Logistic Regression

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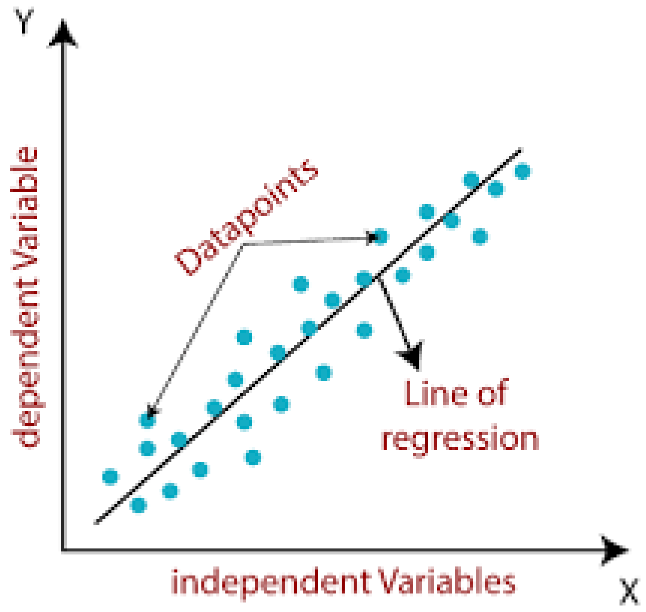
Linear Regression

- Linear regression is a popular regression learning algorithm that learns a model which is a linear combination of features of the input example.

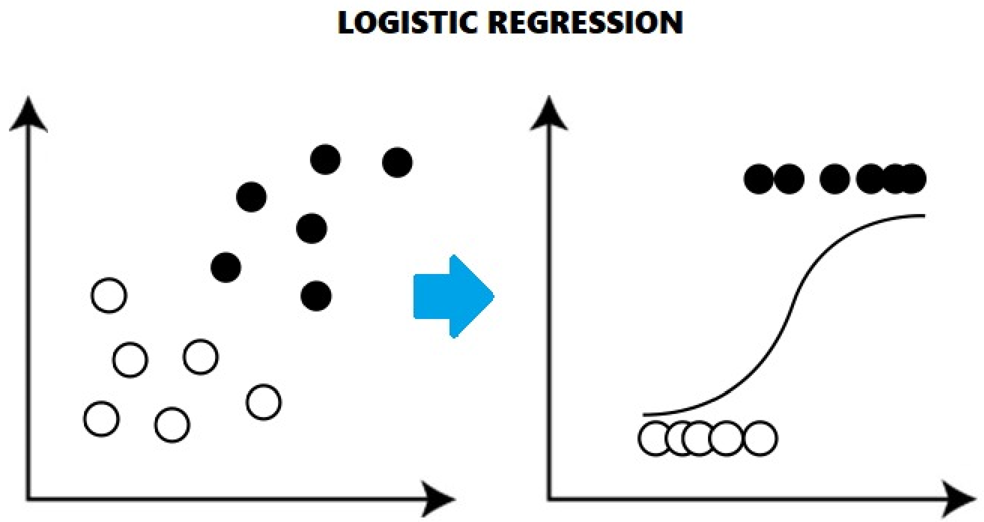
- The hyperplane in linear regression is chosen to be as close to all training examples as possible.



$$y = wx + b$$

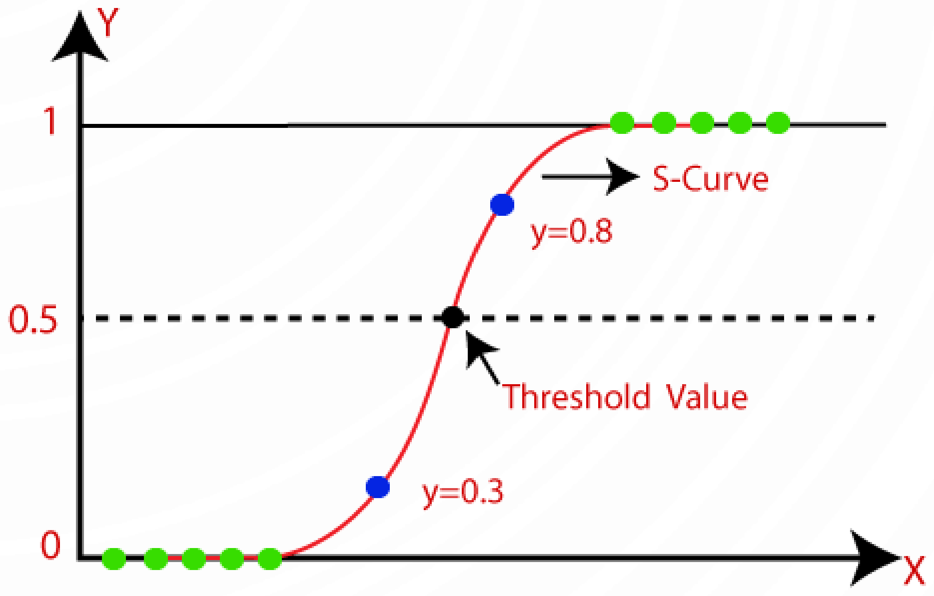
Logistic Regression

- Logistic regression predicts the output of a **categorical** dependent variable.
- Therefore, the outcome must be a categorical or discrete value.
  - Yes or No
  - 0 or 1
  - True or False
  - etc.
- Instead of giving the exact value as 0 and 1, it gives the probabilistic values which lie between 0 and 1.
- Logistic regression is used for solving the **classification** problems.



