```
In [1]: import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn as sns
 In [2]: %matplotlib inline
 In [3]: data = pd.read_csv('feature.csv')
 In [4]: data.head(2)
 Out[4]:
               Mean Standard_Deviation Variance label
          o -0.76913
                             5.5906
                                     31 255
          1 -0.77444
                             5.5941
                                     31.293
 In [ ]:
 In [5]: data.keys()
 Out[5]: Index(['Mean', 'Standard_Deviation', 'Variance', 'label'], dtype='object')
 In [6]: data feat=data[['Mean', 'Standard Deviation', 'Variance']]
 In [7]: data feat.head(2)
 Out[7]:
               Mean Standard_Deviation Variance
          0 -0.76913
                              5.5906
                                     31.255
          1 -0.77444
                             5.5941
                                     31.293
 In [8]: | class_names=['Port 1', 'Port 2']
 In [9]: type(class_names)
 Out[9]: list
In [10]: data_label=data[['label']]
In [11]: data_label.head(2)
Out[11]:
            label
In [12]: from sklearn.model_selection import train_test_split
In [13]: X=data_feat;
         y=data label
         X_train, X_test, y_train, y_test = train_test_split(X, np.ravel(y), test_size=0.30, random_state
In [14]: from sklearn.svm import SVC
In [15]: model=SVC()
In [16]: model.fit(X_train, y_train)
Out[16]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
            max_iter=-1, probability=False, random_state=None, shrinking=True,
            tol=0.001, verbose=False)
```

```
In [17]: predictions = model.predict(X_test)
In [18]: from sklearn.metrics import classification report, confusion matrix
In [19]: print(confusion_matrix(y_test,predictions))
        [[144 0]
         [ 0 156]]
In [20]: print(classification_report(y_test,predictions))
                   precision
                               recall f1-score
                                                support
                        1.00
                                 1.00
                 1
                                          1.00
                                                   144
                        1.00
                                 1.00
                                         1.00
                                                   156
        avg / total
                        1.00
                                 1.00
                                         1.00
                                                   300
In [21]: from sklearn.grid search import GridSearchCV
        /anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationWarning: T
        his module was deprecated in version 0.18 in favor of the model selection module into which
        all the refactored classes and functions are moved. Also note that the interface of the new
        CV iterators are different from that of this module. This module will be removed in 0.20.
          "This module will be removed in 0.20.", DeprecationWarning)
        /anaconda3/lib/python3.6/site-packages/sklearn/grid_search.py:42: DeprecationWarning: This m
        odule was deprecated in version 0.18 in favor of the model_selection module into which all t
        he refactored classes and functions are moved. This module will be removed in 0.20.
         DeprecationWarning)
In [22]: param grid = {'C': [0.1,1, 10, 100, 1000], 'gamma': [1,0.1,0.01,0.001,0.0001], 'kernel': ['rbf
In [23]: grid= GridSearchCV(SVC(), param_grid, refit=True, verbose=3)
In [24]: grid.fit(X_train, y_train)
        Fitting 3 folds for each of 25 candidates, totalling 75 fits
        [CV] C=0.1, gamma=1, kernel=rbf ......
        [CV] .......... C=0.1, gamma=1, kernel=rbf, score=1.000000 - 0.0s
        [CV] C=0.1, gamma=1, kernel=rbf ......
        [CV] ...... C=0.1, gamma=1, kernel=rbf, score=1.000000 - 0.0s
        [CV] C=0.1, gamma=1, kernel=rbf ......
        [CV] ...... C=0.1, gamma=1, kernel=rbf, score=1.000000 - 0.0s
        [CV] C=0.1, gamma=0.1, kernel=rbf ......
        [CV] ...... C=0.1, gamma=0.1, kernel=rbf, score=1.000000 - 0.0s
        [CV] C=0.1, gamma=0.1, kernel=rbf ......
        [CV] ...... C=0.1, gamma=0.1, kernel=rbf, score=1.000000 - 0.0s
        [CV] C=0.1, gamma=0.1, kernel=rbf ......
        [CV] ...... C=0.1, gamma=0.1, kernel=rbf, score=1.000000 - 0.0s
        [CV] C=0.1, gamma=0.01, kernel=rbf ......
        [CV] ...... C=0.1, gamma=0.01, kernel=rbf, score=1.000000 - 0.0s
        [CV] C=0.1, gamma=0.01, kernel=rbf ......
        [CV] ..... C=0.1, gamma=0.01, kernel=rbf, score=1.000000 - 0.0s
        [CV] \dots C=0.1, gamma=0.01, kernel=rbf, score=1.000000 - 0.0s
In [25]: grid.best_params_
Out[25]: {'C': 0.1, 'gamma': 1, 'kernel': 'rbf'}
In [26]: grid.best_estimator_
Out[26]: SVC(C=0.1, cache_size=200, class_weight=None, coef0=0.0,
         decision_function_shape='ovr', degree=3, gamma=1, kernel='rbf',
          max_iter=-1, probability=False, random_state=None, shrinking=True,
          tol=0.001, verbose=False)
In [27]: grid_predictions = grid.predict(X_test)
```

```
In [28]: grid predictions
Out[28]: array([2, 1, 1, 2, 1, 2, 1, 2, 2, 2, 2, 2, 2, 1, 2, 1, 1, 1, 1, 1, 2, 2,
                2, 2, 2, 1, 2, 1, 1, 2, 1, 2, 1, 2, 1, 2, 1, 1, 2, 1, 1, 1, 2, 1,
                1, 1, 2, 2, 2, 2, 1, 2, 1, 2, 1, 1, 2, 2, 1, 2, 2, 1, 2, 2, 2, 1,
                1, 2, 2, 1, 2, 2, 2, 2, 2, 1, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 1,
                1, 1, 2, 1, 2, 1, 2, 1, 2, 2, 2, 1, 2, 1, 1, 2, 1, 1, 2, 1, 1, 2,
                1, 2, 1, 2, 1, 2, 2, 2, 1, 1, 2, 1, 1, 1, 2, 2, 1, 2, 1, 1, 1, 2,
                2, 1, 1, 1, 1, 2, 2, 2, 1, 2, 1, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                2, 1, 1, 1, 2, 1, 1, 1, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 1, 1, 1, 1,
                2, 2, 2, 2, 1, 1, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1,
                2, 2, 2, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 2, 2, 1, 1, 1, 1, 2, 2, 1, 2,
                2, 2, 1, 2, 2, 1, 2, 1, 1, 1, 2, 2, 1, 2, 2, 1, 2, 2, 1, 1, 2, 1,
                1, 1, 2, 2, 1, 1, 1, 2, 1, 1, 1, 1, 2, 2, 2, 2, 1, 1, 1, 2, 1, 2,
                1, 2, 2, 2, 1, 1, 2, 2, 2, 2, 1, 2, 2, 1, 1, 2, 2, 2, 2, 2, 1, 1, 1,
                2, 1, 2, 1, 2, 2, 1, 2, 2, 1, 1, 2, 1, 1])
In [29]: print(confusion_matrix(y_test,grid_predictions))
         [[144
                 0]
          [ 0 156]]
In [30]: print(classification_report(y_test, grid_predictions))
                      precision
                                    recall f1-score
                                                       support
                                      1.00
                    1
                            1.00
                                                1.00
                                                           144
                            1.00
                                      1.00
                                                1.00
                                                           156
         avg / total
                           1.00
                                      1.00
                                                1.00
                                                           300
In [31]: plt.scatter(y test, grid predictions)
Out[31]: <matplotlib.collections.PathCollection at 0x1a13ff3080>
          2.0
          1.8
          1.6
```

