

# Binary Classification & Logistic Regression

## 2304PTDS

December 2023

1 / Objectives

2 / Binary Classification

3 / Logistic Regression

4 / To the code!

# Objectives

By the end of this session you should be able to:

- Understand binary classification
- Understand the basics of Logistic Regression as a classifier
- Distinguish between linear regression and logistic regression



1 / **Objectives**

2 / **Binary Classification**

3 / **Logistic Regression**

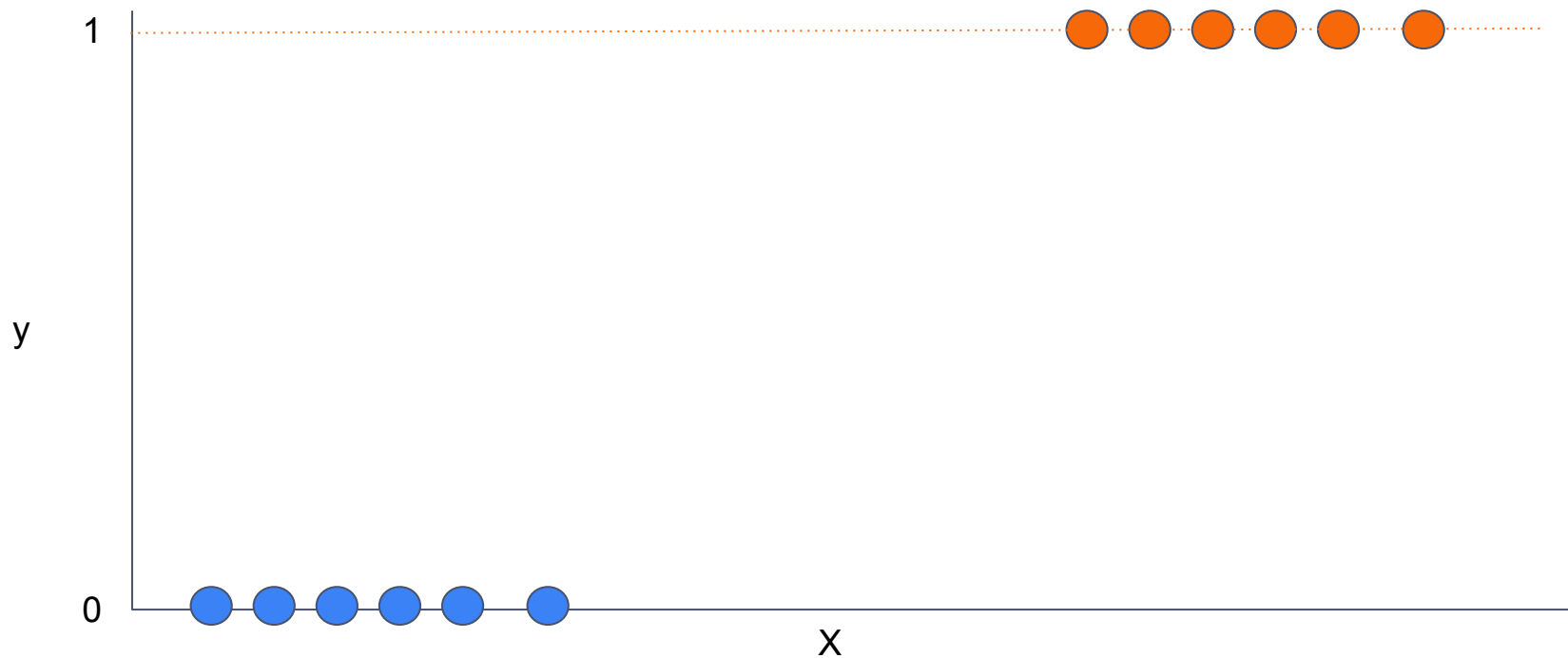
4 / **To the code!**

