Intro to classification - Logistic regression - 1

One should look for what is and not what he thinks should be. (Albert Einstein)

Logistic regression: Topic introduction

In this part of the course, we will cover the following concepts:

- Logistic regression use cases and theory behind it
- Data transformation necessary for logistic regression
- Implementation of logistic regression on a dataset
- Model performance evaluation and tuning

Quick Activity

- Suppose we want to predict whether a person will purchase a certain car or not
  - What numerical data might be relevant for making this prediction?
  - What additional qualitative or categorical data might be relevant?
  - How might you handle variables like marital status, education level, or gender?

Module completion checklist

Objectives	Complete
Determine when to use logistic regression for classification and transformation of target variable	
Summarize the process and the math behind logistic regression	

Logistic regression

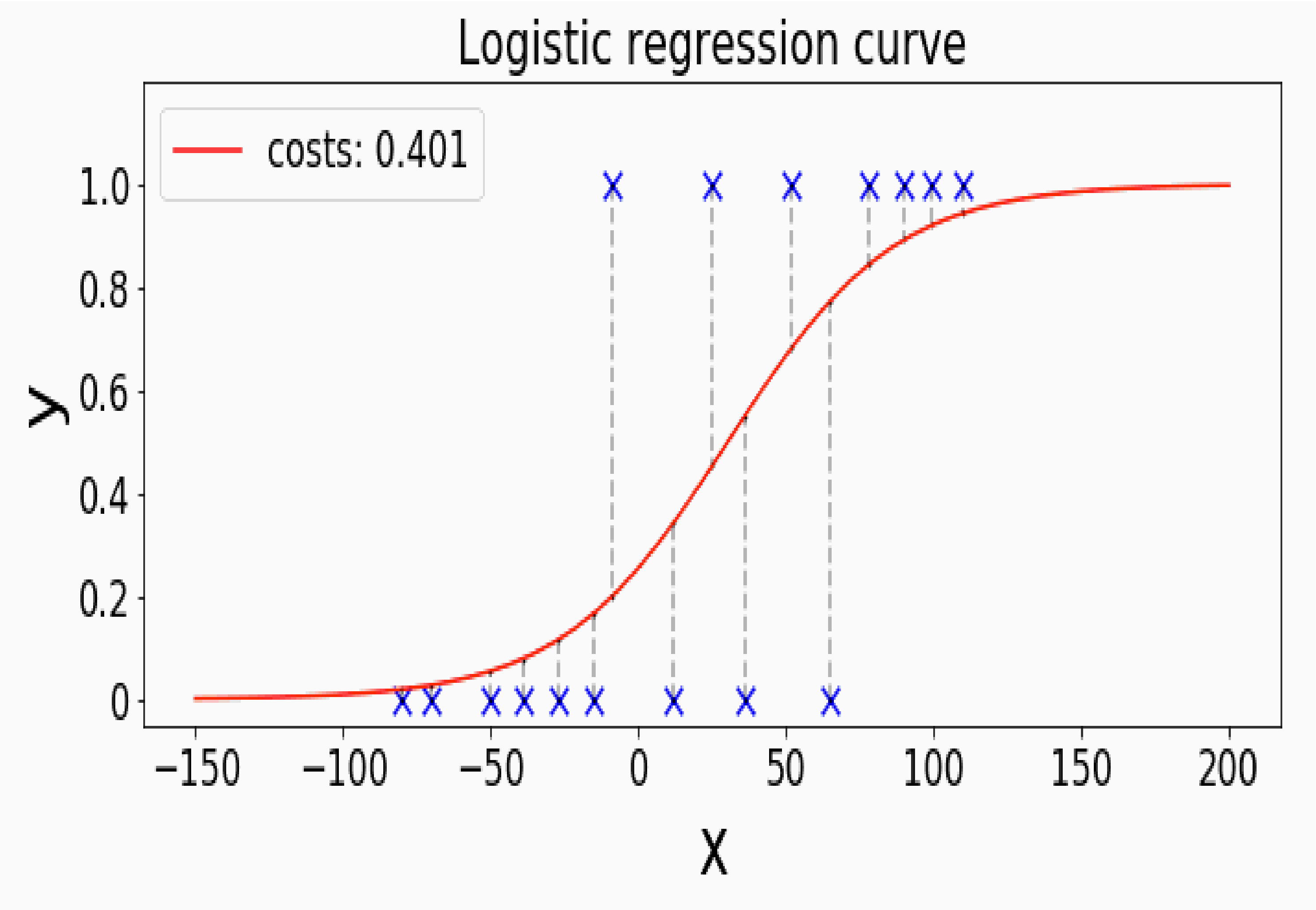
- **Logistic regression** is a **supervised** machine learning method used for classification
- The **target** or **dependent** variable is **binary**
  - Yes or no
  - This or that
  - 1 or 0
- The outputs are numerical **probabilities** that different observations will be in the desired class ($y = 1$), rather than category labels