14

1.2

1.0

1.0

1.2

1.4

1.6

1.8

2.0

```
In [58]: import itertools
         def plot confusion matrix(cm, classes,
                                   normalize=False,
                                   title='Confusion matrix',
                                   cmap=plt.cm.Blues):
             This function prints and plots the confusion matrix.
             Normalization can be applied by setting `normalize=True`.
             if normalize:
                 cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                 print("Normalized confusion matrix")
                 print('Confusion matrix, without normalization')
             print(cm)
             plt.imshow(cm, interpolation='nearest', cmap=cmap)
             plt.title(title)
             plt.colorbar()
             tick marks = np.arange(len(classes))
             plt.xticks(tick_marks, classes, rotation=45)
             plt.yticks(tick_marks, classes)
             fmt = '.2f' if normalize else 'd'
             thresh = cm.max() / 2.
             for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                 plt.text(j, i, format(cm[i, j], fmt),
                          horizontalalignment="center",
                          color="white" if cm[i, j] > thresh else "black")
             plt.ylabel('True label')
             plt.xlabel('Predicted label')
             plt.tight_layout()
         # Compute confusion matrix
         cnf_matrix = confusion_matrix(y_test, grid_predictions)
         np.set printoptions(precision=2)
         # Plot non-normalized confusion matrix
         beingsaved = plt.figure()
         plot_confusion_matrix(cnf_matrix, classes=class_names,
                               title='Confusion matrix, without normalization')
         beingsaved.savefig('destination_path.png', format='png', dpi=1000)
         # Plot normalized confusion matrix
         beingsaved1 = plt.figure()
         plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                               title='Normalized confusion matrix')
         beingsaved1.savefig('destination_path1.png', format='png', dpi=1000)
         plt.show()
         Confusion matrix, without normalization
         [[144 0]
         [ 0 156]]
         Normalized confusion matrix
         [[1. 0.]
          [0. 1.]]
```



