# Logistic Regression for Y with more than 2 Categories

**Logistic Regression** 

Based on Chew C. H. (2020) textbook: AI, Analytics and Data Science. Vol 1., Chap 7.

## Y has 3 or More Possible Categories

- A/B/C/D/E
- Pass/Fail/Inconclusive
- 0/1/2
- Ang Mo Kio, Bedok, Clementi, ....
- Etc...

#### The baseline Reference Level for Y

- Y = 0 serves as the baseline.
- Dummy Variable Concept for Categorical X applies to Y too.



- Even if Y = A, B, C, [i.e. not 0, 1, 2], we can reduce mental effort by mapping Y = 0 to be the actual baseline reference level e.g. Y = A.
- Thus, all the formulas can still apply without any change to notation.
- i.e. it does not matter whether one label categorical Y as A, B, C, D or 0, 1, 2, 3. They are just labels for different categories of Y.

## Logistic Regression Model for Binary Y

$$Y = 0 \text{ or } 1$$

$$Z = b_0 + b_1 X_1 + b_2 X_2 + ... + b_m X_m$$

$$P(Y = 1) = \frac{1}{1+e^{-z}} = \frac{e^{z}}{1+e^{z}}$$

Easier to extend to multicategory Y

#### Two Outcomes Y vs Three Outcomes Y

$$Y = 0 \text{ or } 1$$

$$z = b_0 + b_1 X_1 + b_2 X_2 + \dots + b_m X_m$$

$$P(Y = 1) = \frac{1}{1 + e^{-z}} = \frac{e^{z}}{1 + e^{z}}$$

Denominator to include all Zs.

$$P(Y = 0) = 1 - P(Y = 1)$$

$$Y = 0, 1 \text{ or } 2$$

$$z_1 = b_{1,0} + b_{1,1}X_1 + b_{1,2}X_2 + \dots + b_{1,m}X_m$$

$$z_2 = b_{2,0} + b_{2,1}X_1 + b_{2,2}X_2 + \dots + b_{2,m}X_m$$

$$P(Y=1) = \frac{e^{\mathbf{Z_1}}}{1 + e^{\mathbf{Z_1}} + e^{\mathbf{Z_2}}}$$

$$P(Y=2) = \frac{e^{\mathbf{Z}_2}}{1 + e^{\mathbf{Z}_1} + e^{\mathbf{Z}_2}}$$

$$P(Y = 0) = 1 - P(Y = 1) - P(Y = 2)$$

#### Two Outcomes Y vs Three Outcomes Y

$$Y = 0 \text{ or } 1$$

$$z = b_0 + b_1 X_1 + b_2 X_2 + \dots + b_m X_m$$

$$Odds(Y = 1) \equiv \frac{P(Y = 1)}{1 - P(Y = 1)} \equiv \frac{P(Y = 1)}{P(Y = 0)} = e^{z}$$

$$Y = 0, 1 \text{ or } 2$$

$$z_1 = b_{1,0} + b_{1,1}X_1 + b_{1,2}X_2 + \dots + b_{1,m}X_m$$

$$z_2 = b_{2,0} + b_{2,1}X_1 + b_{2,2}X_2 + \dots + b_{2,m}X_m$$

$$Odds(Y = 1) \equiv \frac{P(Y = 1)}{P(Y = 0)} = e^{Z_1}$$

$$Odds(Y = 2) \equiv \frac{P(Y = 2)}{P(Y = 0)} = e^{Z_2}$$

Y = 0 or 1	Y = 0, 1, or 2	Y = 0, 1, 2, or 3	Y = 0, 1, 2,, k – 1
Y has 2 categories	Y has 3 categories	Y has 4 categories	Y has k categories

Y = 0 or 1	Y = 0, 1, or 2	Y = 0, 1, 2, or 3	Y = 0, 1, 2,, k – 1
Y has 2 categories	Y has 3 categories	Y has 4 categories	Y has k categories
1 linear equation z	2 linear equations $z_1$ and $z_2$ .	3 linear equations $z_1$ , $z_2$ and $z_3$ .	$k-1$ linear equations $z_1$ , $z_2$ and $z_{k-1}$ .

Y = 0 or 1	Y = 0, 1, or 2	Y = 0, 1, 2, or 3	Y = 0, 1, 2,, k – 1
Y has 2 categories	Y has 3 categories	Y has 4 categories	Y has k categories
1 linear equation z	2 linear equations $z_1$ and $z_2$ .	3 linear equations $z_1$ , $z_2$ and $z_3$ .	$k-1$ linear equations $z_1$ , $z_2$ and $z_{k-1}$ .
1 Odds e <sup>z</sup>	2 Odds e <sup>z1</sup> and e <sup>z2</sup>	3 Odds e <sup>z1</sup> , e <sup>z2</sup> and e <sup>z3</sup>	$k-1$ Odds $e^{z1}$ , $e^{z2}$ and $e^{z\_k-1}$

Y = 0 or 1	Y = 0, 1, or 2	Y = 0, 1, 2, or 3	Y = 0, 1, 2,, k – 1
Y has 2 categories	Y has 3 categories	Y has 4 categories	Y has k categories
1 linear equation z	2 linear equations $z_1$ and $z_2$ .	3 linear equations $z_1$ , $z_2$ and $z_3$ .	$k-1$ linear equations $z_1$ , $z_2$ and $z_{k-1}$ .
1 Odds e <sup>z</sup>	2 Odds e <sup>z1</sup> and e <sup>z2</sup>	3 Odds e <sup>z1</sup> , e <sup>z2</sup> and e <sup>z3</sup>	$k-1$ Odds $e^{z1}$ , $e^{z2}$ and $e^{z\_k-1}$
2 probabilities	3 probabilities	4 probabilities	k probabilities

### Computing Exercise in Ex 7.1

- Dataset: ratings.csv
- Y is Service Rating:
  - Bad
  - Neutral
  - Good
- Try to complete this exercise before class.

### Summary

#### Logistic Regression:

- Predicting categorical Y
- From linear equation that combines all Xs to Probability of Y, via logistic function.
- From probability of Y to model predicted category of Y, via threshold.
- From predicted categories to Confusion Matrix, by comparing model predicted categories vs actual categories of Y.
- Binary Y vs Multi-categorical Y.
- Main weakness of Logistic Regression Perfect Separation.
  - As number of X increases, risk of perfect separation increases.
  - Do Ex 7.1.

#### Odds Ratio:

- Interpretation of each model coefficients.
- Identify and Quantify Risk Factors.
  - Freitas et. al. (2012) Factors influencing hospital high length of stay outliers, BMC Health Services Research vol 12:265.