

106-1 生物統計學二 實習課

R : Logistic Regression

周芷妤

2017.11.02

大綱

- Review
- Logistic Regression
 - Fit logistic model
 - Test the usefulness of model
 - Add mean response to scatter plot

Review

Review

- Linear regression
 - ✓ Homework 3 & 4
 - ✓ Homework 4 (Lab)

Logistic Regression

Fit logistic model

Test the usefulness of model

Add mean response to scatter plot

Fit **g**eneralized **l**inear **m**odel

- Fit **logistic** regression model

model <- **glm**(Y ~ X1 + X2 + ... + Xp , family = binomial , data = 資料檔名稱)

- 告知R現在要建立的是 logistic regression
- 也可打成 **family = binomial(link="logit")**

- 產生model配適結果的總結

summary(model)

Example : Low Birth Weight data

Goal: risk factors associated with low infant birth weight

* 資料檔 : lbw.csv (逗號分隔)

Coding Book	
變項名稱	變項描述
low	1 = birth weight of a baby is under 2500g 0 = birth weight of a baby is over 2500g
smoke	smoking status during pregnancy 1 = yes , 0 = no
race	mother's race 1 = white, 2 = black, 3 = other
age	mother's age in years
lwt	mother's weight in pounds at last menstrual period
ptl	number of previous premature labours
ht	1 = history of hypertension 0 = no hypertension
ui	presence of uterine irritability 1 = yes , 0 = no
ftv	number of physician visits in 1st trimester
bwt	birth weight in grams

Example : Low Birth Weight data

Q : lwt及race是否會影響嬰兒出生體重過輕?

Variables

Y : low

X_1 : lwt

X_2 : race = $\begin{cases} \text{white} \\ \text{black} \\ \text{other} \end{cases}$

Coding book

race	$X_{2(1)}$	$X_{2(2)}$
white	1	0
black	0	1
other	0	0

Reference →

Model 1

$Y|X \sim \text{Ber}(p_X)$

$$p_X = P(Y = 1|X) = E[Y|X]$$

$$\text{logit}(p_X) = \ln\left(\frac{p_X}{1-p_X}\right) = \beta_0 + \beta_1 X_1 + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}$$

$$\Rightarrow p_X = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}}$$

Meaning of β_1

$$\ln\left(\frac{p_X}{1-p_X}\right) = \beta_0 + \beta_1 X_1 + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}$$

$$\Rightarrow \frac{p_X}{1-p_X} = \frac{P(Y=1|\mathbf{X}_1, X_{2(1)}, X_{2(2)})}{1-P(Y=1|\mathbf{X}_1, X_{2(1)}, X_{2(2)})} = e^{\beta_0 + \beta_1 \mathbf{X}_1 + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}$$

While controlling $X_{2(1)}$ & $X_{2(2)}$,

$$\text{➤ } X_1 = x + 1 \Rightarrow \frac{P(Y=1|\mathbf{X}_1=x+1, X_{2(1)}, X_{2(2)})}{1-P(Y=1|\mathbf{X}_1=x+1, X_{2(1)}, X_{2(2)})} = e^{\beta_0 + \beta_1 (x+1) + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}$$

$$\text{➤ } X_1 = x \Rightarrow \frac{P(Y=1|\mathbf{X}_1=x, X_{2(1)}, X_{2(2)})}{1-P(Y=1|\mathbf{X}_1=x, X_{2(1)}, X_{2(2)})} = e^{\beta_0 + \beta_1 (x) + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}$$

$$\Rightarrow \text{Odds Ratio (OR) of } X_1 = \frac{e^{\beta_0 + \beta_1 (x+1) + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}}{e^{\beta_0 + \beta_1 (x) + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}} = e^{\beta_1}$$

