

STAT347: Generalized Linear Models

Lecture 6

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Today's topics:

- Some applications of Binary GLM
- Binary GLM inference
- Fitting logistic regression and the infinite estimates
- Binary GLM example (part II)

2 X 2 table

When Both the X_i and y_i are binary, the grouped data can be represented by a 2×2 table.

- Number of grouped samples: 2.
- Number of total ungrouped observations: $N = n_1 + n_2$ (Table 5.2 of the Agresti book)
- Assume that (X_i, y_i) are i.i.d. Odds ratio (OR) for the response variable Y :

$$\text{OR} = \frac{\mathbb{P}(Y = 1 \mid X = 1)/\mathbb{P}(Y = 0 \mid X = 1)}{\mathbb{P}(Y = 1 \mid X = 0)/\mathbb{P}(Y = 0 \mid X = 0)}$$

- Interpretation of the coefficient β_1 in the binary GLM with logit link:
 $\text{logit}(p_i) = \beta_0 + \beta_1 X_i$

$$e^{\beta_1} = \text{OR}$$

		Event	
		Yes	No
Exposure	Yes	a	b
	No	c	d

Prospective V.S. retrospective design

- We want to know the effect of a risk factor (say smoking) on an outcome (say lung cancer)
- **Prospective design:** randomly select smokers and non-smokers from the population and observe whether they will develop cancer in the future.
 - We can compare $\mathbb{E}(Y = 1|X = 1)$ with $\mathbb{E}(Y = 1|X = 0)$
 - Drawbacks: the study takes a long time; lung cancer is a rare disease, may observe very few cancer samples.
- **Retrospective design (case-control study):** We randomly select some samples from patients who develop cancer and some samples from healthy controls. Then, we check whether the person has been a smoker or not.
 - Only compare $\mathbb{E}(X = 1|Y = 1)$ with $\mathbb{E}(X = 1|Y = 0)$
 - The study takes a shorter time, and we can obtain enough cancer cases.

Case-control study

Why is the case-control study popular?

$$\begin{aligned} \text{OR} &= \frac{\mathbb{P}(Y = 1 \mid X = 1)/\mathbb{P}(Y = 0 \mid X = 1)}{\mathbb{P}(Y = 1 \mid X = 0)/\mathbb{P}(Y = 0 \mid X = 0)} \\ &= \frac{\mathbb{P}(X = 1 \mid Y = 1)/\mathbb{P}(X = 0 \mid Y = 1)}{\mathbb{P}(X = 1 \mid Y = 0)/\mathbb{P}(X = 0 \mid Y = 0)} \end{aligned}$$

We can also include other covariates \tilde{X} :

$$\begin{aligned} \text{OR} \mid_{\tilde{X}=x} &= \frac{\mathbb{P}(Y = 1 \mid X = 1, \tilde{X} = x)/\mathbb{P}(Y = 0 \mid X = 1, \tilde{X} = x)}{\mathbb{P}(Y = 1 \mid X = 0, \tilde{X} = x)/\mathbb{P}(Y = 0 \mid X = 0, \tilde{X} = x)} \\ &= \frac{\mathbb{P}(X = 1 \mid Y = 1, \tilde{X} = x)/\mathbb{P}(X = 0 \mid Y = 1, \tilde{X} = x)}{\mathbb{P}(X = 1 \mid Y = 0, \tilde{X} = x)/\mathbb{P}(X = 0 \mid Y = 0, \tilde{X} = x)} \end{aligned}$$

Thus, we can study estimate the odds ratio of the risk factor from case-control studies.

Thus, building the logistic regression using case-control study samples is the same as building the model using prospective samples:

$$e^{\beta_1} \equiv \text{OR} \mid_{\tilde{X}=x}$$

Classification

Table 5.1 A Classification Table

		Prediction \hat{y}	
		0	1
y	0		
	1		

Cell counts in such tables yield estimates of sensitivity = $P(\hat{y} = 1 | y = 1)$ and specificity = $P(\hat{y} = 0 | y = 0)$.

