delta})} \\ \text{pr}(Y_{i1}, Y_{i2} = (1, 0)) &= \frac{e^{\lambda_i}}{(1 + e^{\lambda_i})(1 + e^{\lambda_i + \Delta})} \\ \text{pr}(Y_{i1}, Y_{i2} = (0, 1) | \text{mixed}) &= \frac{e^{\lambda_i + \Delta}}{e^{\lambda_i} + e^{\lambda_i + \Delta}} \\ &= e^\Delta / (1 + e^\Delta)\end{aligned}$$

Hence the mixed pairs are conditionally iid

The conditional distribution given $n_{10} + n_{01} = S$

$$n_{01} \sim \text{Bin}(S, e^\Delta / (1 + e^\Delta))$$

Conditional mle is $\hat{\Delta}_c = \log(n_{01}/n_{10}) = \hat{\Delta}/2$