同一種族的人(調整種族的影響後)，
lwt 每增加一單位，導致嬰兒出生體重過輕的OR增加 e^{β_1} 倍

Example : Low Birth Weight data

```
> # 將race轉成dummy variable
> data.lbw$race.w <- ifelse(data.lbw$race=="1", 1, 0)
> data.lbw$race.b <- ifelse(data.lbw$race=="2", 1, 0)

> model.1 <- glm(low ~ lwt + race.w + race.b, family = binomial, data = data.lbw)
> summary(model.1)
```

```
Call:
glm(formula = low ~ lwt + race.w + race.b, family = binomial,
    data = data.lbw)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.3486	-0.8917	-0.7197	1.2527	2.0987

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	1.283996	0.796553	1.612	0.1070
lwt	-0.015201	0.006438	-2.361	0.0182 *
race.w	-0.481036	0.356646	-1.349	0.1774
race.b	0.599683	0.508863	1.178	0.2386

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 234.67 on 188 degrees of freedom
Residual deviance: 223.28 on 185 degrees of freedom
AIC: 231.28

Number of Fisher Scoring iterations: 4

在相同種族下(調整種族的影響後)，
lwt 每增加一單位，導致嬰兒出生體重過輕
的危險性(OR)多 $e^{-0.015201} = 0.9849141$ 倍

$$H_0: \beta_1 = 0 \quad \text{vs.} \quad H_1: \beta_1 \neq 0$$
$$Z = \frac{-0.015201}{0.006438} = -2.361$$
$$p\text{-value} = 0.0182 < \alpha = 0.05$$

Example : Low Birth Weight data

- Test the usefulness of logistic model

$$H_0 : \beta_1 = \beta_{2(1)} = \beta_{2(2)} = 0 \quad \text{vs.} \quad H_1 : \text{at least one } \beta_j \neq 0, \quad j = 1, 2(1), 2(2)$$

建立只有截距項的logistic model

