Supervised Learning with scikit-learn

3). Finetuning your model

a). Metrics for Classification

```
# Import necessary modules
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix

# Create training and test set
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4, random_state=42)

# Instantiate a k-NN classifier: knn
knn = KNeighborsClassifier(n_neighbors=6)

# Fit the classifier to the training data
knn.fit(X_train, y_train)

# Predict the labels of the test data: y_pred
y_pred = knn.predict(X_test)

# Generate the confusion matrix and classification report
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

<script.py> output:

```
[[176  30]
 [ 52  50]]
             precision    recall  f1-score   support

          0       0.77      0.85      0.81       206
          1       0.62      0.49      0.55       102

avg / total       0.72      0.73      0.72       308
```

c). <u>Building a logisticregression Model</u>

```
# Import the necessary modules
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report

# Create training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4, random_state=42)

# Create the classifier: logreg
logreg = LogisticRegression()

# Fit the classifier to the training data
logreg.fit(X_train,y_train)

# Predict the labels of the test set: y_pred
y_pred = logreg.predict(X_test)

# Compute and print the confusion matrix and classification report
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
<script.py> output:
  [[176  30]
   [ 35  67]]
             precision    recall  f1-score   support

          0       0.83      0.85      0.84       206
          1       0.69      0.66      0.67       102

avg / total       0.79      0.79      0.79       308
```

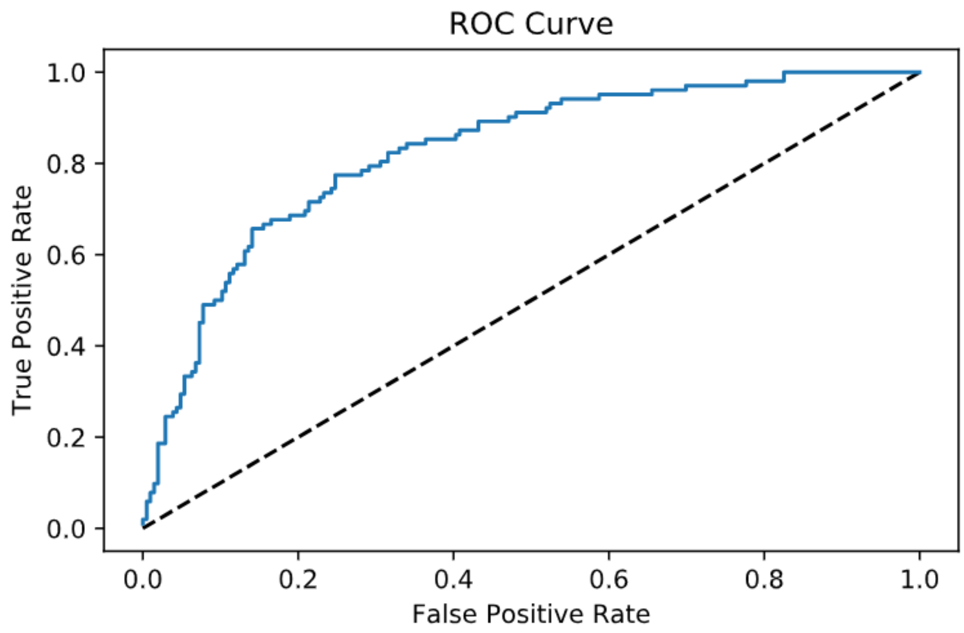
d). Plotting an ROC curve

```
# Import necessary modules
from sklearn.metrics import roc_curve

# Compute predicted probabilities: y_pred_prob
y_pred_prob = logreg.predict_proba(X_test)[:,1]

# Generate ROC curve values: fpr, tpr, thresholds
fpr, tpr, threshold = roc_curve(y_test, y_pred_prob)

# Plot ROC curve
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()
```



e). AUC Computation

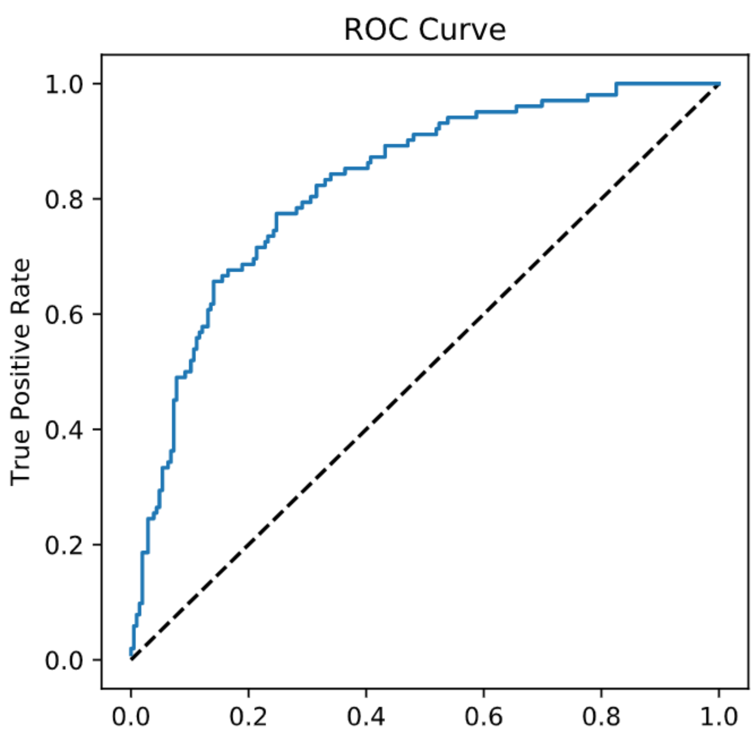
```
# Import necessary modules
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import cross_val_score

