How can I plot multiple ROC curves in Python with an example?

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"Plotting multiple ROC curves in Python allows for the comparison of the performance of multiple classification models on a single graph. This can be achieved by using the Matplotlib library and the sklearn.metrics.roc_curve function. An example of this can be seen by first importing the necessary libraries, then generating the ROC curves for each model, and finally plotting them on the same graph. This method provides a visual representation of the effectiveness of each model and aids in determining the best performing one. By following this process, one can efficiently evaluate and compare the performance of multiple classification models in Python."

Plot Multiple ROC Curves in Python (With Example)

One way to visualize the performance of in machine learning is by creating a ROC curve, which stands for "receiver operating characteristic" curve.

Often you may want to fit several classification models to one dataset and create a ROC curve for each model to visualize which model performs best on the data.

The following step-by-step example shows how plot multiple ROC curves in Python.

Step 1: Import Necessary Packages

First, we'll import several necessary packages in Python:

```
from sklearn import metrics
from sklearn import datasets
from sklearn.model_selectionimport train_test_split
```

```
from sklearn.linear_modelimport LogisticRegression
from sklearn.ensembleimport GradientBoostingClassifier
import numpy as np
import matplotlib.pyplotas plt
```

Step 2: Create Fake Data

Next, we'll use the function from sklearn to create a fake dataset with 1,000 rows, four predictor variables, and one binary response variable:

```
#create fake dataset
X, y = datasets.make_classification(n_samples=1000,
n_features=4,
n_informative=3,
n_redundant=1,
random_state=0)

#split dataset into training and testing set
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=.3,random_state=0)
```

Step 3: Fit Multiple Models & Plot ROC Curves

Next, we'll fit a logistic regression model and then a

gradient boosted model to the data and plot the ROC curve for each model on the same plot:

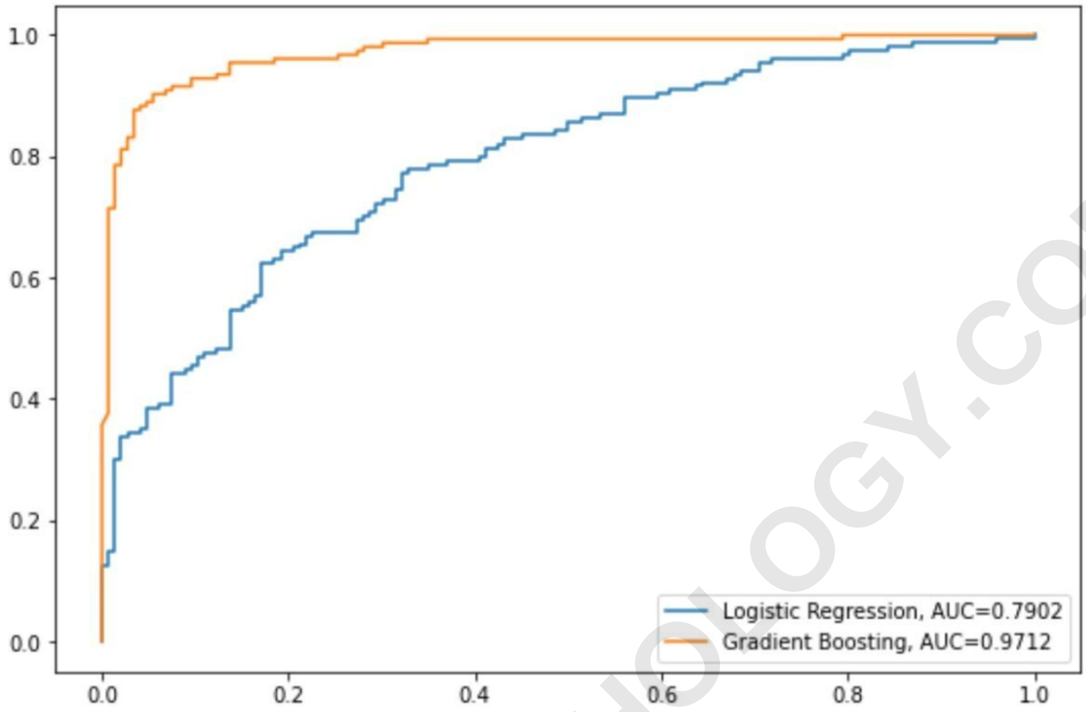
```
#set up plotting area
plt.figure(0).clf()

#fit logistic regression model and plot ROC curve
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict_proba(X_test)
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="Logistic Regression, AUC="+str(auc))

#fit gradient boosted model and plot ROC curve
model = GradientBoostingClassifier()
model.fit(X_train, y_train)
y_pred = model.predict_proba(X_test)
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="Gradient Boosting, AUC="+str(auc))

#add legend
```

plt.legend()



The blue line shows the ROC curve for the logistic regression model and the orange line shows the ROC curve for the gradient boosted model.

The more that a ROC curve hugs the top left corner of the plot, the better the model does at classifying the data into categories.

To quantify this, we can calculate the AUC - area under the curve - which tells us how much of the plot is located under the curve.

The closer AUC is to 1, the better the model.

AUC of logistic regression model: 0.7902AUC of gradient boosted model: 0.9712

Clearly the gradient boosted model does a better job of classifying the data into categories compared to the logistic regression model.

Additional Resources

The following tutorials provide additional information about classification models and ROC curves: