



**Data Science
Bootcamp**

Hyperiondev

Logistic Regression & Model Evaluation

Welcome

Your Lecturer for this session



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Lecture – Housekeeping

- ❑ The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly.
- ❑ No question is daft or silly - **ask them!**
- ❑ There are Q/A sessions midway and at the end of the session, should you wish to ask any follow-up questions.
- ❑ You can also submit questions here:
hyperiondev.com/sbc4-ds-questions
- ❑ For all non-academic questions, please submit a query:
hyperiondev.com/support
- ❑ Report a safeguarding incident:
hyperiondev.com/safeguardreporting
- ❑ We would love your feedback on lectures:
<https://hyperiondev.wufoo.com/forms/zsgv4m40ui4i0g/>

Lecture – Code Repo

Go to: github.com/HyperionDevBootcamps

Then click on the “**C4_DS_lecture_examples**” repository, do view or download the code.

Objectives

- Understanding error
- Evaluating our models
- Learn about what Logistic regression is

Regression Model

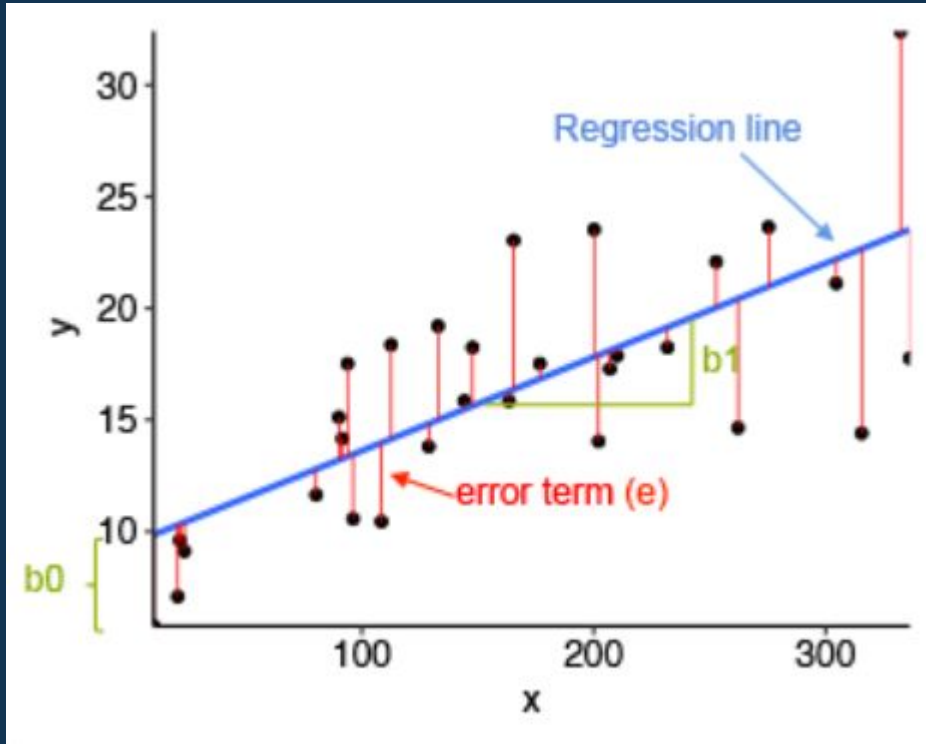
$$Y = \text{Sales} = 2.939 + 0.046 \text{ TV} + 0.189 \text{ Radio} + (-0.001) \text{ Billboard}$$

- ★ This is an approximate model i.e., $Y \approx \beta_0 + \beta_1 X_i$
So really what we obtain is the approximate number of Sales

$$\begin{aligned} \text{Sales} &\approx 2.939 + 0.046 \text{ TV} + 0.189 \text{ Radio} + (-0.001) \text{ Billboard} \\ \text{or} \quad \hat{Y} &= 2.939 + 0.046 \text{ TV} + 0.189 \text{ Radio} + (-0.001) \text{ Billboard} \end{aligned}$$

- ★ A minimised difference is still a difference: after linear regression, there is still some difference between observed values for Y , and values for Y predicted by f . If your data, when plotted, does not seem to fall along a straight line, linear regression is not the right model for the problem. But even if it does, the straight line is only a model of the data, hence the use of the symbol “ \approx ”.

Regression Model



✓ $\hat{y} = mx + b$

✓ $y = mx + b + \text{error}$

error = actual - predicted
 $\text{error} = y - (mx + b)$
 $y = mx + b + \text{error}$

How we make predictions

- ★ Run your regression in Python

SIMPLE LINEAR REGRESSION: $\text{Sales} = \beta_0 + \beta_1 \text{TV Budget}$

```
[0.04753664]  
7.032593549127695
```

$$\hat{Y} = 7.0326 + 0.0475 \text{ TV Budget} = 7.0326 + 0.0475(100) = 11.783$$

Or use:

```
reg.predict(np.array([[100]]))
```

To get the same result.