# What is Binary Classification?

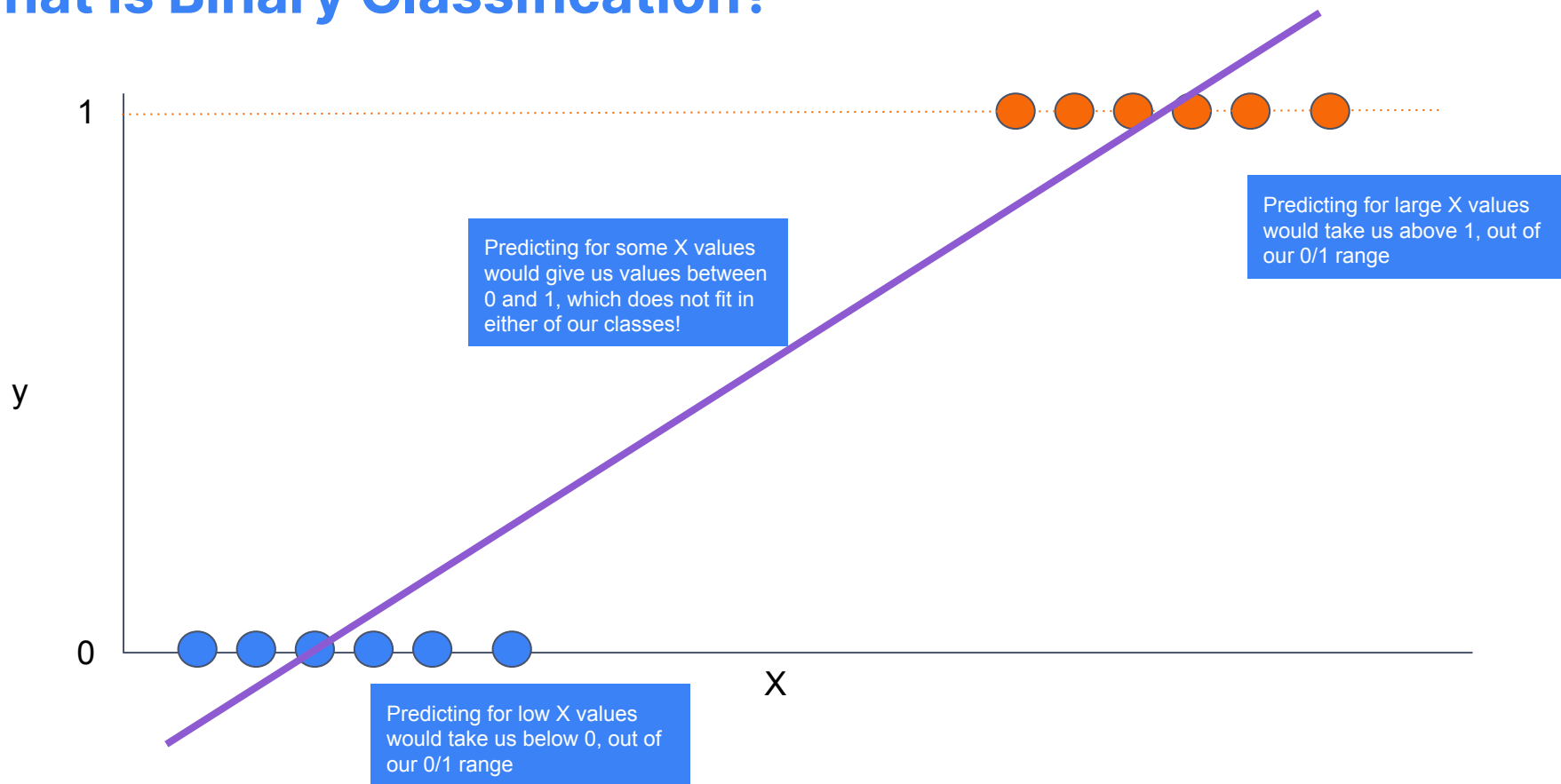
- Classification = when we are working with and trying to predict for categorical target
- Very simply put: classifying data into one of two categories
  - Yes/No,
  - Fraud/Not Fraud,
  - Spam/Not Spam,
  - True/False...
- Usually converted to 1s and 0s for use with machine learning models
- **But what happens when we plot them?**

X	y	y_encoded
23.4	Yes	1
45.3	No	0
56.4	No	0
12.3	No	0
43.5	Yes	1
18.6	Yes	1
24.6	No	0
33.7	No	0
26.1	Yes	1
48.9	No	0
23.4	No	0