```
> model.0 <- glm(low ~ 1, family = binomial, data = data.lbw)
```

```
> anova(model.0, model.1, test="Chisq")
```

Analysis of Deviance Table

Model 1: low ~ 1

Model 2: low ~ lwt + race.w + race.b

	Resid. Df	Resid. Dev	Df	Deviance	Pr(>Chi)
--	-----------	------------	----	----------	----------

1	188	234.67			
---	-----	--------	--	--	--

2	185	223.28	3	11.395	0.00977 **
---	-----	--------	---	--------	------------

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

p-value = 0.00977 < $\alpha = 0.05$

Plot **curve**

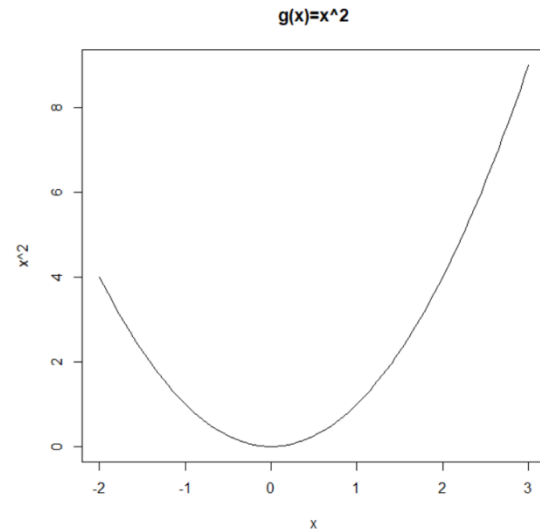
- 繪製曲線

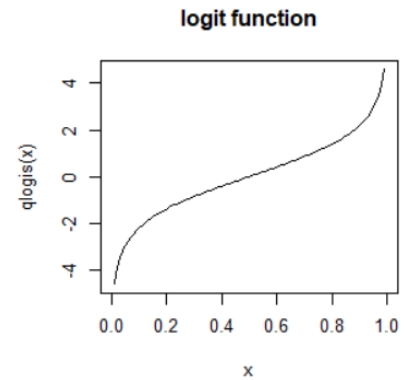
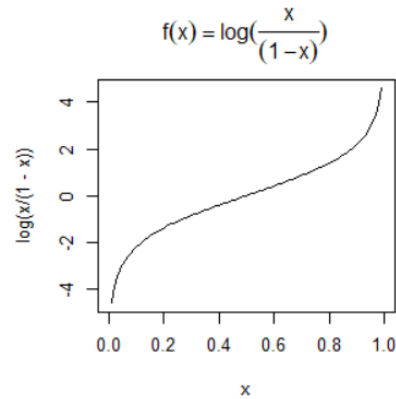
curve(函數名稱 or 表達式, from = a, to = b, add = F)

- R內建函數的自變數預設為x
- **from = a** , **to = b** → 以x=a到x=b 繪製函數
- **add = F** → 不在上一張圖加上曲線 (預設為FALSE)

➤ e.g. 繪製 $g(x) = x^2$, $-2 \leq x \leq 3$

curve(x^2 , -2, 3, main = "g(x)=x^2")

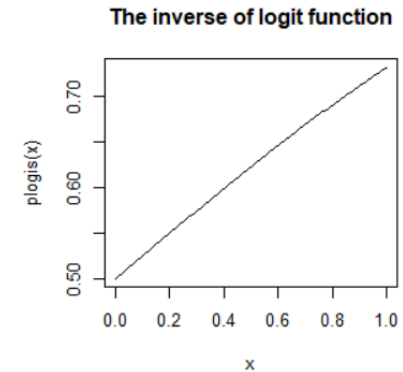
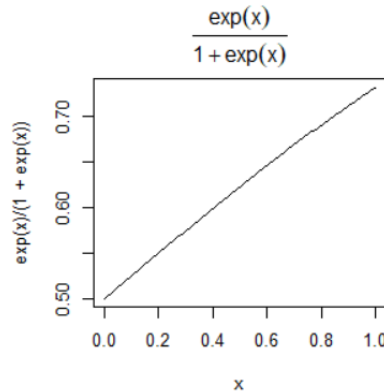




➤ e.g. 繪製 $f(x) = \text{logit}(x) = \ln\left(\frac{x}{1-x}\right)$

`curve(log(x/(1-x)), main = expression(f(x)==log(frac(x, (1-x)))))`

`curve(qlogis(x), main = "logit function")`



➤ e.g. 繪製 $\text{logit}^{-1}(x) = \left(\frac{e^x}{1+e^x}\right)$

`curve(exp(x)/(1+exp(x)), main = expression(frac(exp(x),1+exp(x))))`

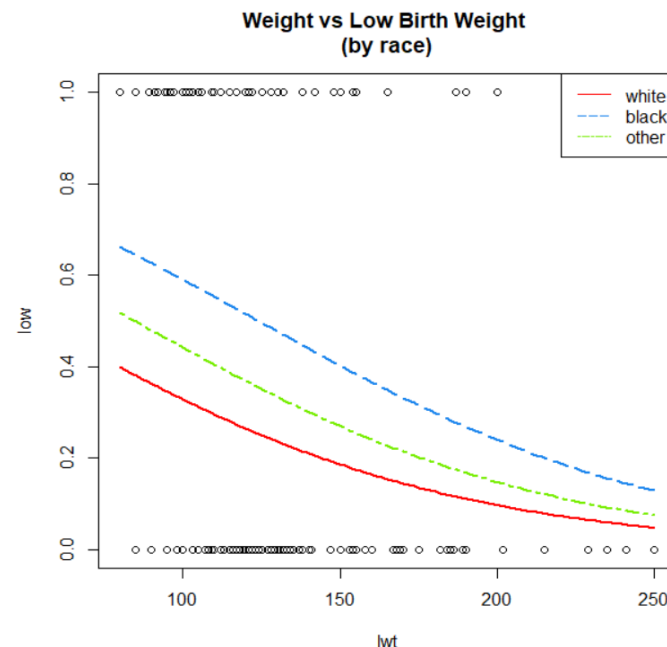
`curve(plogis(x), main = "The inverse of logit function")`

Add mean response to scatter plot

Method 1

利用 **predict** 計算 mean response

$$E[Y|X_1, X_{2(1)}, X_{2(2)}] = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_{2(1)} X_{2(1)} + \beta_{2(2)} X_{2(2)}}}$$