- Sensitivity (recall, true positive rate, tpr): $P(\hat{y} = 1 | y = 1)$
- Specificity: $P(\hat{y} = 0 | y = 0)$
- False positive rate (fpr): $1 - \text{specificity} = P(\hat{y} = 1 | y = 0)$

ROC curve

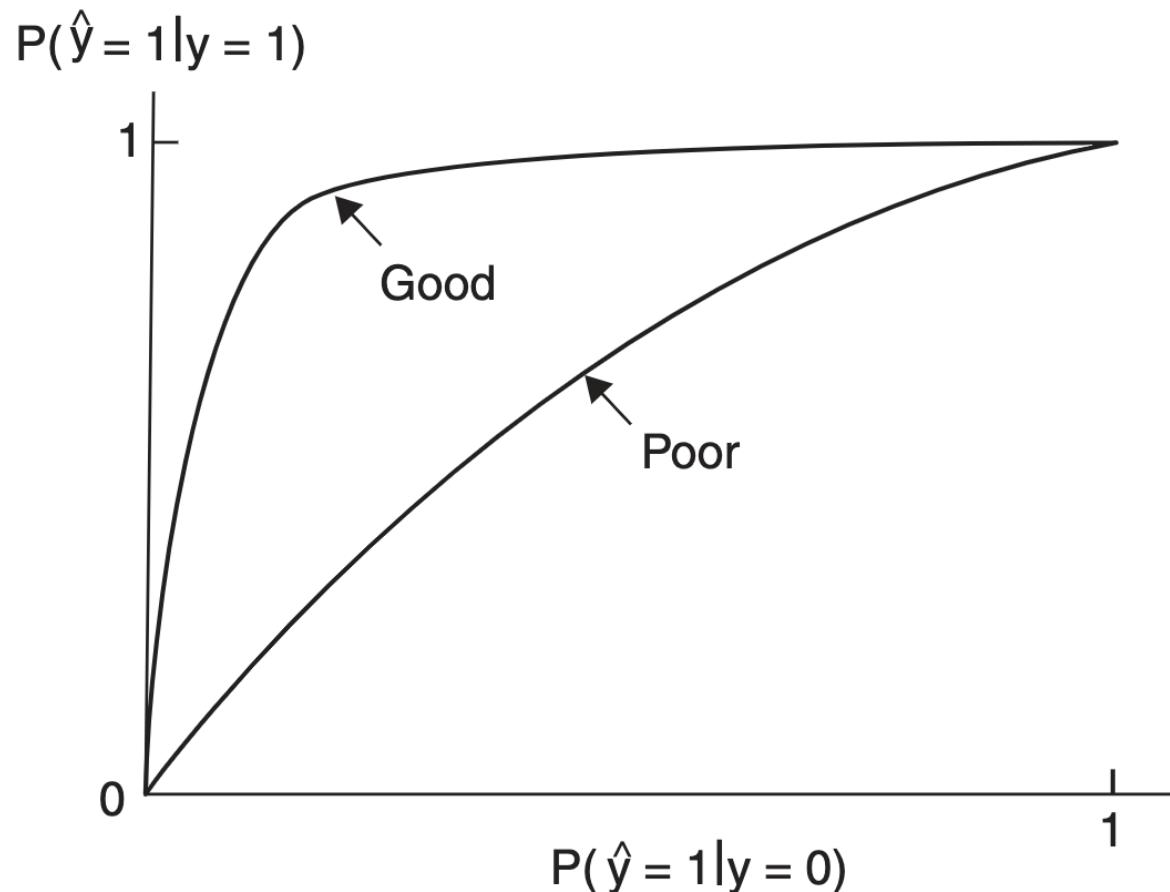


Figure 5.2 ROC curves for a binary GLM having good predictive power and for a binary GLM having poor predictive power.