# What is Binary Classification?



# What is Binary Classification?



1 / **Objectives**

2 / **Binary Classification**

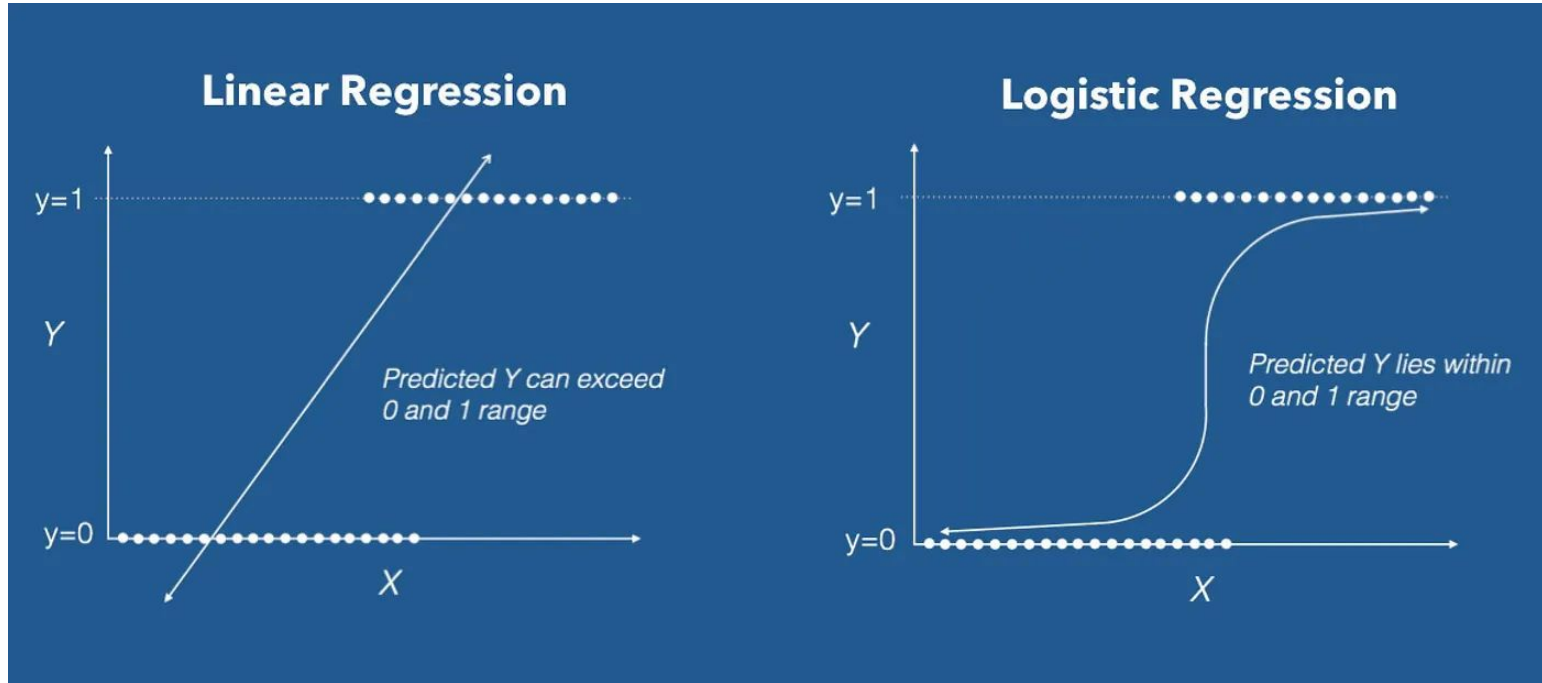
3 / **Logistic Regression**

4 / **To the code!**



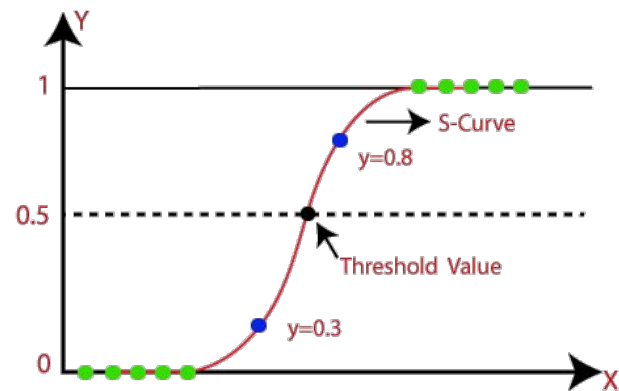
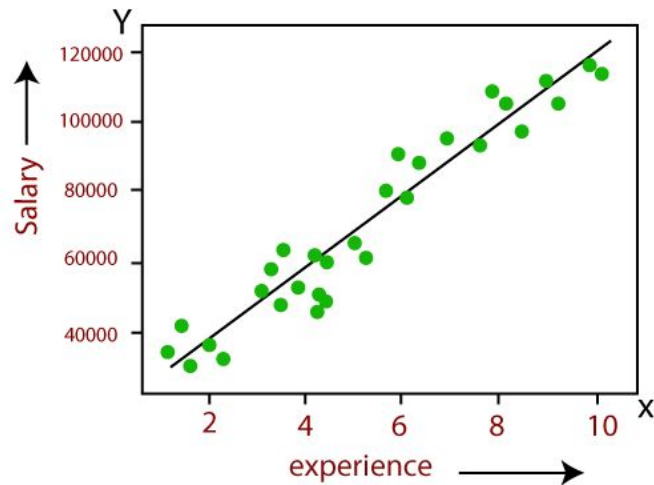
# What is Logistic Regression?