What logistic regression looks like

- The “logistic” in logistic regression comes from the `logit` function (*a.k.a. sigmoid function*)
- The model solves for coefficients to create a curve maximizing the likelihood of correct classification

What logistic regression looks like (cont'd)

- The model's performance can be changed by adjusting the **cut-off probability** where the curve bends, with no need to re-run the model with new parameters
- Note that we convert the target variable to binary values or either 0 or 1 depending on this cut-off or **threshold**



Source

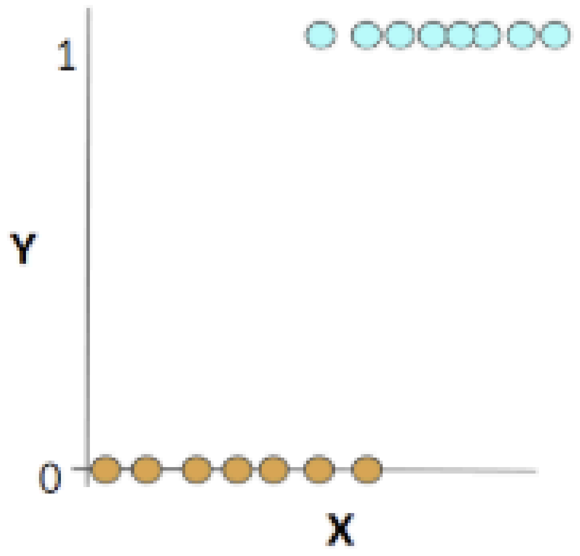
Logistic regression: process

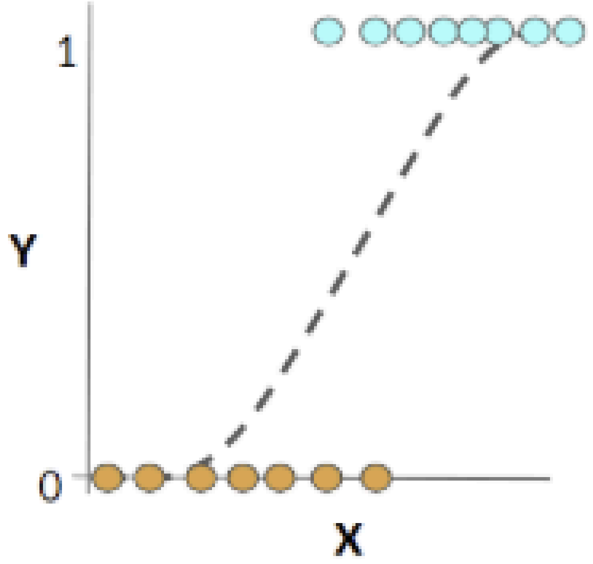
Step 1:
Convert target variable to 1/0

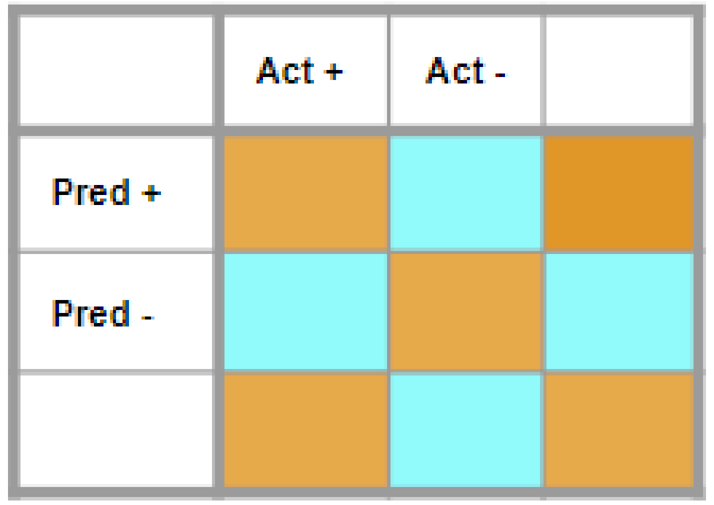
Step 2:
Logistic regression on training data