ROC curve

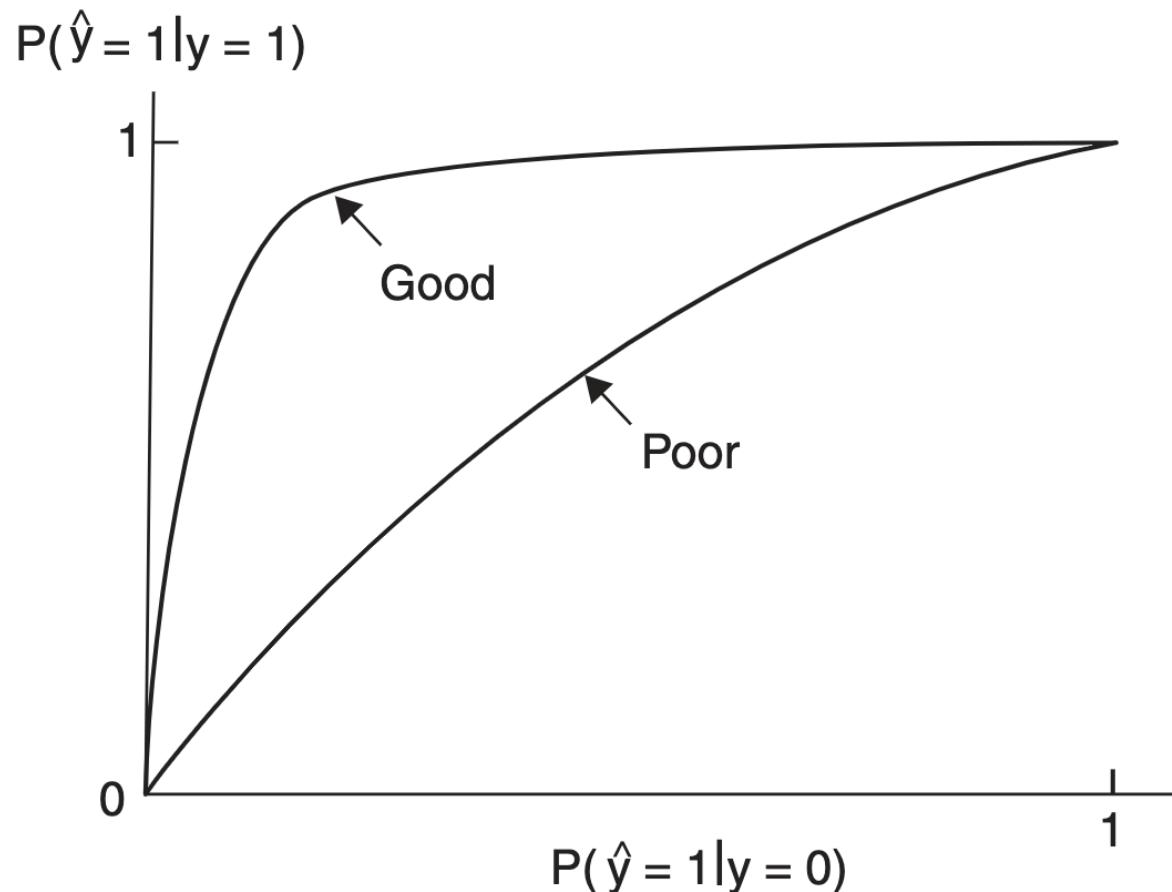


Figure 5.2 ROC curves for a binary GLM having good predictive power and for a binary GLM having poor predictive power.

Score equation in logistic regression

For logistic regression, as the logit link is the canonical link, the score equation is:

$$\frac{\partial L}{\partial \beta_j} = \sum_i (y_i - n_i p_i) x_{ij} = \sum_i \left(y_i - \frac{n_i e^{X_i^T \beta}}{1 + e^{X_i^T \beta}} \right) x_{ij} = 0$$

We have derived that as $n \rightarrow \infty$

$$\text{Var}(\hat{\beta}) \rightarrow (X^T W X)^{-1}$$

where $W = D^2 V^{-1}$ is a diagonal matrix. For logistic regression where the logit link is the canonical link, we have $W = V$ so

$$W_{ii} = n_i p_i (1 - p_i), \quad \widehat{W}_{ii} = n_i \frac{e^{X_i^T \hat{\beta}}}{(1 + e^{X_i^T \hat{\beta}})^2}$$