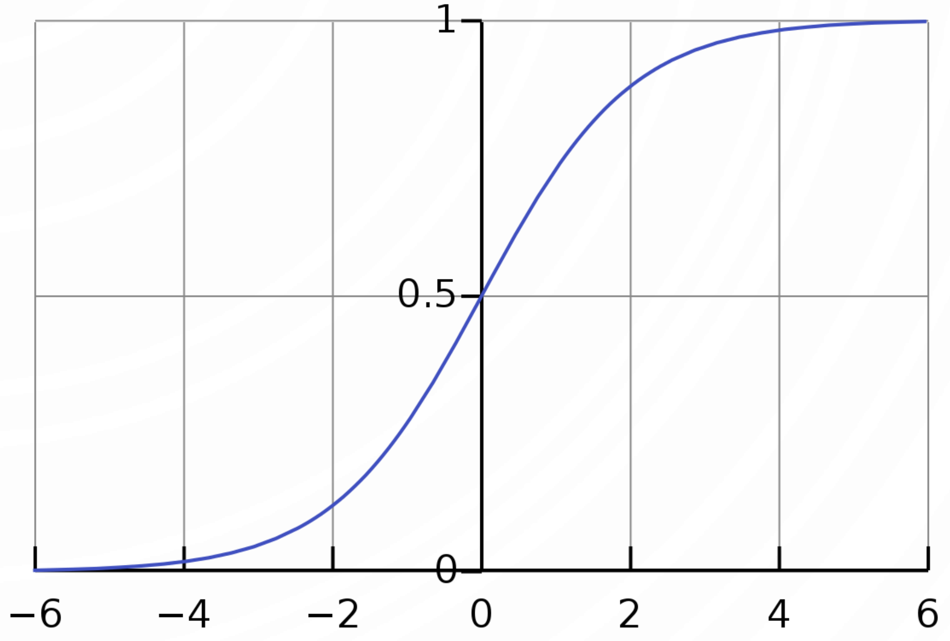
Logistic Regression

- In Logistic regression, instead of fitting a regression line, we fit an "S" shaped logistic function
  - Predicts two maximum values (0 or 1).
- The curve from the logistic function indicates the **likelihood of something**
  - Such as whether the cells are cancerous or not, a mouse is obese or not based on its weight, etc.



Logistic Function (Sigmoid Function)

$$f(x) = \frac{1}{1 + e^{-(x)}}$$



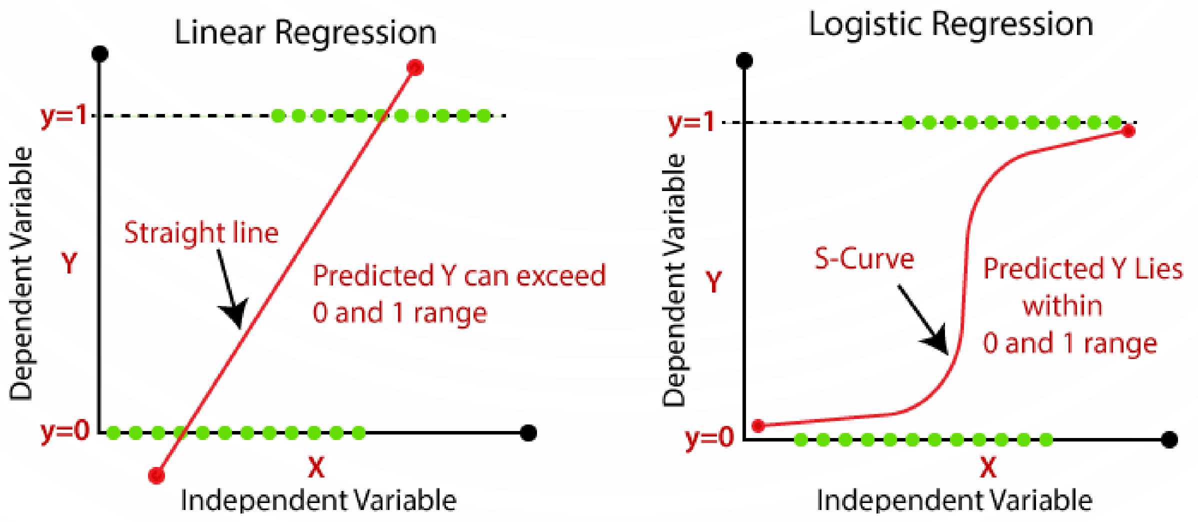
It maps any real value into another value within a range of 0 and 1

Logistic Regression Model

$$f_{w,b}(x) = \frac{1}{1 + e^{-(wx+b)}}$$

Logistic vs Linear Regression

- Both utilize a linear equation to arrive at predictions.
- In Linear regression, the result is continuous.
- In Logistic Regression, the outcome is a continuous number between the values of 0 and 1.