How we make predictions

- ★ Run your regression in Python

MULTIPLE LINEAR REGRESSION:

```
Coefficients: [ 0.04576465  0.18853002 -0.00103749]  
Intercept:  2.9388893694594085
```

$$\hat{Y} = 2.939 + 0.046 \text{ TV} + 0.189 \text{ Radio} + (-0.001) \text{ Billboard}$$

$$\hat{Y} = 2.939 + 0.046(100) = 7.539 \text{ which is 7539 units}$$

Or use the following to get the same result:

```
reg.predict(np.array([[100,0,0]]))
```

Evaluating our models

- ★ We need to split our dataset into training and testing data
- ★ We can interpret a useful statistical measure called R-squared

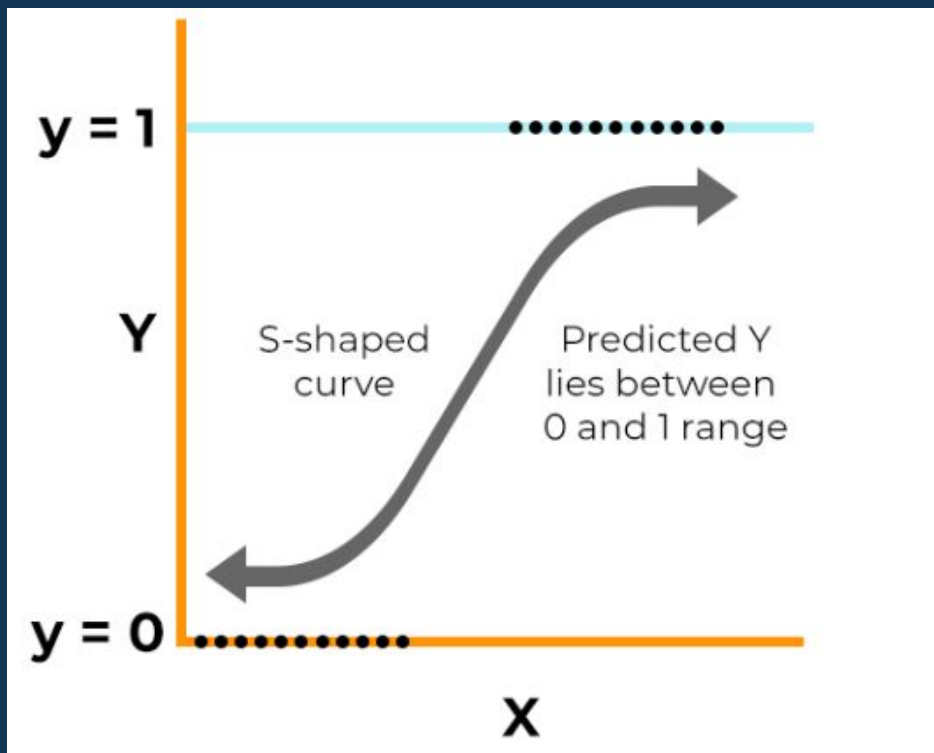
Classification Problems

- ★ When linear regression models were discussed previously, we assumed that our dependent variables **Y** is a **continuous numerical variable**. However it very common in machine learning problems instead to be dealing with **categorical variables**. These variables take on distinct non-continuous values which will correspond to a specific set of categories.
- ★ Predicting categorical variables is called **classification**. Classification problems are very common, perhaps even more so than for problems suited for regression.

Logistic Regression

- ★ One approach to classification is logistic regression, which is a common way to do binary logistic regression, which is classifying into two categories. It works by using the logistic function, also known as the sigmoid function. This is an S-shaped curve that maps input values to x output values y .
- ★ Logistic regression is similar to linear regression, however the output is not continuous along a line, but a value between 0 and 1.
- ★ That value can then be interpreted as the probability of that the instance belongs to a certain category.

Logistic Regression

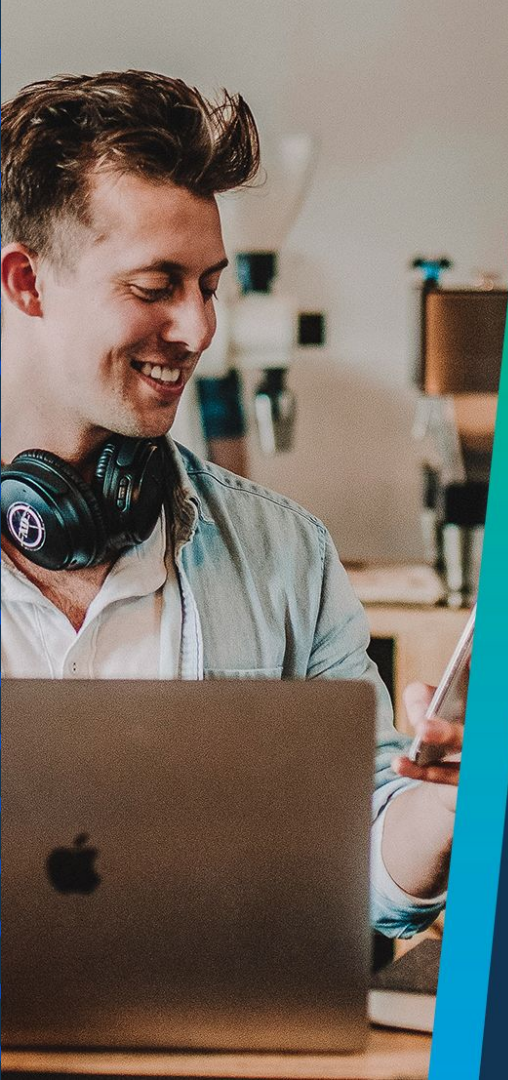


$$P = \frac{e^{a+bX}}{1 + e^{a+bX}}$$

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Q & A Section

Please use this time to ask any questions relating to the topic explained, should you have any



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**Thank you
for joining us**