Residual deviance is different for grouped and ungroup data

$$\begin{aligned} D_+(y, \hat{\mu}) &= \sum_i D(y_i, n_i \hat{p}_i) \\ &= -2 \sum_i \log \left[f(y_i, \hat{\theta}_i) / f(y_i, \theta_{y_i}) \right] \\ &= -2 \sum_i \log \left[\frac{\hat{p}_i^{y_i} (1 - \hat{p}_i)^{n_i - y_i}}{(y_i/n_i)^{y_i} (1 - y_i/n_i)^{n_i - y_i}} \right] \\ &= 2 \sum_i y_i \log \frac{y_i}{n_i \hat{p}_i} + 2 \sum_i (n_i - y_i) \log \frac{n_i - y_i}{n_i - n_i \hat{p}_i} \end{aligned}$$

- For the ungrouped data, each observation is y_i
 - The saturated model is $\hat{p}_i = y_i$ for each individual sample
- For the grouped data each observation is \tilde{y}_k
 - The saturated model is $\hat{p}_k = \tilde{y}_k$ for each group (so that \hat{p}_i for each individual sample in the saturated model is \tilde{y}_k instead of y_i)

Residual deviance for grouped data

- The group level data can be presented by a $K \times 2$ count table, where each row is a group, and the two columns store the number of success \tilde{y}_k and the number of failure $n_k - \tilde{y}_k$ respectively in each cell.
- Residual deviance for the group data

$$\begin{aligned} G^2 = D_+(y, \hat{\mu}) &= 2 \sum_k \tilde{y}_k \log \frac{\tilde{y}_k}{n_k \hat{p}_k} + 2 \sum_k (n_k - \tilde{y}_k) \log \frac{n_k - \tilde{y}_k}{n_k - n_k \hat{p}_k} \\ &= 2 \sum_{2K \text{ cells}} \text{observed} \times \log \left(\frac{\text{observed}}{\text{fitted}} \right) \end{aligned}$$

- When the number of groups K is fixed while the total samples size $N = \sum_k n_k$ is large, then the residual deviance is the likelihood ratio satisfying

$$G^2 = D_+(y, \hat{\mu}) \xrightarrow{p} \chi^2_{K-p}$$

Goodness-of-fit test of the fitted model

- Residual deviance for goodness of fit

$$G^2 = D_+(y, \hat{\mu}) \xrightarrow{p} \chi^2_{K-p}$$

- Pearson's statistics for goodness of fit

$$\begin{aligned} X^2 &= \sum_{2K \text{ cells}} \frac{(\text{observed} - \text{fitted})^2}{\text{fitted}} \\ &= \sum_k \frac{(n_k \tilde{y}_k - n_k \hat{p}_k)^2}{n_k \hat{p}_k} + \sum_k \frac{[(n_k - \tilde{y}_k) - (n_k - n_k \hat{p}_k)]^2}{n_k - n_k \hat{p}_k} \\ &= \sum_k \frac{(\tilde{y}_k - n_k \hat{p}_k)^2}{n_k \hat{p}_k (1 - \hat{p}_k)} \xrightarrow{p} \chi^2_{K-p} \end{aligned}$$

Comparison between G^2 and X^2

- $X^2 = \sum_k e_k^2$
sum square of Pearson residuals of grouped data. X^2 in general converges to χ^2_{K-p} more quickly, so it works better than G^2 for N not too large.
- $G^2 = \sum_k d_k^2$
sum square of deviance residuals of grouped data. G^2 gives more reliable p-values than X^2 when some cells have small expected counts (≤ 5).

Binary GLM computation

For logistic regression, Newton's method = Fisher scoring = IRLS.

For IRLS, the t th iteration is

$$X^T W^{(t)} (z^{(t)} - X\beta) = 0$$

where

$$\begin{aligned} z_i^{(t)} &= X_i^T \beta^{(t)} + \left(D_{ii}^{(t)} \right)^{-1} (y_i - \mu_i^{(t)}) \\ &= \log \left(\frac{p_i^{(t)}}{1 - p_i^{(t)}} \right) + \frac{y_i - n_i p_i^{(t)}}{n_i p_i^{(t)} (1 - p_i^{(t)})} \end{aligned}$$

and

$$W_{ii}^{(t)} = V_{ii}^{(t)} = n_i p_i^{(t)} (1 - p_i^{(t)})$$

Infinite parameter estimates in logistic regression

```
-----  
> x <- c(1,2,3,4,5,6); y <- c(1,1,1,0,0,0) # complete separation  
> fit <- glm(y ~ x, family = binomial(link = logit))  
> summary(fit)  
Coefficients:  
            Estimate Std. Error z value Pr(>|z|)  
(Intercept) 165.32    407521.43      0      1 # x estimate is  
x           -47.23    115264.41      0      1 # actually -infinity  
  
Number of Fisher Scoring iterations: 25 # unusually large  
> logLik(fit)  
'log Lik.' -1.107576e-10 (df=2) # maximized log-likelihood = 0  
-----
```