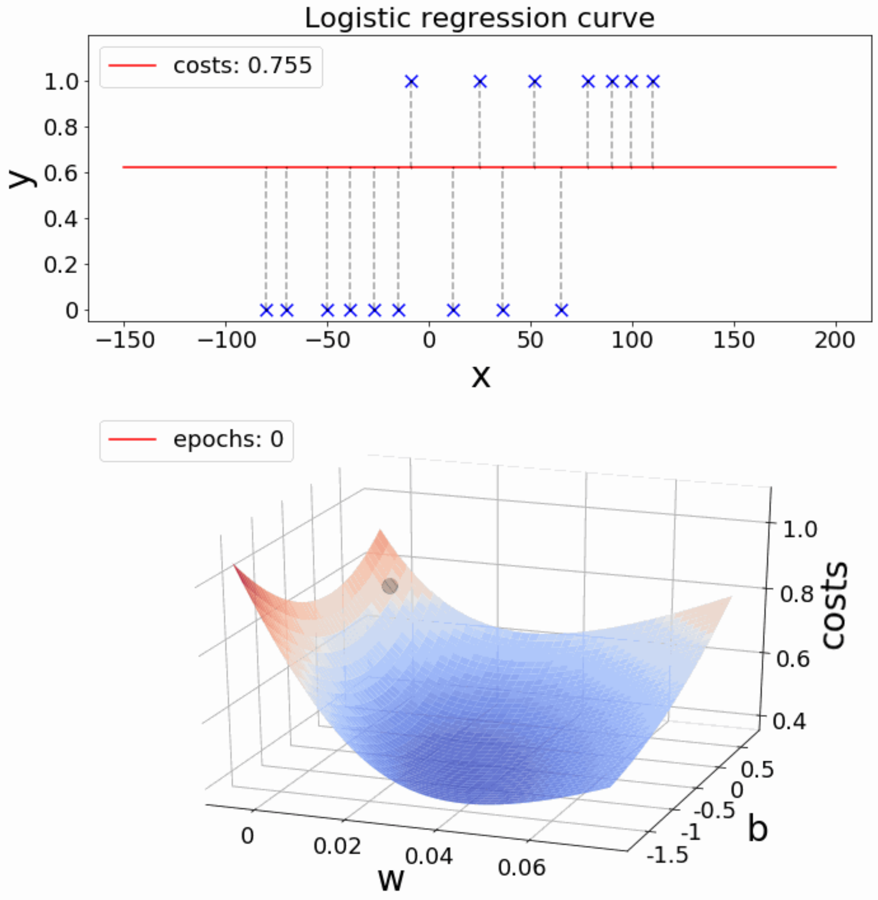


Likelihood Function

- In statistics, the likelihood function defines how likely the observation (an example) is according to our model.
- The optimization criterion in logistic regression is called **maximum likelihood**, we now maximize the likelihood of the training data according to our model:

$$L_{w,b} = \prod_{i=1}^{n} \left(f_{w,b}(x_i)\right)^{y_i} \left(1 - f_{w,b}(x_i)\right)^{(1-y_i)}$$

Parameters Learning



Classification Evaluation

- Many metrics can be used to evaluate the predictions for these problems
- Here are some:
  1. Classification Accuracy
  2. Confusion Matrix
  3. Precision, Recall, and F_1 score
  4. Area Under ROC Curve (AUC)

* We will study it later

Classification Accuracy

- It is the number of **correct predictions made over all predictions made**
- This is only suitable when there is an equal number of observations in each class (balanced dataset) and all predictions and prediction errors are of equal importance
- The most common evaluation metric for classification problems

Logistic Regression
Python Cheatsheet

Data Preprocessing

import pandas as pd
df.isnull( )
df.isull( ).count( )
df.isnull( ).sum( )

df.drop( )
df.dropna( )
df.fillna( )

Feature Engineering & EDA

import matplotlib.pyplot
df[<column>].plot()

df[<column>].quantile(...)

import LabelEncoder
LabelEncoder().fit_transform()

import seaborn
df.corr( )
sns.heatmap( )

Model Building

import train_test_split
train_test_split(...)

import LogisticRegression
LogisticRegression(...)
reg.fit(X_train, y_train)
reg.predict(X_test)
reg.predict_proba(X_test)

Model Evaluation

import metrics
metrics.plot_confusion_mat
rix()
metrics.accuracy_score( )
metrics.roc_curve( )
etrics.roc_auc_score( )

visit www.visual-design.net for step by step guide

Google Colab Example

- https://colab.research.google.com/drive/1HweQRlgnm3SrO5TfZpumEjLm8xwaQAMw?usp=sharing

Thank you