Logistic Regression

Classification techniques are an essential part of machine learning and data mining applications. Approximately 70% of problems in Data Science are classification problems. There are lots of classification problems that are available, but the logistics regression is common and is a useful regression method for solving the binary classification problem. Another category of classification is Multinomial classification, which handles the issues where multiple classes are present in the target variable. For example, IRIS dataset a very famous example of multi-class classification. Other examples are classifying article/blog/document category.

Logistic Regression can be used for various classification problems such as spam detection. Diabetes prediction, if a given customer will purchase a particular product or will they churn another competitor, whether the user will click on a given advertisement link or not, and many more examples are in the bucket.

Logistic Regression is one of the most simple and commonly used Machine Learning algorithms for two-class classification. It is easy to implement and can be used as the baseline for any binary classification problem. Its basic fundamental concepts are also constructive in deep learning. Logistic regression describes and estimates the relationship between one dependent binary variable and independent variables.

In this tutorial, you will learn the following things in Logistic Regression:

- Introduction to Logistic Regression
- Linear Regression Vs. Logistic Regression
- Maximum Likelihood Estimation Vs. Ordinary Least Square Method
- How does Logistic Regression work?
- Model building in Scikit-learn
- Model Evaluation using Confusion Matrix.
- Advantages and Disadvantages of Logistic Regression

Logistic Regression

Logistic regression is a statistical method for predicting binary classes. The outcome or target variable is dichotomous in nature. Dichotomous means there are only two possible classes. For example, it can be used for cancer detection problems. It computes the probability of an event occurrence.

It is a special case of linear regression where the target variable is categorical in nature. It uses a log of odds as the dependent variable. Logistic Regression predicts the probability of occurrence of a binary event utilizing a logit function.

Linear Regression Equation:

$$y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots\ldots + \beta nXn$$

Where, y is dependent variable and x1, x2 ... and Xn are explanatory variables.

Sigmoid Function:

$$p = 1/1 + e^{-y}$$

Apply Sigmoid function on linear regression:

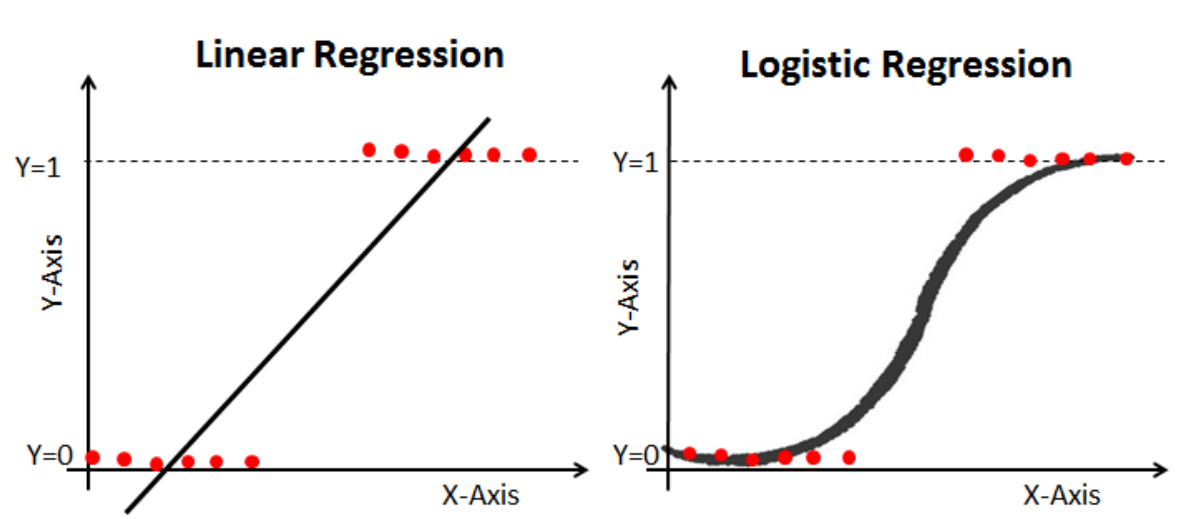
$$p = 1/1 + e^{-(\beta 0 + \beta 1X1 + \beta 2X2 \ldots\ldots \beta nXn)}$$

Properties of Logistic Regression:

- The dependent variable in logistic regression follows Bernoulli Distribution.
- Estimation is done through maximum likelihood.
- No R Square, Model fitness is calculated through Concordance, KS-Statistics.

Linear Regression Vs. Logistic Regression

Linear regression gives you a continuous output, but logistic regression provides a constant output. An example of the continuous output is house price and stock price. Example's of the discrete output is predicting whether a patient has cancer or not, predicting whether the customer will churn. Linear regression is estimated using Ordinary Least Squares (OLS) while logistic regression is estimated using Maximum Likelihood Estimation (MLE) approach.