# Compute predicted probabilities: y_pred_prob
y_pred_prob = logreg.predict_proba(X_test)[:,1]

# Compute and print AUC score
print("AUC: {}".format(roc_auc_score(y_test, y_pred_prob)))

# Compute cross-validated AUC scores: cv_auc
cv_auc = cross_val_score(logreg, X, y, cv=5, scoring='roc_auc')

# Print list of AUC scores
print("AUC scores computed using 5-fold cross-validation: {}".format(cv_auc))
```



f). <u>Hyperparameter tuning with gridsearchCV()</u>

```
# Import necessary modules
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Setup the hyperparameter grid
c_space = np.logspace(-5, 8, 15)
param_grid = {'C': c_space}

# Instantiate a logistic regression classifier: logreg
logreg = LogisticRegression()

# Instantiate the GridSearchCV object: logreg_cv
logreg_cv = GridSearchCV(logreg, param_grid, cv=5)

# Fit it to the data
logreg_cv.fit(X,y)

# Print the tuned parameters and score
print("Tuned Logistic Regression Parameters: {}".format(logreg_cv.best_params_))
print("Best score is {}".format(logreg_cv.best_score_))
```

<script.py> output:

```
Tuned Logistic Regression Parameters: {'C': 3.727593720314938}
Best score is 0.7708333333333334
```

g). <u>Hyperparameter tuning with RandomizedSearchCV</u>

```
# Import necessary modules
from scipy.stats import randint
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import  RandomizedSearchCV

# Setup the parameters and distributions to sample from: param_dist
param_dist = {"max_depth": [3, None],
              "max_features": randint(1, 9),
              "min_samples_leaf": randint(1, 9),
              "criterion": ["gini", "entropy"]}

# Instantiate a Decision Tree classifier: tree
tree = DecisionTreeClassifier()

# Instantiate the RandomizedSearchCV object: tree_cv
tree_cv = RandomizedSearchCV(tree, param_dist, cv=5)

# Fit it to the data
tree_cv.fit(X,y)

# Print the tuned parameters and score
print("Tuned Decision Tree Parameters: {}".format(tree_cv.best_params_))
print("Best score is {}".format(tree_cv.best_score_))
```

<script.py> output:

Tuned Decision Tree Parameters: {'criterion': 'entropy', 'max_features': 7, 'min_samples_leaf': 8, 'max_depth': None}

Best score is 0.7200520833333334

h). Hold-out set in practice I: Classification

```
# Import necessary modules
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Create the hyperparameter grid
c_space = np.logspace(-5, 8, 15)
param_grid = {'C': c_space, 'penalty': ['l1', 'l2']}

# Instantiate the logistic regression classifier: logreg
logreg = LogisticRegression()

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=42)

# Instantiate the GridSearchCV object: logreg_cv
logreg_cv = GridSearchCV(logreg, param_grid, cv=5)

# Fit it to the training data
logreg_cv.fit(X_train, y_train)

# Print the optimal parameters and best score
print("Tuned Logistic Regression Parameter: {}".format(logreg_cv.best_params_))
print("Tuned Logistic Regression Accuracy: {}".format(logreg_cv.best_score_))
```

<script.py> output:

```
Tuned Logistic Regression Parameter: {'C': 0.43939705607607948, 'penalty': 'l1'}
Tuned Logistic Regression Accuracy: 0.7652173913043478
```

i). Hold out set in Practice II: Regression

```
# Import necessary modules
from sklearn.linear_model import ElasticNet
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4, random_state=42 )

# Create the hyperparameter grid
l1_space = np.linspace(0, 1, 30)
param_grid = {'l1_ratio': l1_space}

# Instantiate the ElasticNet regressor: elastic_net
elastic_net = ElasticNet()

# Setup the GridSearchCV object: gm_cv
gm_cv = GridSearchCV(elastic_net, param_grid, cv=5)

# Fit it to the training data
gm_cv.fit(X_train, y_train)

# Predict on the test set and compute metrics
y_pred = gm_cv.predict(X_test)
r2 = gm_cv.score(X_test, y_test)
mse = mean_squared_error(y_test, y_pred)
print("Tuned ElasticNet l1 ratio: {}".format(gm_cv.best_params_))
print("Tuned ElasticNet R squared: {}".format(r2))
print("Tuned ElasticNet MSE: {}".format(mse))
```

<script.py> output:

Tuned ElasticNet l1 ratio: {'l1_ratio': 0.20689655172413793}

Tuned ElasticNet R squared: 0.8668305372460283

Tuned ElasticNet MSE: 10.05791413339844