Classification: Logistic Regression - A Comprehensive Guide with Mathematical Derivation and Python Code

Rafiq Islam

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## Introduction

Logistic Regression is a popular classification algorithm used for binary and multi-class classification problems. Unlike Linear Regression, which is used for regression problems, Logistic Regression is used to predict categorical outcomes. In binary classification, the output is either 0 or 1, and the relationship between the input features and the outcome is modeled using a logistic function (also called the sigmoid function).

## What is Logistic Regression?

Logistic Regression is a type of regression analysis used when the dependent variable is categorical. In binary logistic regression, the output can have only two possible outcomes (e.g., 0 or 1, pass or fail, spam or not spam). Logistic Regression works by modeling the probability of an event occurring based on one or more input features. It estimates the probability that a given input belongs to a particular category (0 or 1) using the **logistic function (sigmoid function)**.

## The Sigmoid Function

The sigmoid function maps any real-valued number to a value between 0 and 1, making it ideal for modeling probabilities.

The sigmoid function is given by the formula:

Where:

* is the input to the sigmoid function (in logistic regression, )
* is the base of the natural logarithm

The output of the sigmoid function is interpreted as the probability .

## Logistic Regression Model

In Logistic Regression, the hypothesis is modeled as:

Where:

* is the input feature vector
* is the parameter vector (weights)

## Cost Function for Logistic Regression

Unlike Linear Regression, which uses the Mean Squared Error (MSE) as the cost function, Logistic Regression uses **log loss** or **binary cross-entropy** as the cost function, as the output is binary (0 or 1).

So, basically we model probability from the given data. In other words, we can write

Where, and is the dimension of the data. For single data vector the binary cross-entropy function can be written as

Since we have of those i.i.d data vectors therefore, we can write

Since our goal is to minimize the loss, we need to perform derivatives of the loss function. Therefore, to change from the product form to addition form we take negative log of the above expression

For the ease of calculation, let’s rewrite the above equation in terms of and where and .

Where:

* is the number of training examples
* is the number of features
* is the true label of the example
* is the bias for the example

## Gradient Descent

To minimize the cost function and find the optimal values for , we use **gradient descent**. We start from the last form of the loss function and convert this to a form that is easy to take the partial dervivatives.

Now we again use the beautiful features of the sigmoid function

Finally, we are ready to take the partial derivatives of the loss function with respect to and ,

Using this gradient, we update the parameter vector iteratively:

Where:

* is the learning rate
* is the partial derivative of the cost function with respect to and

## Python Code Implementation from Scratch

Here’s how to implement Logistic Regression from scratch in Python. We will use two different forms for our class

import numpy as np  
  
class LogisticRegression1:  
 def \_\_init\_\_(self, learning\_rate = 0.1, n\_iterations = 1000):  
 """  
 Hyper Parameters  
 - learning\_rate: learning rate; float; default 0.01  
 - n\_itearations: number of iterations; int; default 1000  
 Model Parameters  
 - weights: weights of the features; float or int  
 - bias: bias of the model; float or int  
 """  
 self.learning\_rate = learning\_rate  
 self.n\_iterations = n\_iterations   
 self.weights = None  
 self.bias = None   
   
 def \_sigmoid(self, x):  
 return 1/(1+np.exp(-x))  
  
 def fit(self, X,y):  
 """  
 n\_sample = number of samples in the data set: the value n  
 n\_features = number of features or the dimension of the data set: the value d  
 """  
 n\_sample,n\_features = X.shape  
 self.weights = np.zeros(n\_features)   
 self.bias = 0  
  
 for \_ in range(self.n\_iterations):  
 linear = np.dot(X, self.weights) + self.bias  
 pred = self.\_sigmoid(linear)  
  
 dw = (1/n\_sample)\* np.dot(X.T,(pred-y))  
 db = (1/n\_sample) \* np.sum(pred-y)  
  
 self.weights = self.weights - self.learning\_rate \* dw   
 self.bias = self.bias - self.learning\_rate \* db  
   
 def predict(self, X):  
 linear = np.dot(X, self.weights) + self.bias  
 predicted\_y = self.\_sigmoid(linear)  
 class\_of\_y = [0 if y<=0.5 else 1 for y in predicted\_y]  
 return class\_of\_y

Now let’s use this using the scikit-learn breast cancer data set.

import pandas as pd  
from sklearn.datasets import load\_breast\_cancer  
from sklearn.model\_selection import train\_test\_split  
from sklearn.metrics import accuracy\_score  
  
b\_cancer = load\_breast\_cancer()  
X, y = b\_cancer.data, b\_cancer.target  
X\_train, X\_test, y\_train, y\_test = train\_test\_split(X,y, random\_state=123, stratify=y, test\_size=0.30)  
  
clf1 = LogisticRegression1(learning\_rate=0.01)  
clf1.fit(X\_train, y\_train)  
predicted\_y = clf1.predict(X\_test)  
print(np.round(accuracy\_score(predicted\_y, y\_test),2))

0.91

Now lets compare this with the standard scikit-learn library

from sklearn.linear\_model import LogisticRegression  
  
clf2 = LogisticRegression()  
clf2.fit(X\_train, y\_train)  
predicted\_y = clf2.predict(X\_test)  
print(np.round(accuracy\_score(predicted\_y, y\_test),2))

0.96

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