```
Introduction to Logistic Regression and Support Vector Machine Models
In [83]: import pandas as pd
         import numpy as np
         from pandas import DataFrame
         from sklearn.datasets import load_boston
         X, y = load boston(return X y=True)
         X.shape, y.shape
Out[83]: ((506, 13), (506,))
In [84]: from sklearn.linear_model import LogisticRegression
         from sklearn.model_selection import train_test_split
         \#binary_y = np.array(y >= 40).astype(int)
         X_train, X_test, y_train, y_test = train_test_split(X,
                     binary_y, test_size=0.33, random_state=5)
         logistic = LogisticRegression()
         logistic.fit(X_train,y_train)
         from sklearn.metrics import accuracy_score
         print('In-sample accuracy: %0.3f' %
               accuracy_score(y_train, logistic.predict(X_train)))
         print('Out-of-sample accuracy: %0.3f' %
               accuracy_score(y_test, logistic.predict(X_test)))
         In-sample accuracy: 0.982
         Out-of-sample accuracy: 0.964
         /Users/admin/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:940: Converge
         nceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/module
         s/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-lear
         n.org/stable/modules/linear model.html#logistic-regression)
           extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
In [85]: boston=load_boston()
In [86]: | for var,coef in zip(boston.feature_names,
                             logistic.coef_[0]):
                 print ("%7s : %7.3f" %(var, coef))
            CRIM : 0.070
              ZN: 0.004
           INDUS : 0.106
            CHAS : -0.151
            NOX: 0.012
             RM: 1.084
             AGE: -0.006
             DIS: -0.258
             RAD : 0.541
             TAX : -0.013
         PTRATIO : -0.936
              B: 0.031
           LSTAT : -0.907
In [87]: print('\nclasses:',logistic.classes )
         print('\nProbs:\n',logistic.predict_proba(X_test)[:3,:])
         classes: [0 1]
         Probs:
          [[2.41596449e-01 7.58403551e-01]
          [9.88748862e-01 1.12511385e-02]
          [9.99866981e-01 1.33018891e-04]]
```

Introduction to SVC Model

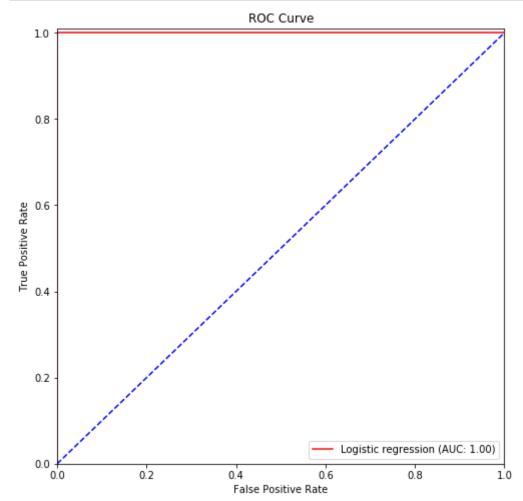
```
In [88]: import pandas as pd
          import numpy as np
          from pandas import Series,DataFrame
          from sklearn.datasets import load_boston
          boston=load_boston()
          # Reset data as pandas DataFrame
          boston_df = pd.DataFrame(boston.data)
          # Label columns
          boston_df.columns = boston.feature_names
          # Show first five rows
          boston_df.head()
Out[88]:
               CRIM
                      ZN INDUS CHAS
                                        NOX
                                               RM AGE
                                                          DIS RAD
                                                                     TAX PTRATIO
                                                                                       B LSTAT
                                                   65.2 4.0900
           0 0.00632
                     18.0
                            2.31
                                   0.0 0.538
                                             6.575
                                                                1.0
                                                                    296.0
                                                                              15.3 396.90
                                                                                           4.98
                            7.07
                                            6.421
                                                                2.0 242.0
             0.02731
                      0.0
                                   0.0 0.469
                                                   78.9 4.9671
                                                                              17.8 396.90
                                                                                           9.14
             0.02729
                      0.0
                            7.07
                                   0.0
                                       0.469
                                             7.185
                                                   61.1 4.9671
                                                                2.0
                                                                    242.0
                                                                              17.8 392.83
                                                                                           4.03
             0.03237
                      0.0
                            2.18
                                       0.458
                                             6.998
                                                   45.8 6.0622
                                                                3.0
                                                                    222.0
                                                                              18.7 394.63
                                                                                           2.94
                                                                3.0 222.0
             0.06905
                      0.0
                            2.18
                                   0.0 0.458 7.147 54.2 6.0622
                                                                              18.7 396.90
                                                                                           5.33
In [89]: # Define the label 'TAX CATEGORY'
          def value_check(x):
               if x > 225:
                   return 1
               else:
                   return 0
          boston_df['TAX_CAT'] = boston_df['TAX'].apply(value_check)
          boston_df
Out[89]:
                 CRIM
                        ZN INDUS CHAS
                                          NOX
                                                 RM
                                                     AGE
                                                            DIS RAD
                                                                       TAX PTRATIO
                                                                                        B LSTAT TAX_CAT
             0 0.00632
                       18.0
                              2.31
                                     0.0
                                         0.538 6.575
                                                     65.2 4.0900
                                                                  1.0
                                                                      296.0
                                                                                15.3 396.90
                                                                                             4.98
                                                                                                        1
               0.02731
                        0.0
                              7.07
                                     0.0 0.469 6.421
                                                    78.9 4.9671
                                                                  2.0 242.0
                                                                                17.8 396.90
                                                                                             9.14
                                                                                                        1
               0.02729
                                                    61.1 4.9671
                                                                                17.8 392.83
                        0.0
                              7.07
                                     0.0 0.469 7.185
                                                                  2.0 242.0
                                                                                             4.03
                                                                                                        1
                                                                  3.0 222.0
               0.03237
                                         0.458 6.998
                                                     45.8 6.0622
                                                                                18.7 394.63
                                                                                                        0
                              2.18
                                                                                             2.94
               0.06905
                        0.0
                              2.18
                                     0.0 0.458 7.147 54.2 6.0622
                                                                  3.0 222.0
                                                                                18.7 396.90
                                                                                             5.33
                                                                                                        0
               0.06263
                        0.0
                             11.93
                                     0.0 0.573 6.593
                                                     69.1 2.4786
                                                                  1.0 273.0
                                                                                21.0 391.99
                                                                                             9.67
                                                                                                        1
           501
               0.04527
                                                     76.7 2.2875
                                                                  1.0 273.0
                                                                                21.0 396.90
           502
                        0.0
                             11.93
                                     0.0 0.573 6.120
                                                                                             9.08
               0.06076
                        0.0
                             11.93
                                     0.0 0.573 6.976
                                                    91.0 2.1675
                                                                  1.0 273.0
                                                                                21.0 396.90
                                                                                             5.64
                                                                                21.0 393.45
               0.10959
                        0.0
                             11.93
                                     0.0 0.573 6.794
                                                     89.3 2.3889
                                                                  1.0 273.0
                                                                                             6.48
                                                                                                        1
           504
           505 0.04741
                        0.0
                             11.93
                                     0.0 0.573 6.030 80.8 2.5050
                                                                  1.0 273.0
                                                                                21.0 396.90
                                                                                             7.88
                                                                                                        1
          506 \text{ rows} \times 14 \text{ columns}
In [90]: y=boston_df['TAX_CAT']
In [91]: from sklearn.model_selection import train_test_split, cross_val_score
          from sklearn.preprocessing import MinMaxScaler
           # We keep 30% random examples for test
          X_train, X_test, y_train, y_test = train_test_split(X,
                                 y, test_size=0.3, random_state=101)
          # We scale the data in the range [-1,1]
          scaling = MinMaxScaler(feature_range=(-1, 1)).fit(X_train)
          X_train = scaling.transform(X_train)
           X_test = scaling.transform(X_test)
          from sklearn.svm import SVC
          svm = SVC()
          cv_performance = cross_val_score(svm, X_train, y_train,
                                                cv=10)
          test_performance = svm.fit(X_train, y_train).score(X_test,
          print ('Cross-validation accuracy score: %0.3f,'
                   ' test accuracy score: %0.3f'
                  % (np.mean(cv_performance),test_performance))
```