- The answer to our problems (for now)!



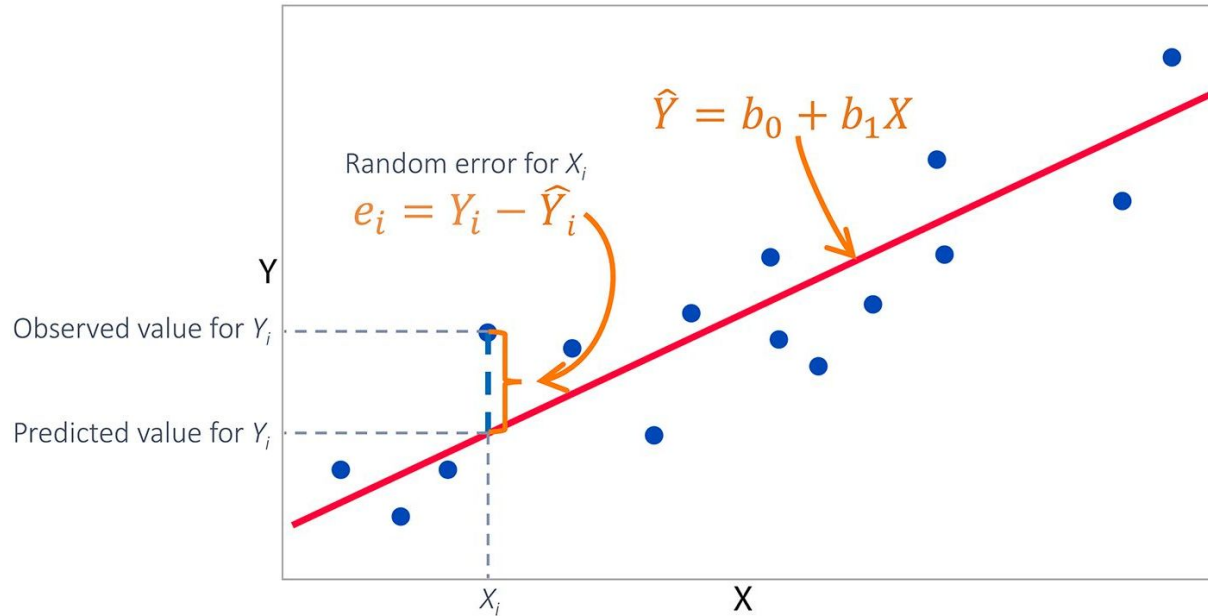
# What is Logistic Regression?

- Uses a sigmoid curve to squeeze the output values between 0 and 1 (S-shaped curve)
- Why is it still called regression though?
  - Technically, we are still doing a linear regression, we're just squeezing it between 0 and 1
  - Linear regression gives a continuous value of Y as the output
  - Logistic regression gives a continuous value of  $P(Y=1)$  as the output



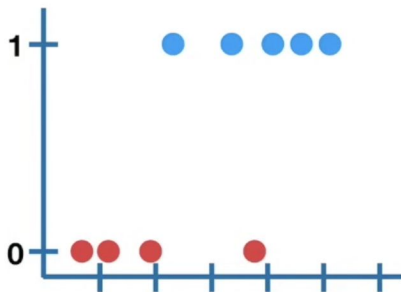
# Line of Best Fit

- A throwback to **residuals** from Regression and finding the **line of best fit**...
- We used residuals and **least squares** to fit this line!

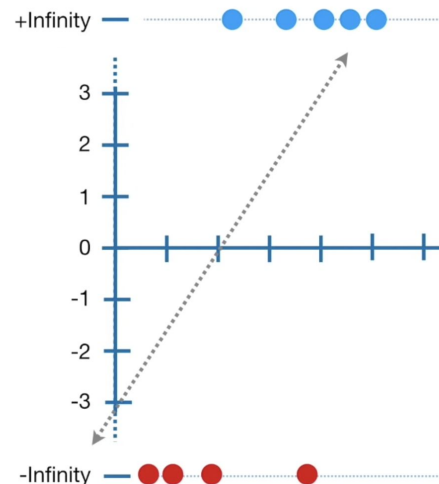


# Maximum Likelihood Estimation

- But how do we find the curve that fits the best for Logistic Regression?
- **Maximum Likelihood Estimation**
  - Parameters are chosen to maximize the likelihood that the assumed model results in the observed data.
- Data is mapped onto a set of axes using the log(odds) on the y-axis



