Estimation, Detection and Analysis II

06 - Detection of outliers

Univariate

Multivariate

1. install the libraries pyod , combo. At the terminal:

```
pip install pyod
pip install combo
```

2. Import the necessary libraries

```
import pandas as pd
import seaborn as sns
from sklearn.ensemble import IsolationForest
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt
import matplotlib.font_manager
from sklearn.preprocessing import MinMaxScaler
from pyod.models.cblof import CBLOF
from pyod.models.feature_bagging import FeatureBagging
from pyod.models.iforest import IForest
from pyod.models.knn import KNN
from pyod.models.lof import LOF
```

3. Load the data (Superstore.xls dataset available in Moodle)

```
df = pd.read_excel ('Superstore.xls')
```

4. View statistics for column "Sales"

```
print( df ['Sales']. describe ())
```

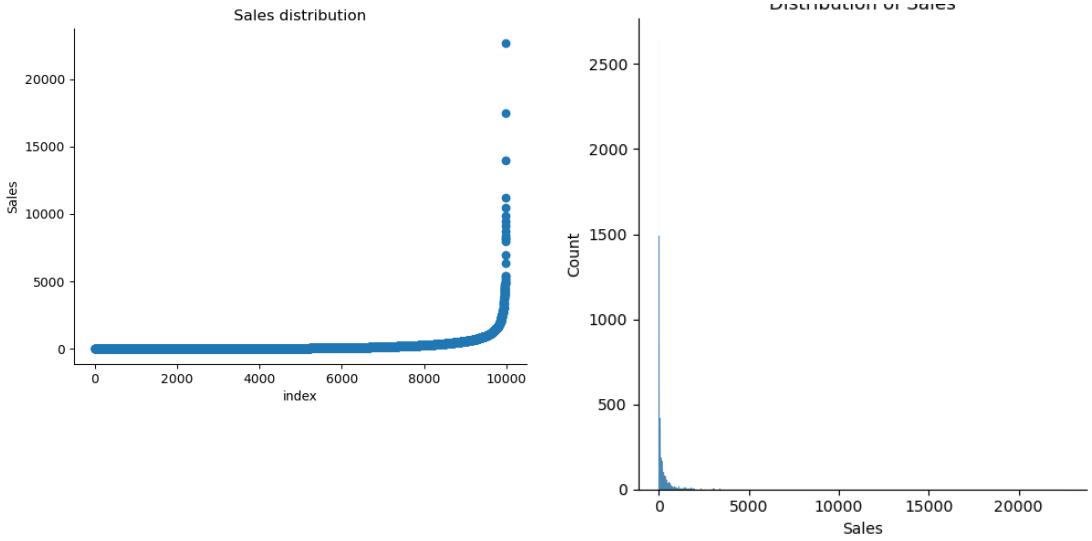
Result:

```
count 9994.000000
mean 229.858001
std 623.245101
min 0.444000
25% 17.280000
50% 54.490000
75% 209.940000
max 22638.480000
Name : Sales, dtype : float64
```

5. View distribution of column "Sales" values

```
plt.scatter (range( df.shape [0]), np.sort ( df ['Sales']. values ))
plt.xlabel (' index ')
plt.ylabel ('Sales')
plt.title ("Sales distribution ")
sns.despine ()
plt.show ()

sns.displot ( df ['Sales'])
plt.title (" Distribution of Sales")
sns.despine ()
plt.show ()
```

Result:



6. View skewness and kurtosis from column "Sales"

```
print(" Skewness : %f" % df ['Sales']. skew ())
print(" Kurtosis : %f" % df ['Sales']. kurt ())
```

Result:

```
Skewness : 12.972752
Kurtosis : 305.311753
```

The "Sales" column is far from the normal distribution, showing a long and narrow right tail, with most of the data concentrated in the left part of the figure. There is less chance of
data appears in the right part of the figure

7. View statistics of column " Profit "

```
df [' Profit ']. describe ()
```

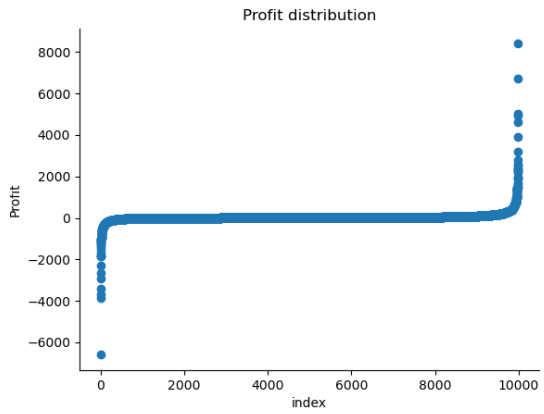
Result:

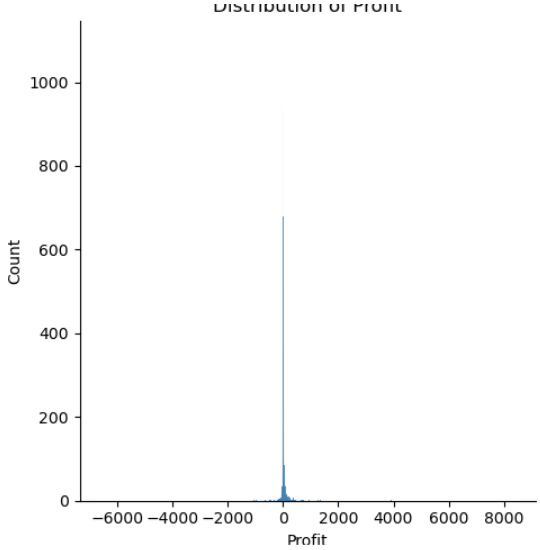
```
count 9994.000000
mean 28.656896
std 234.260108
min -6599.978000
25% 1.728750
50% 8.666500
75% 29.364000
max 8399.976000
Name : Profit , dtype : float64
```

8. Visualize distribution of values of column " Profit "

```
plt.scatter (range( df.shape [0]), np.sort ( df [' Profit ']. values ))
plt.xlabel (' index ')
plt.ylabel (' Profit ')
plt.title (" Profit distribution ")
sns.despine ()
plt.show ()

sns.displot ( df [' Profit '])
plt.title (" Distribution of profit ")
sns.despine ()
plt.show ()
```

Result:





9. View skewness and kurtosis from column " Profit "

```
print(" Skewness : %f" % df [' Profit ']. skew ())
print(" Kurtosis : %f" % df [' Profit ']. kurt ())
```

Result:

```
Skewness : 7.561432
Kurtosis : 397.188515
```

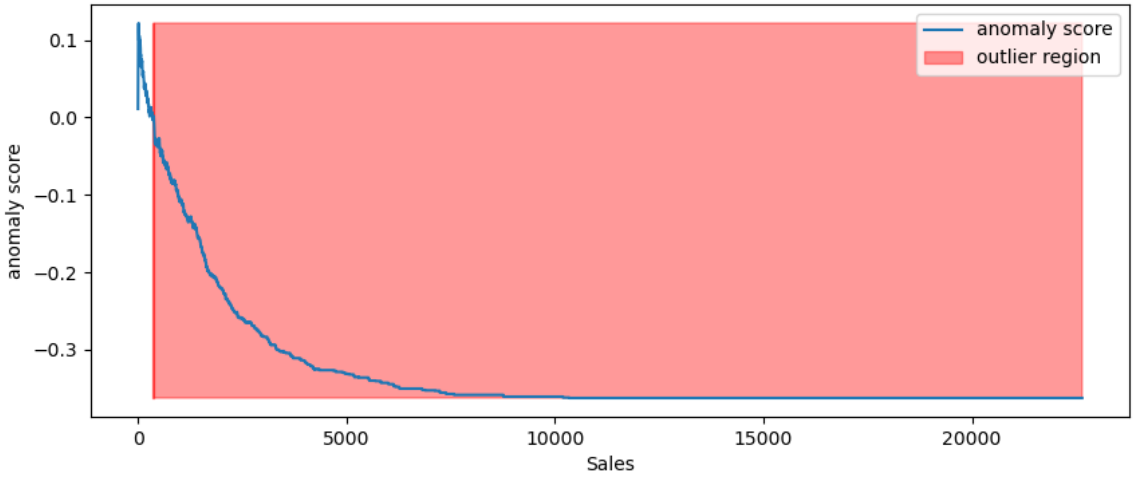
Profit " column has positive and negative tails. There are two regions where outliers can appear : the left and right edges of the figure.

univariate

10. Determine outliers in "Sales" using the " Isolation " algorithm Forest "

```
isolation_forest = IsolationForest ( n_estimators =100)
isolation_forest.fit ( df ['Sales']. values.reshape (-1, 1))
xx = np.linspace ( df ['Sales'].min(), df ['Sales']. max (), len ( df )). reshape (-1,1)
anomaly_score = isolation_forest.decision_function ( xx )
outlier = isolation_forest.predict ( xx )
plt.figure ( figsize =(10,4))
plt.plot ( xx , anomaly_score , label =' anomaly score')
plt.fill_between ( xx.T [0], np.min ( anomaly_score ), np.max ( anomaly_score ),
                  where = outlier ==-1, color='r',
                  alpha =.4, label =' outlier region ')
plt.legend ()
plt.ylabel (' anomaly score')
plt.xlabel ('Sales')
plt.show ()
```

Result:

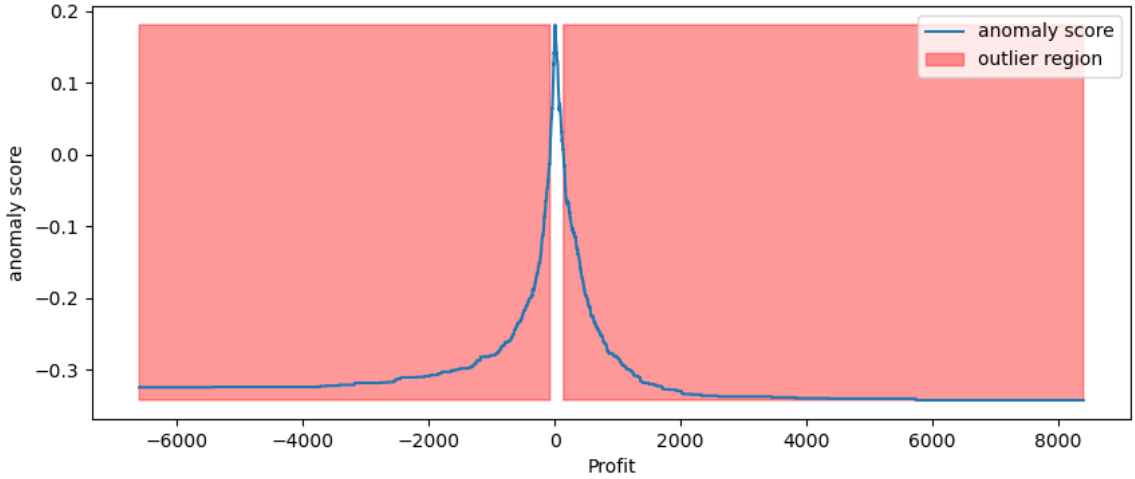


According to the figure, "Sales" greater than 1000 will be considered as outliers

11. Determine outliers in " Profit " using the " Isolation" algorithm Forest "

```
isolation_forest = IsolationForest ( n_estimators =100)
isolation_forest.fit ( df [' Profit ']. values.reshape (-1, 1))
xx = np.linspace ( df [' Profit '].min(), df [' Profit ']. max (), len ( df )). reshape
(-1,1)
anomaly_score = isolation_forest.decision_function ( xx )
outlier = isolation_forest.predict ( xx )
plt.figure ( figsize =(10,4))
plt.plot ( xx , anomaly_score , label =' anomaly score')
plt.fill_between ( xx.T [0], np.min ( anomaly_score ), np.max ( anomaly_score ),
                  where = outlier ==-1, color='r',
                  alpha =.4, label =' outlier region ')
plt.legend ()
plt.ylabel (' anomaly score')
plt.xlabel (' Profit ')
plt.show ()
```

Result:



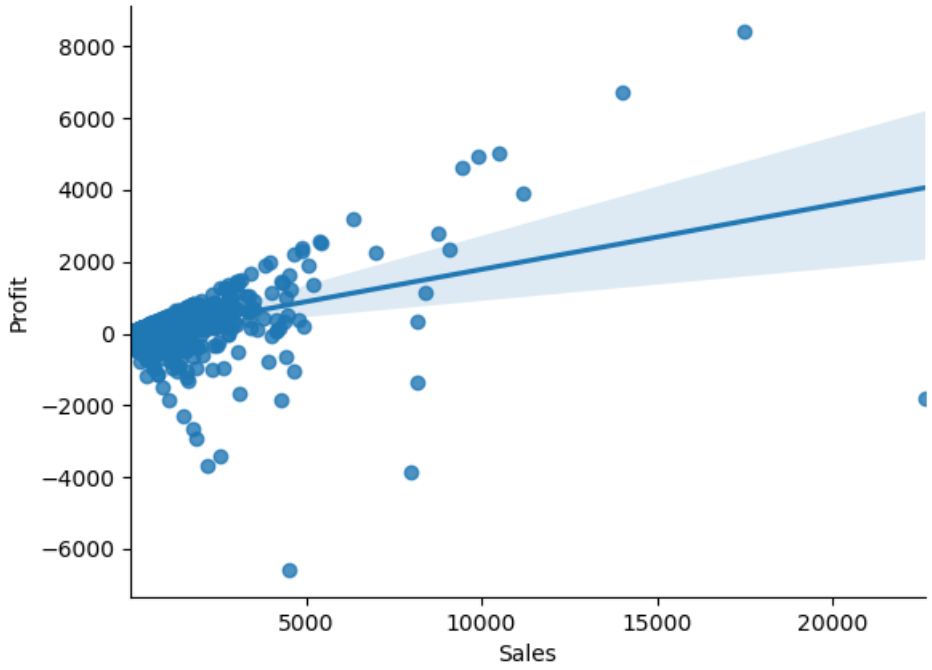
According to the figure, " Profit " less than -100 or greater than 100 can be considered as outliers

Multivariate

12. View the correlation graph between "Sales" and " Profit "

```
sns.regplot (x="Sales", y=" Profit ", data= df )
sns.despine ()
plt.show ()
```

Result:



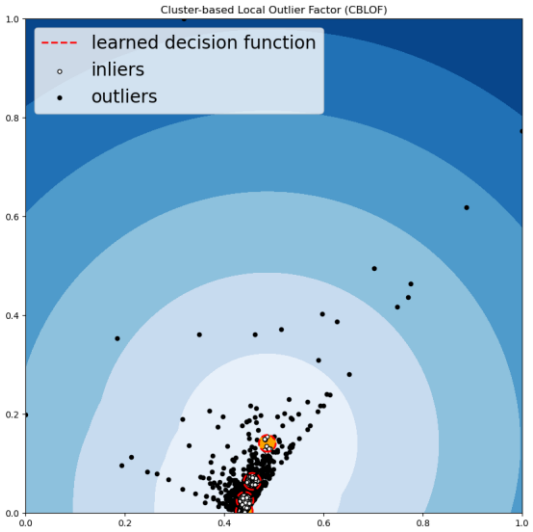
We managed to detect some outliers - too high or too low values

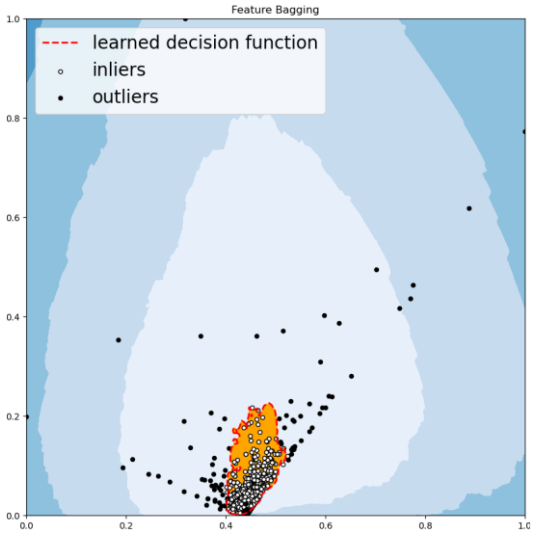
13. outlier detection methods from the library pyod

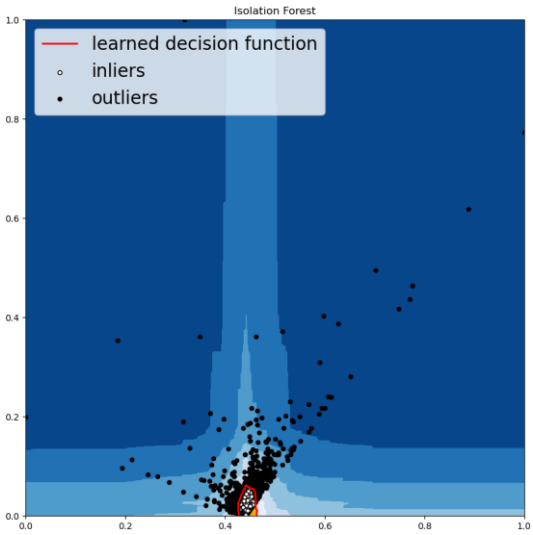
```
scaler = MinMaxScaler ( feature_range =(0, 1))
df [[' Profit ', 'Sales']] = scaler.fit_transform ( df [[' Profit ', 'Sales']])
X1 = df [' Profit ']. values.reshape (-1, 1)
X2 = df ['Sales']. values.reshape (-1, 1)
X = np.concatenate ((X1, X2), axis =1)

random_state = np.random.RandomState (42)
outliers_fraction = 0.05
# define seven outlier detection tools to be compared
classifiers = {
'Cluster- based Local Outlier Factor (CBLOF)': CBLOF( contamination = outliers_fraction
,
        check_estimator =False, random_state = random_state ),
' Feature Bagging ': FeatureBagging (LOF( n_neighbors =35),
       contamination = outliers_fraction , check_estimator =False,
       random_state = random_state ),
' Isolation Forest ': IForest ( contamination = outliers_fraction ,
        random_state = random_state ),
'K Nearest Neighbors (KNN)': KNN( contamination = outliers_fraction ),
' Average KNN': KNN( method =' mean ', contamination = outliers_fraction )
}
```