Or sometimes one may see the following warning message:

Warning message: glm.fit: fitted probabilities numerically 0 or 1 occurred

Perfect (complete) separation

There exists β_s such that if

$X_i^T \beta_s > 0$ then $y_i = 1$
otherwise $y_i = 0$.

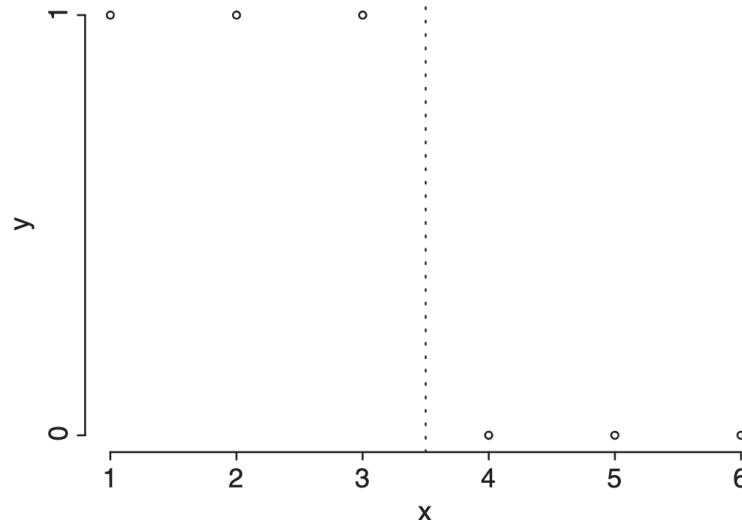


Figure 5.3 Complete separation of explanatory variable values, such as $y = 1$ when $x < 3.5$ and $y = 0$ when $x > 3.5$, causes an infinite ML effect estimate.

We proof that the MLE for β does not exist. Let $\eta_i = kX_i^T \beta_s$.

When $k \rightarrow \infty$, then

$$p_i = \frac{e^{kX_i^T \beta_s}}{1 + e^{kX_i^T \beta_s}} \rightarrow \begin{cases} 1 & \text{if } X_i^T \beta_s > 0, \text{ or equivalently } y_i = 1 \\ 0 & \text{else} \end{cases}$$

Thus, $\frac{\partial L}{\partial \beta} \rightarrow 0$ if $k \rightarrow \infty$ so the solution of the score equation is infinite. In other words, the MLE does not exist.

Quasi-complete separation

There exists β_s such that if

$X_i^T \beta_s > 0$ then $y_i = 1$,

$X_i^T \beta_s < 0$ then $y_i = 0$,

$X_i^T \beta_s = 0$ then $y_i = 0$ or 1

We can also show that the MLE for β does not exist (Albert and Anderson, *Biometrika* 1984). Any value β can be decomposed as $\beta = \beta_s + \gamma$. Denote $\beta_k = k\beta_s + \gamma$. Let $\eta_i = kX_i^T \beta_s + X_i^T \gamma$. When $k \rightarrow \infty$, then

$$p_i = \frac{e^{kX_i^T \beta_s + X_i^T \gamma}}{1 + e^{kX_i^T \beta_s + X_i^T \gamma}} \rightarrow \begin{cases} 1 & \text{if } X_i^T \beta_s > 0 \\ 0 & \text{if } X_i^T \beta_s < 0 \\ \frac{e^{X_i^T \gamma}}{1 + e^{X_i^T \gamma}} & \text{if } X_i^T \beta_s = 0 \end{cases}$$

This tells us that for any β , we can find β_k with large enough k so that the log-likelihood $L(\beta_k) > L(\beta)$, so the log-likelihood function $L(\cdot)$ does not have a finite maximum point. In other words, the MLE does not exist.

R data example for binary / binomial GLM (part II)

- Check Example3_2 R notebook