Cross-validation accuracy score: 0.921, test accuracy score: 0.941

```
from sklearn.preprocessing import MinMaxScaler
          # We keep 30% random examples for test
          X_train, X_test, y_train, y_test = train_test_split(X,
                             y, test_size=0.3, random_state=101)
          # We scale the data in the range [-1,1]
          scaling = MinMaxScaler(feature_range=(-1, 1)).fit(X_train)
          X_train = scaling.transform(X_train)
          X_test = scaling.transform(X_test)
          from sklearn.linear_model import LogisticRegression
          lr = LogisticRegression()
          cv performance lr = cross val score(lr, X train, y train,
                                           cv=10)
          test_performance_lr = lr.fit(X_train, y_train).score(X_test,
          print ('Cross-validation accuracy score: %0.3f,'
                 ' test accuracy score: %0.3f'
                 % (np.mean(cv_performance_lr),test_performance_lr))
          Cross-validation accuracy score: 0.921, test accuracy score: 0.961
In [100]: from sklearn.metrics import confusion_matrix, classification_report
          from sklearn.model_selection import GridSearchCV
          param_grid = {'C': [0.001, 0.01, 0.1, 0.5, 1, 10, 100]}
          grid = GridSearchCV(lr, param_grid, scoring="roc_auc", cv=5)
          lr_train = grid.fit(X_train, y_train)
          pred_lr = lr_train.predict(X_test)
          confusion = confusion_matrix(y_test, pred_lr)
          print('Confusion Matrix: \n', confusion[::-1,::1])
          print('Classification Report: ',classification_report(y_test, pred_lr))
          Confusion Matrix:
           [[ 3 140]
                1]]
           [ 8
          Classification Report:
                                                           recall f1-score support
                                                precision
                     0
                           0.73 0.89
                                               0.80
                                                              9
                             0.99
                                     0.98
                     1
                                                0.99
                                                            143
                                                 0.97
                                                            152
              accuracy
                                       0.93
                                                 0.89
                                                            152
             macro avg
                             0.86
                             0.98
                                       0.97
          weighted avg
                                                 0.97
                                                            152
          /Users/admin/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:940: Converge
          nceWarning: lbfgs failed to converge (status=1):
          STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
          Increase the number of iterations (max_iter) or scale the data as shown in:
              https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/module
          s/preprocessing.html)
          Please also refer to the documentation for alternative solver options:
              https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-lear
          n.org/stable/modules/linear_model.html#logistic-regression)
            extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
In [101]: # Accuracy score
          from sklearn.metrics import accuracy score
          print('LR Classification Accuracy Score: %0.2f'% accuracy_score(pred_lr, lr.predict(X_test)))
          LR Classification Accuracy Score: 0.95
In [102]: # Compute true and false predictions
          i = confusion.shape
          truePred = 0
          falsePred = 0
          for row in range(i[0]):
                for j in range(i[1]):
                      if row == j:
                          truePred +=confusion[row,j]
                      else:
                          falsePred += confusion[row,j]
          print('True predictions: ', truePred)
          print('\nFalse predictions', falsePred)
          print('\nAccuracy of the model is: ', round(truePred/(confusion.sum()),2))
          True predictions: 148
          False predictions 4
          Accuracy of the model is: 0.97
```

In [99]: from sklearn.model\_selection import train\_test\_split, cross\_val\_score

```
In [103]: # Receiver Operating Curve (ROC)
          Y_scores = lr.decision_function(X_test)
          from sklearn.metrics import roc_curve
          fpr, tpr, thresholds = roc_curve(pred_lr, Y_scores)
          # Area Under the Curve (AUC)
          from sklearn.metrics import auc
          auc(fpr, tpr)
          # ROC curve with Matplotlib
          import matplotlib.pyplot as plt
          %matplotlib inline
          plt.figure(figsize=(8, 8))
          plt.plot(fpr, tpr, color='red', label='Logistic regression (AUC: %.2f)'
          % auc(fpr, tpr))
          plt.plot([0, 1], [0, 1], color='blue', linestyle='--')
          plt.xlim([0.0, 1.0])
          plt.ylim([0.0, 1.01])
          plt.title('ROC Curve')
          plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          plt.legend(loc="lower right")
          plt.show()
```



Using Pipeline to group tasks

```
In [113]: from sklearn.pipeline import Pipeline
    pipe = Pipeline([('scaling', MinMaxScaler()), ('lr', LogisticRegression())])
    pipe.fit(X_train, y_train)
    Pipeline(steps=[('scaling', MinMaxScaler()), ('lr', LogisticRegression())])
    print('Pipe Score: \n%0.2f'% pipe.score(X_test, y_test))
Pipe Score:
0.94
```

Finding the Optimal SVC Model

```
In [114]: from sklearn.model_selection import GridSearchCV
          import numpy as np
          best_SVC = SVC(kernel='linear', random_state=101)
          search_space = [{'kernel': ['linear'],
                           'C': np.logspace(-3, 3, 7)},
                          {'kernel': ['rbf'],
                           'C':np.logspace(-3, 3, 7),
                           'gamma': np.logspace(-3, 2, 6)}]
          gridsearch = GridSearchCV(best_SVC,
                                    param_grid=search_space,
                                    refit=True, cv=10)
          gridsearch.fit(X_train,y_train)
          print ('Best parameter: %s'
                 % str(gridsearch.best_params_))
          print ('Best score: %s'
                 % str(gridsearch.best_score_))
          print ('Best index: %s'
                 % str(gridsearch.best_index_))
          Best parameter: {'C': 100.0, 'kernel': 'linear'}
          Best score: 0.9971428571428571
          Best index: 5
```

In [ ]: