How do I perform Logistic Regression in Python step-by-step?

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Logistic Regression is a popular statistical method used for predicting binary outcomes, such as yes/no or true/false. In Python, there are several libraries available that can be used to perform Logistic Regression, such as scikit-learn, statsmodels, and keras. To perform Logistic Regression in Python step-by-step, the following steps can be followed:

1. Import the necessary libraries: The first step is to import the required libraries for data manipulation and modeling, such as pandas, numpy, and sklearn.

2. Load the data: The next step is to load the dataset into the Python environment. This can be done using the read_csv function in pandas or by importing the data from another source.

3. Preprocess the data: Before applying Logistic Regression, it is essential to preprocess the data, including handling missing values, removing outliers, and encoding categorical variables.

4. Split the data into training and test sets: To evaluate the performance of the Logistic Regression model, the dataset needs to be divided into training and test sets. The training set is used to train the model, and the test set is used to evaluate its performance.

5. Train the model: Once the data is prepared, the next step is to train the Logistic Regression model using the fit function.

6. Make predictions: After training the model, we can use it to make predictions on the test set using the predict function.

7. Evaluate the model: To assess the performance of the model, various metrics such as accuracy, precision, and recall can be used.

8. Tune hyperparameters: To improve the performance of the model, we can tune the hyperparameters using techniques like grid search or randomized search.

9. Visualize the results: Finally, we can visualize the results of the Logistic Regression model using plots and graphs to gain insights into the data.

By following these steps, we can perform Logistic Regression in Python and analyze the relationship between the independent variables and the binary outcome variable.

Perform Logistic Regression in Python (Step-by-Step)

Logistic regression is a method we can use to fit a regression model when the **response variable** is binary.

Logistic regression uses a method known as *maximum likelihood estimation* to find an equation of the following form:

log = β0 + β1X1 + β2X2 + ... + βpXp

where:

Xj: The jth predictor variableβj: The coefficient estimate for the jth predictor variable

The formula on the right side of the equation predicts the log odds of the response variable taking on a value of 1.

Thus, when we fit a logistic regression model we can use the following equation to calculate the probability that a given observation takes on a value of 1:

p(X) = eβ0 + β1X1 + β2X2 + ... + βpXp / (1 + eβ0 + β1X1 + β2X2 + ... + βpXp)

We then use some probability threshold to classify the observation as either 1 or 0.

For example, we might say that observations with a

probability greater than or equal to 0.5 will be classified as "1" and all other observations will be classified as "0."

This tutorial provides a step-by-step example of how to perform logistic regression in R.

Step 1: Import Necessary Packages

First, we'll import the necessary packages to perform logistic regression in Python:

```
import pandas as pd
import numpy as np
from sklearn.model_selectionimport train_test_split
from sklearn.linear_modelimport LogisticRegression
from sklearn import metrics
import matplotlib.pyplotas plt
```

Step 2: Load the Data

For this example, we'll use the Default dataset from the Introduction to Statistical Learning book. We can use the following code to load and view a summary of the dataset:

```
#import dataset from CSV file on Github
url = "https://raw.githubusercontent.com/Statology/Python-Guides/main/default.csv"
data = pd.read_csv(url)
#view first six rows of dataset
data

default student balance income
0 0 0 729.526495 44361.625074
1 0 1 817.180407 12106.134700
2 0 0 1073.549164 31767.138947
3 0 0 529.250605 35704.493935
4 0 0 785.655883 38463.495879
5 0 1 919.588530 7491.558572

#find total observations in dataset
len(data.index)

10000
```

default: Indicates whether or not an individual defaulted.student: Indicates whether or not an individual is a student.balance: Average balance carried by an individual.income: Income of the individual.

We will use student status, bank balance, and income to build a logistic regression model that predicts the probability that a given individual defaults.

Step 3: Create Training and Test Samples

Next, we'll split the dataset into a training set to *train* the model on and a testing set to *test* the model on.

```
#define the predictor variables and the response variable
X = data]
y = data

#split the dataset into training (70%) and testing (30%) sets
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=0)
```

Step 4: Fit the Logistic Regression Model

Next, we'll use the LogisticRegression() function to fit a logistic regression model to the dataset:

```
#instantiate the model
log_regression = LogisticRegression()
```

#fit the model using the training data
log_regression.fit(X_train,y_train)

#use model to make predictions on test data
y_pred = log_regression.predict(X_test)

Step 5: Model Diagnostics

Once we fit the regression model, we can then analyze how well our model performs on the test dataset.

First, we'll create the confusion matrix for the model:

cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix

array(,
])

From the confusion matrix we can see that:

#True positive predictions: 2886#True negative predictions: 0#False positive predictions: 113#False negative predictions: 1

We can also obtain the accuracy of the model, which

tells us the percentage of correction predictions the model made:

```
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))l
```

Accuracy: 0.962

This tells us that the model made the correct prediction for whether or not an individual would default 96.2% of the time.

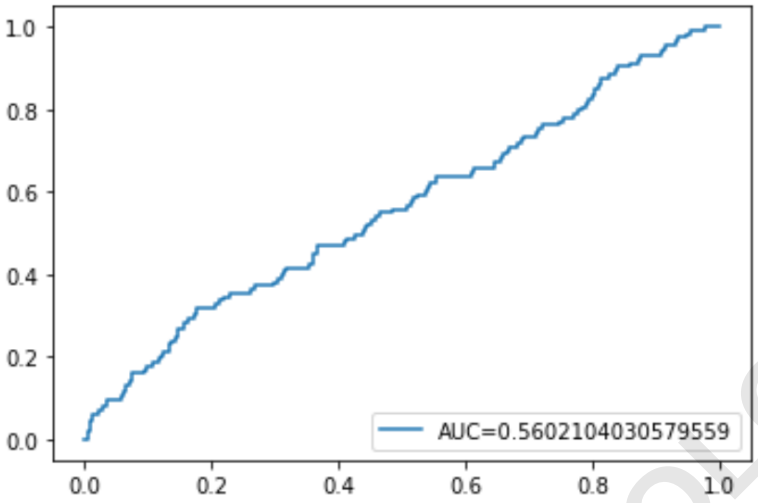
Lastly, we can plot the ROC (Receiver Operating Characteristic) Curve which displays the percentage of true positives predicted by the model as the prediction probability cutoff is lowered from 1 to 0.

The higher the AUC (area under the curve), the more accurately our model is able to predict outcomes:

```
#define metrics
y_pred_proba = log_regression.predict_proba(X_test)
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)

#create ROC curve
```

```
plt.plot(fpr,tpr,label="AUC="+str(auc))
plt.legend(loc=4)
plt.show()
```



The complete Python code used in this tutorial can be found here.

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