```
> attach(data.lbw)
> plot(lwt, low, main="Weight vs Low Birth Weight \n(by race)")
> # 加上race各類別的 mean response
> curve(predict(model.1, data.frame(lwt=x, race.w=1, race.b=0), type="response"),
+       add = T, col="red", lty=1, lwd=2)
> curve(predict(model.1, data.frame(lwt=x, race.w=0, race.b=1), type="response"),
+       add = T, col="dodgerblue2", lty=5, lwd=2)
> curve(predict(model.1, data.frame(lwt=x, race.w=0, race.b=0), type="response"),
+       add = T, col="chartreuse2", lty=6, lwd=2)
>
> legend("topright", c("white", "black", "other"),
+       col=c("red", "dodgerblue2", "chartreuse2"), lty=c(1, 5, 6))
```

用哪些變項來預測

要預測的類型為
predicted probabilities

Add mean response to scatter plot

Method 2

利用 **plogis** 計算 mean response

For race = white,

$$E[Y|X_1, X_{2(1)} = 1, X_{2(2)} = 0] = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_{2(1)}}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_{2(1)}}}$$

$$\Rightarrow \hat{E}[Y|X_1, X_{2(1)} = 1, X_{2(2)} = 0] = \frac{e^{\hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_{2(1)}}}{1 + e^{\hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_{2(1)}}}$$

```
> model.1$coefficients
(Intercept)      lwt      race.w      race.b
 1.28399570 -0.01520088 -0.48103631  0.59968312
```

```
> # 定義變項
```

```
> b0 <- model.1$coefficients[1]
```

```
> b1 <- model.1$coefficients[2]
```

```
> b21 <- model.1$coefficients[3]
```

```
> b22 <- model.1$coefficients[4]
```

```
>
```

```
> plot(lwt, low, main="Weight vs Low Birth Weight \n(by race)")
```

```
> curve(plogis( b0 + b21 + b1*x), add = T, col="red", lty=1, lwd=2)
```

```
> curve(plogis( b0 + b22 + b1*x), add = T, col="dodgerblue2", lty=5, lwd=2)
```

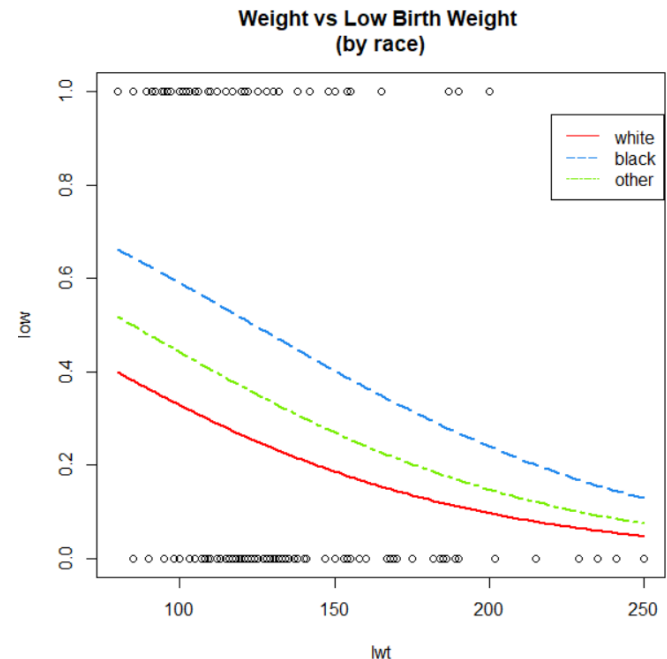
```
> curve(plogis( b0 + b1*x), add = T, col="chartreuse2", lty=6, lwd=2)
```

```
>
```

```
> legend(220, 0.95, c("white", "black", "other"),
```

```
+      col=c("red", "dodgerblue2", "chartreuse2"), lty=c(1, 5, 6))
```

R內建函數的自變數預設為x



課堂練習

- **Model 2**：在**不同種族**間懷孕前末次經期的體重(lwt)對於嬰兒出生體重過輕(low)的風險可能不同
 - 請寫下建立的Model 2 (請將符號定義清楚)
 - 請執行 logistic regression，並解釋說明在不同種族之間 lwt 對 low 的影響 (如: 對於白人而言，lwt 每增加一單位...)
 - Model 2有用嗎？
 - 請在scatter plot上畫出不同種族之間 lwt 對 low 的 mean response，並加上legend作說明