

Multinomial regression

Motivating example: earthquake data

We have data from the 2015 Gorkha earthquake in Nepal. After the earthquake, a large scale survey was conducted to determine the amount of damage the earthquake caused for homes, businesses and other structures. Variables include:

- + Damage: the amount of damage suffered by the building (none, moderate, severe)
- + age: the age of the building (in years)
- + condition: a de-identified variable recording the condition of the land surrounding the building

$$\text{Damage}_i \sim \text{categorical}(\pi_{i(\text{none})}, \pi_{i(\text{moderate})}, \pi_{i(\text{severe})})$$
$$\log \left(\frac{\pi_{i(\text{moderate})}}{\pi_{i(\text{none})}} \right) = \beta_{(\text{moderate})}^T X_i$$
$$\log \left(\frac{\pi_{i(\text{severe})}}{\pi_{i(\text{none})}} \right) = \beta_{(\text{severe})}^T X_i$$

$$\mu_i = \frac{\partial u(\theta_i)}{\partial \theta_i}$$

$$\frac{\partial \mu_i}{\partial \theta_i} = v(\mu_i)$$

$$v(\mu) = \begin{bmatrix} \pi_1(1-\pi_1) & -\pi_1\pi_2 & \dots \\ -\pi_2\pi_1 & \pi_2(1-\pi_2) & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

Fisher scoring

$$u(\beta) = \frac{1}{\emptyset} \sum_{i=1}^n x_i^{*\top} (\gamma_i^* - \mu_i)$$

(multivariate EDM
w/ canonical link)

multinomial : $\emptyset = 1$, $\gamma_{ij}^* = \begin{cases} 1 & \gamma_i = j \\ 0 & \gamma_i \neq j \end{cases}$, $\mu_i = \begin{pmatrix} \pi_{i1} \\ \pi_{i2} \\ \vdots \\ \pi_{i,J-1} \end{pmatrix}$

$$\frac{\partial u(\beta)}{\partial \beta} = -\frac{1}{\emptyset} \sum_{i=1}^n \frac{\partial}{\partial \beta} (x_i^{*\top} \mu_i)$$

$$\frac{\partial}{\partial \beta} (x_i^{*\top} \mu_i) = \underbrace{\frac{\partial \mu_i}{\partial \beta}}_{\frac{\partial \theta_i}{\partial \beta} \frac{\partial \mu_i}{\partial \theta_i}} \underbrace{\frac{\partial x_i^{*\top} \mu_i}{\partial \mu_i}}_{x_i^*}$$

(chain-rule)

(canonical link)

$$\theta_i = x_i^* \beta$$

$$\Rightarrow \frac{\partial u(\beta)}{\partial \beta} = -\frac{1}{\emptyset} \sum_{i=1}^n x_i^{*\top} v(\mu_i) x_i^* \Rightarrow \lambda(\beta) = \frac{1}{\emptyset} \sum_{i=1}^n x_i^{*\top} v(\mu_i) x_i^*$$

$$H_0: \beta_{1(\text{moderate})} = 0$$

$$Z = \frac{0.375}{0.017} \approx 22.1$$

$$p\text{-value} \approx 0$$

Wald tests $H_A: \beta_{1(\text{moderate})} \neq 0$

...

Coefficients:

```
##          (Intercept) sqrt(age)  conditiono conditiont
## moderate    0.6581163 0.3747641 -0.45376940 -0.5803708
## severe      0.1881145 0.4251732  0.04706934 -0.4623774
##
```

Std. Errors:

```
##          (Intercept) sqrt(age)  conditiono conditiont
## moderate    0.1208913 0.01684468  0.2305975  0.1155475
## severe      0.1243799 0.01725782  0.2292533  0.1180182
```

...

Suppose we want to know whether there is a relationship between age and the odds of moderate vs. no damage, after accounting for surface condition. What hypotheses would we test?

$\sqrt{\text{cov}(\text{model})}$

$$H_0: \beta_{1(\text{moderate})} = \beta_{1(\text{severe})}$$

$$\beta = \begin{pmatrix} \beta_{0(\text{moderate})} \\ \vdots \\ \beta_{3(\text{moderate})} \\ \beta_{0(\text{severe})} \\ \vdots \\ \beta_{3(\text{severe})} \end{pmatrix}$$

Wald tests $H_A: \beta_{1(\text{moderate})} \neq \beta_{1(\text{severe})}$

$$\dots \alpha^T = (0, -1, 0, 0, 0, 1, 0, 0)$$

$$Z = \frac{\alpha^T \hat{\beta} - 0}{\sqrt{\alpha^T \text{var}(\hat{\beta}) \alpha}}$$

Coefficients:

```
##           (Intercept)  sqrt(age)  conditiono  conditiont
## moderate    0.6581163  0.3747641  -0.45376940 -0.5803708
## severe      0.1881145  0.4251732   0.04706934 -0.4623774
```

$$\text{var}(\alpha^T \hat{\beta}) = \alpha^T \text{var}(\hat{\beta}) \alpha$$

Std. Errors:

```
##           (Intercept)  sqrt(age)  conditiono  conditiont
## moderate    0.1208913  0.01684468   0.2305975   0.1155475
## severe      0.1243799  0.01725782   0.2292533   0.1180182
```

$$\dots \text{var}(y_1 - y_2) = \text{var}(y_1) + \text{var}(y_2) - 2\text{cov}(y_1, y_2)$$

Suppose we want to know whether the relationship between age and the odds of moderate vs. no damage is the *same* as the relationship between age and the odds of severe vs. no damage. What hypotheses would we test?

Wald tests

```
diff <- t(c(0, -1, 0, 0, 0, 1, 0, 0)) %*%  
  c(t(coef(m1)))  
std_err <- sqrt(t(c(0, -1, 0, 0, 0, 1, 0, 0)) %*%  
  vcov(m1) %*%  
  c(0, -1, 0, 0, 0, 1, 0, 0))  
(diff - 0)/std_err
```

```
##           [,1]  
## [1,] 4.95677
```

```
2*pnorm((diff - 0)/std_err, lower.tail = F)
```

```
##           [,1]  
## [1,] 7.167478e-07
```

$$H_0: \beta_{2(\text{moderate})} = \beta_{2(\text{severe})} = \beta_{3(m)} = \beta_{3(s)} = 0$$

Likelihood ratio tests

$$H_A: \text{at least one of } \beta_{2(m)}, \beta_{2(s)},$$

$$G = \text{reduced deviance} - \text{full deviance} \sim \chi^2 \text{ of } df = 4$$

```
...
## Coefficients:
##      (Intercept) sqrt(age) conditiono conditiont
## moderate      0.6581163  0.3747641 -0.45376940 -0.5803708
## severe        0.1881145  0.4251732   0.04706934 -0.4623774
##
## Std. Errors:
##      (Intercept)  sqrt(age) conditiono conditiont
## moderate      0.1208913  0.01684468   0.2305975   0.1155475
## severe        0.1243799  0.01725782   0.2292533   0.1180182
...
```

Suppose we want to know whether there is a relationship between surface condition and damage, after accounting for building age. What hypotheses would we test?

Likelihood ratio tests

```
m1 <- multinom(Damage ~ sqrt(age) + condition,  
               data = earthquake)  
m2 <- multinom(Damage ~ sqrt(age),  
               data = earthquake)  
  
pchisq(m2$deviance - m1$deviance, df = 4,  
       lower.tail=F)  
  
## [1] 2.452814e-08
```


Deviance for multivariate EDM

$$f(y; \theta, \phi) = a(y, \phi) \exp \left\{ \frac{y^T \theta - \eta(\theta)}{\phi} \right\}$$

Dispersion model form: $f(y; \theta, \phi) = b(y, \phi) \exp \left\{ - \frac{\phi(y, \mu)}{2\phi} \right\}$

$$t(y, \mu) = y^T \theta - \eta(\theta) \quad (\theta = g(\mu))$$

$$\phi(y, \mu) = 2(t(y, y) - t(y, \mu))$$

Multinomial regression : $\theta = \left(\log \left(\frac{\pi_j}{1 - \sum_{j=1}^{J-1} \pi_j} \right), \dots, \log \left(\frac{\pi_{J-1}}{1 - \sum_{j=1}^{J-1} \pi_j} \right) \right)^T$

$$\eta(\theta) = -\log \left(1 - \sum_{j=1}^{J-1} \pi_j \right)$$

$$t(y, y) : \pi_j = y_j^* \Rightarrow \sum_{j=1}^{J-1} y_j^* \log \left(\frac{y_j^*}{1 - \sum_{k=1}^{J-1} y_k^*} \right) + \log \left(1 - \sum_{k=1}^{J-1} y_k^* \right)$$

$$= \sum_{j=1}^J y_j^* \log(y_j^*)$$

$$t(y, \mu) = \sum_{j=1}^J y_j^* \log(\pi_j)$$

$$\Rightarrow \phi(y, \mu) = 2 \sum_{j=1}^J y_j^* \log \left(\frac{y_j^*}{\pi_j} \right)$$

$$y_j^* = \begin{cases} 1 & y = j \\ 0 & y \neq j \end{cases}$$

Class activity

https://sta712-f22.github.io/class_activities/ca_lecture_36.html