## One-Class Support Vector Machine | Example 1

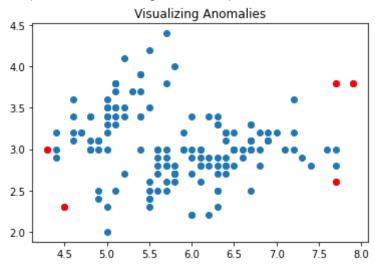
- 1 # import libraries
- 2 import pandas as pd
- 3 from sklearn.svm import OneClassSVM
- 4 import matplotlib.pyplot as plt
- 5 from numpy import where
- 1 # import data
- 2 data = pd.read\_csv("https://raw.githubusercontent.com/uiuc-cse/data-fa14/gh-pages/data/iris.csv")
- 3 # input data
- 4 df = data[["sepal\_length", "sepal\_width"]]
- 1 # model specification
- 2 # nu = 0.03 means that the algorithm will designate 3% data as outliers.
- 3 model = OneClassSVM(kernel = 'rbf', gamma = 0.001, nu = 0.03).fit(df)
- 1 # prediction
- 2 y\_pred = model.predict(df)
- 3 y\_pred

- 1 # filter outlier index
- 2 outlier\_index = where(y\_pred == -1)
- 3 # filter outlier values
- 4 outlier\_values = df.iloc[outlier\_index]
- 5 outlier\_values

	sepal_length	sepal_width	
13	4.3	3.0	
41	4.5	2.3	
117	7.7	3.8	
118	7.7	2.6	
131	7.9	3.8	

- 1 # visualize outputs
- 2 plt.scatter(data["sepal\_length"], df["sepal\_width"])
- 3 plt.scatter(outlier\_values["sepal\_length"], outlier\_values["sepal\_width"], c = "r")
- 4 plt.title("Visualizing Anomalies")

Text(0.5, 1.0, 'Visualizing Anomalies')



## One-Class Support Vector Machine | Example 2

- 1 # one-class svm for imbalanced binary classification
- 2 from sklearn.datasets import make classification
- 3 from sklearn.model\_selection import train\_test\_split
- 4 from sklearn.metrics import f1 score, classification report, confusion matrix, plot confusion matrix
- 5 from sklearn.svm import OneClassSVM
- 6 # generate dataset
- 7 X, y = make classification(n samples=10000, n features=2, n redundant=0,
- 8 n\_clusters\_per\_class=1, weights=[0.999], flip\_y=0, random\_state=4)
- 9 # split into train/test sets
- trainX, testX, trainy, testy = train\_test\_split(X, y, test\_size=0.5, random\_state=2, stratify=y)
- 11 # define outlier detection model
- model = OneClassSVM(gamma='scale', nu=0.01)
- 13 # fit on majority class
- 14 trainX = trainX[trainy==0]
- 15 model.fit(trainX)
- 16 # detect outliers in the test set
- 17 yhat = model.predict(testX)
- 18 # mark inliers 1, outliers -1
- 19 testy[testy == 1] = -1
- 20 testy[testy == 0] = 1
- 21 # calculate F1 score
- score = f1 score(testy, yhat, pos label=-1)
- 23 print('F1 Score: %.3f' % score)
- 24 # Classification report
- 25 target\_names = ['class 0', 'class 1']
- print(classification\_report(testy, yhat, target\_names=target\_names))
- 07 print/IClassification Donorty I alassification report

```
21
```

17

# generate dataset

```
F1 Score: 0.123
        precision recall f1-score support
             0.07
                                      5
  class 0
                    0.80
                            0.12
                                    4995
                            0.99
  class 1
             1.00
                    0.99
                          0.99
                                  5000
  accuracy
 macro avg
               0.53
                       0.89
                              0.56
                                      5000
weighted avg
                1.00
                        0.99
                               0.99
                                       5000
```

Classification Report: <function classification\_report at 0x7f0976cb48c0>

Local Outlier Factor Method. A simple approach to identifying outliers is to locate those examples that are far from the other examples in the feature space.

This can work well for feature spaces with low dimensionality (few features), although it can become less reliable as the number of features is increased, referred to as the curse of dimensionality.

The local outlier factor, or LOF for short, is a technique that attempts to harness the idea of nearest neighbors for outlier detection. Each example is assigned a scoring of how isolated or how likely it is to be outliers based on the size of its local neighborhood. Those examples with the largest score are more likely to be outliers.

```
1
     # local outlier factor for imbalanced classification
 2
     from numpy import vstack
 3
     from sklearn.datasets import make_classification
 4
     from sklearn.model selection import train test split
     from sklearn.metrics import f1_score
 5
 6
     from sklearn.neighbors import LocalOutlierFactor
 7
 8
      # make a prediction with a lof model
 9
      def lof predict(model, trainX, testX):
10
       # create one large dataset
       composite = vstack((trainX, testX))
11
       # make prediction on composite dataset
12
13
       yhat = model.fit predict(composite)
14
       # return just the predictions on the test set
15
       return yhat[len(trainX):]
16
```

```
X, y = make_classification(n_samples=10000, n_features=2, n_redundant=0,
18
19
       n_clusters_per_class=1, weights=[0.999], flip_y=0, random_state=4)
20
      # split into train/test sets
21
     trainX, testX, trainy, testy = train_test_split(X, y, test_size=0.5, random_state=2, stratify=y)
22
     # define outlier detection model
23
      model = LocalOutlierFactor(contamination=0.01)
24
     # get examples for just the majority class
25
     trainX = trainX[trainy==0]
     # detect outliers in the test set
26
27
     yhat = lof_predict(model, trainX, testX)
28
     # mark inliers 1, outliers -1
29
     testy[testy == 1] = -1
30
     testy[testy == 0] = 1
31
     # calculate score
32
      score = f1_score(testy, yhat, pos_label=-1)
      print('F1 Score: %.3f' % score)
33
34
      # Classification report
      target_names = ['class 0', 'class 1']
35
36
      print(classification_report(testy, yhat, target_names=target_names))
37
      print('Classification Report: ', classification_report)
      F1 Score: 0.138
              precision recall f1-score support
                    80.0
         class 0
                            0.80
                                     0.14
                                               5
         class 1
                    1.00
                            0.99
                                     0.99
                                             4995
        accuracy
                                  0.99
                                           5000
        macro avg
                       0.54
                               0.90
                                       0.57
                                               5000
      weighted avg
                       1.00
                                0.99
                                        0.99
                                                5000
```

Classification Report: <function classification\_report at 0x7f0976cb48c0>