Step 3:
Use ROC curve & AUC to pick threshold

Step 4:
Check performance on test data

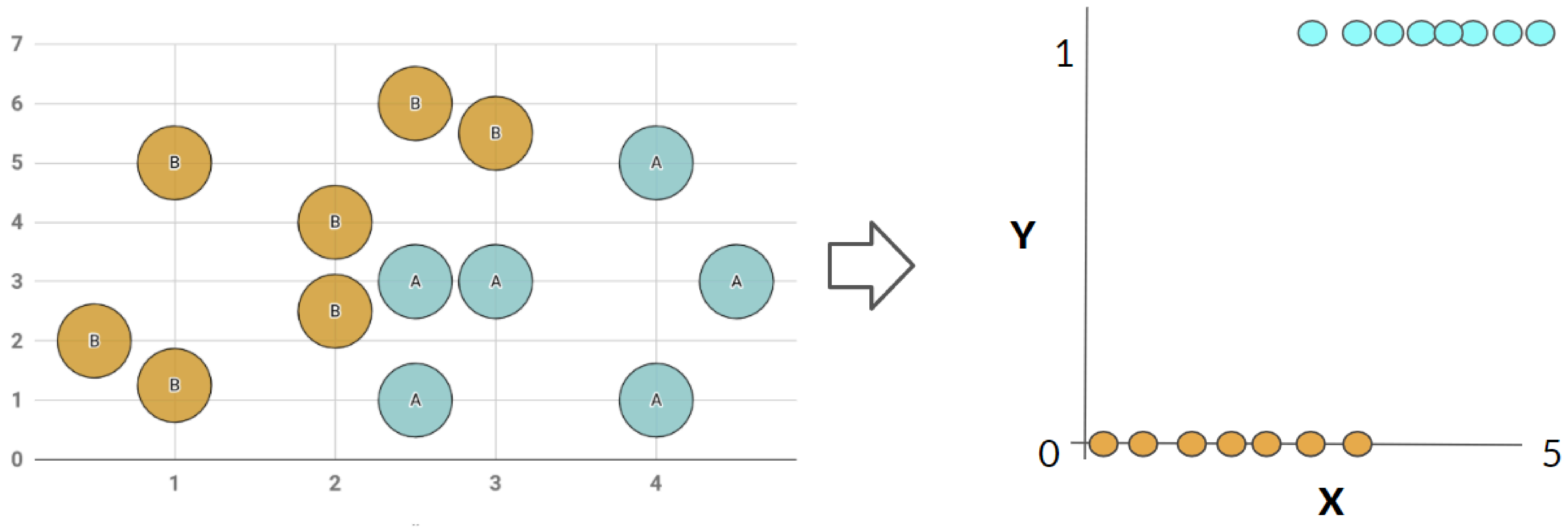






Converting categorical to binary variable

- There are two main ways to prepare the target variable:
  - **First method:** translate an existing binary variable (i.e., any categorical variable with 2 classes) into 1 and `0`



Converting continuous to binary variable

- **Second method:** convert a continuous numeric variable into a binary one
  - We can do this by using a **threshold** and labeling observations that are higher than that threshold as `1` and `0` otherwise
  - If the median for the example below was `100`, then any point below the median is coded as `0`, and any point above is `1`

Charge
193.89
0
39.99
201.65
117.9
200.88
79.99

Charge
1
0
0
1
1
1
0

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Determine when to use logistic regression for classification and transformation of target variable	✔
Summarize the process and the math behind logistic regression	

Linear vs. logistic regression

Linear regression line

- For data points $x_1, \ldots, x_n$, we have $y = 0$ or $y = 1$
- The function that “fits” the points is a simple line $\hat{y} = ax + b$

Logistic regression curve

- For the same data points $x_1, \ldots, x_n$, $y = 0$ or $y = 1$
- The function that “fits” the data points is a sigmoid $p(y = 1) = \frac{exp(ax+b)}{1+exp(ax+b)}$

Logistic regression: function

- For every value of x, we find p (i.e., probability of success) or probability that $y = 1$
- To solve for p, logistic regression uses an expression called a **sigmoid function:**

$$p = \frac{exp(ax + b)}{1 + exp(ax + b)}$$

- Although it may look a little scary, we can see a very familiar equation inside of the parentheses: $ax + b$
- This is virtually identical to $y = mx + b$

Logistic regression: the odds ratio

- Through some algebraic transformations that are beyond the scope of this course, we can change this equation...

$$p = \frac{exp(ax + b)}{1 + exp(ax + b)}$$

- into a logarithmic expression

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

- Since p is the **probability of success**, 1 − p is the **probability of failure**
- The ratio $\left(\frac{p}{1-p}\right)$ is called the **odds** ratio - it tells us the **odds** of having a successful outcome with respect to the opposite
- Knowing this provides useful insight into interpreting the resulting **coefficients**

Logistic regression: coefficients

- In **linear** regression, the coefficients in the equation can easily be interpreted

$$ax + b$$

- An increase in x will result in an increase in y and vice versa
- However, in **logistic** regression, the simplest way to interpret a positive coefficient is with an increase in **likelihood**
- A larger value of x increases the likelihood that $y = 1$

Knowledge check

Link: ***https://forms.gle/NucjSoLP9z4RDwiDA***

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Congratulations on completing this module!