Maximum Likelihood Estimation Vs. Least Square Method

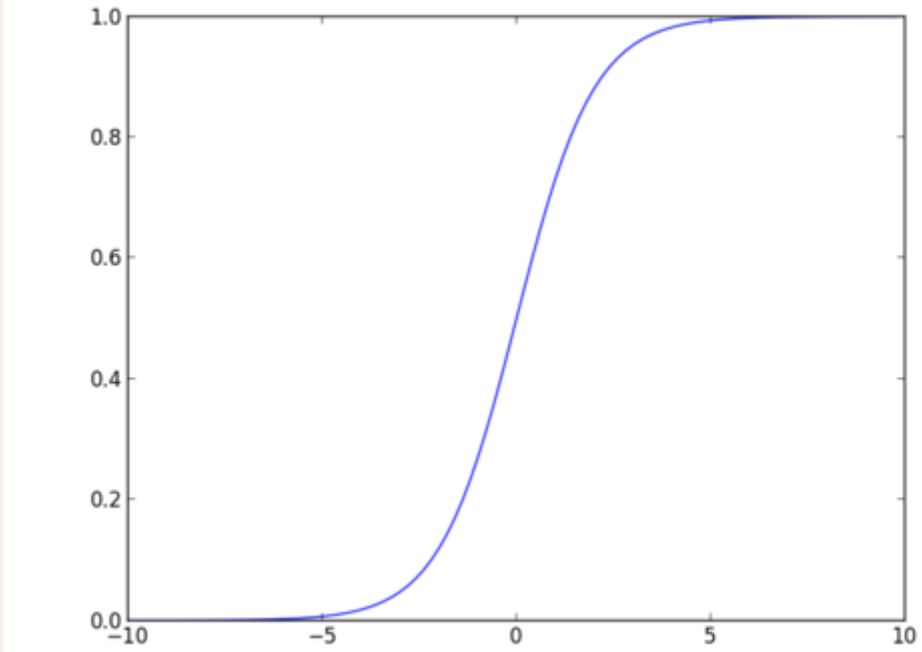
The MLE is a "likelihood" maximization method, while OLS is a distance-minimizing approximation method. Maximizing the likelihood function determines the parameters that are most likely to produce the observed data. From a statistical point of view, MLE sets the mean and variance as parameters in determining the specific parametric values for a given model. This set of parameters can be used for predicting the data needed in a normal distribution.

Ordinary Least squares estimates are computed by fitting a regression line on given data points that has the minimum sum of the squared deviations (least square error). Both are used to estimate the parameters of a linear regression model. MLE assumes a joint probability mass function, while OLS doesn't require any stochastic assumptions for minimizing distance.

Sigmoid Function

The sigmoid function, also called logistic function gives an ‘S’ shaped curve that can take any real-valued number and map it into a value between 0 and 1. If the curve goes to positive infinity, y predicted will become 1, and if the curve goes to negative infinity, y predicted will become 0. If the output of the sigmoid function is more than 0.5, we can classify the outcome as 1 or YES, and if it is less than 0.5, we can classify it as 0 or NO. The output cannot For example: If the output is 0.75, we can say in terms of probability as: There is a 75 percent chance that patient will suffer from cancer.

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



Types of Logistic Regression

Types of Logistic Regression:

- Binary Logistic Regression: The target variable has only two possible outcomes such as Spam or Not Spam, Cancer or No Cancer.
- Multinomial Logistic Regression: The target variable has three or more nominal categories such as predicting the type of Wine.
- Ordinal Logistic Regression: the target variable has three or more ordinal categories such as restaurant or product rating from 1 to 5.

Why is Logistic Regression termed as Regression and not classification?

The major difference between Regression and classification problem statements is that the target variable in the Regression is numerical (or continuous) whereas in classification it is categorical (or discrete).

Logistic Regression is basically a supervised classification algorithm. However, the Logistic Regression builds a model just like linear regression in order to predict the probability that a given data point belongs to the category numbered as “1”.

For Example, Let’s have a binary classification problem, and ‘x’ be some feature and ‘y’ be the target outcome which can be either 0 or 1.

The probability that the target outcome is 1 given its input can be represented as:

$$P(y = 1 \mid x)$$

If we predict the probability by using linear Regression, we can describe it as:

$$p(X) = \beta_0 + \beta_1 X.$$

where, p(x) = p(y=1|x)

Logistic regression models generate predicted probabilities as any number ranging from neg to pos infinity while the probability of an outcome can only lie between **0< P(x)<1**.

However, to solve the problem of outliers, a sigmoid function is used in Logistic Regression. The Linear equation is put in the sigmoid function.

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