$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right)$$

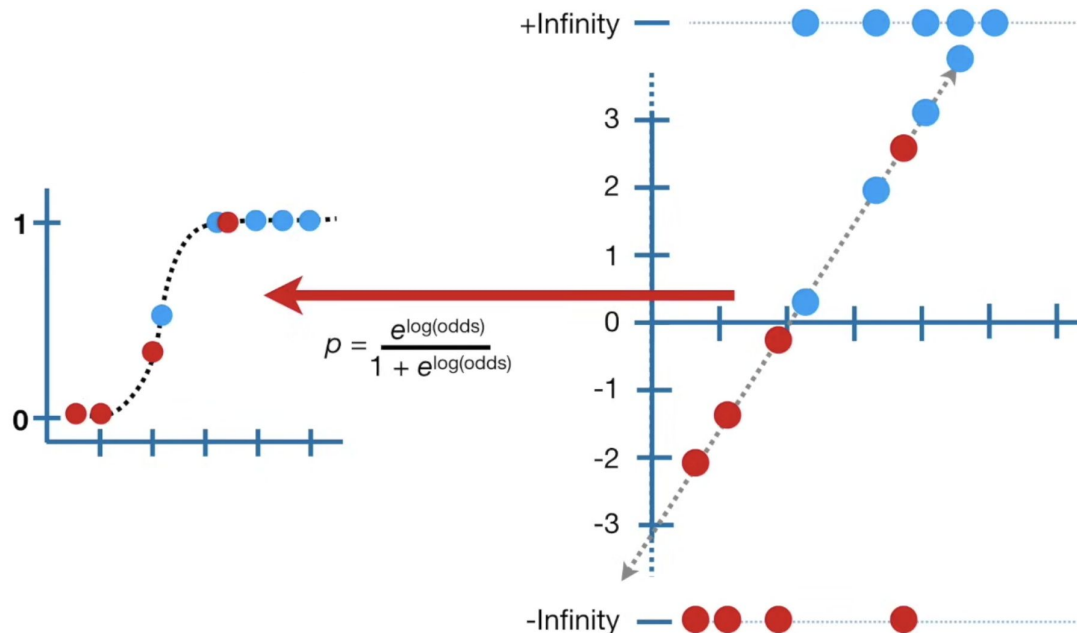


# Maximum Likelihood Estimation

- Each point is mapped onto this line
- We use an equation to map each point back to the original graph based on its log(odds)

Likelihoods of all of these plotted points are then calculated and multiplied together

We keep changing the straight line on the log(odds) graph and repeating the process to get the line with the Maximum Likelihood Estimation (i.e. the largest likelihood from the above calculation)



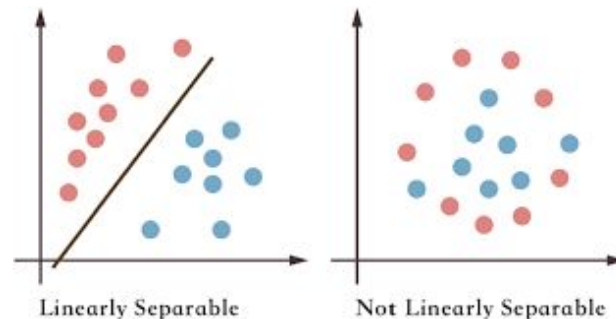
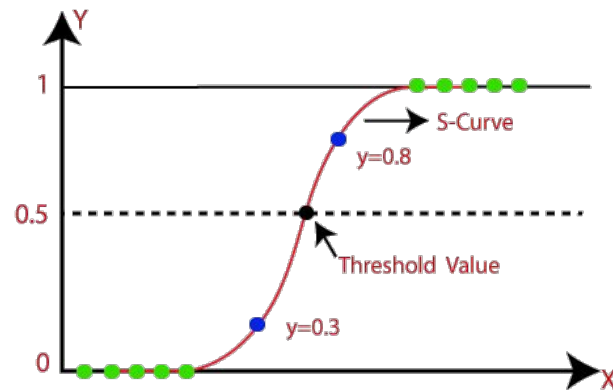
# Logistic Regression

## Advantages

- Convenient probability scores for observations
- Collinearity is not as bad as it is for linear regression

## Disadvantages

- Can overfit when data is unbalanced (when we have far more observations in one class than the other)
- Doesn't handle large number of categorical variables well.
- Does not work well with **non-linearly separable data**



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# Questions?