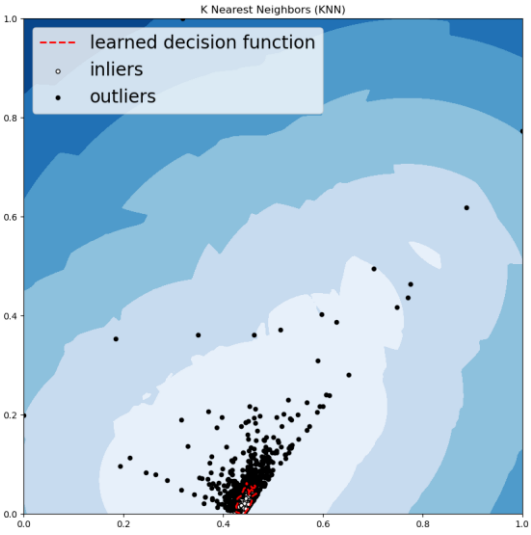
```
xx , yy = np.meshgrid ( np.linspace (0, 1, 200), np.linspace (0, 1, 200))
for i, ( clf_name , clf ) in enumerate ( classifiers.items ()):
    clf.fit (X)
# predict raw abnormally score
    scores_pred = clf.decision_function (X) * -1

# prediction from a datapoint category outlier or inlier
    y_pred = clf.predict (X)
    n_inliers = len ( y_pred ) - np.count_nonzero ( y_pred )
    n_outliers = np.count_nonzero ( y_pred == 1)
    plt.figure ( figsize =(10, 10))

# copy of dataframe
    dfx = df
    dfx [' outlier '] = y_pred.tolist ()

# IX1 - inlier feature 1, IX2 - inlier feature 2
IX1 = np.array ( dfx [' Profit '][ dfx [' outlier '] == 0]). reshape (-1, 1)
IX2 = np.array ( dfx ['Sales'][ dfx [' outlier '] == 0]). reshape (-1, 1)

# OX1 - outlier feature 1, OX2 - outlier feature 2
OX1 = dfx [' Profit '][ dfx [' outlier '] == 1]. values.reshape (-1, 1)
OX2 = dfx ['Sales'][ dfx [' outlier '] == 1]. values.reshape (-1, 1)

print('OUTLIERS : ', n_outliers , 'INLIERS : ', n_inliers , clf_name )

# threshold value to consider a datapoint inlier or outlier
    threshold = stats.scoreatpercentile ( scores_pred , 100 * outliers_fraction )

# decision function calculates the raw anomaly score for every point
Z = clf.decision_function ( np.c _[ xx.ravel (), yy.ravel ()]) * -1
Z = Z.reshape ( xx.shape )

# fill blue map colormap from minimum anomaly score to threshold value
    plt.contourf ( xx , yy , Z, levels = np.linspace ( Z.min (), threshold , 7),
         cmap = plt.cm.Blues_r )

# draw red contour line Onde abnormally score is equal to thresold
a = plt.contour ( xx , yy , Z, levels =[ threshold ], linewidths =2, colors =' red ')

# fill orange contour lines where range of abnormally score is from threshold
        to maximum abnormally score
    plt.contourf ( xx , yy , Z, levels =[ threshold , Z.max ()], colors =' orange ')

b = plt.scatter (IX1, IX2, c=' white ', s=20, edgecolor ='k')

c = plt.scatter (OX1, OX2, c=' black ', s=20, edgecolor ='k')

    plt.axis (' tight ')

# location =2 is used for the top left corner
    plt.legend (
[ a.collections [0], b, c],
[' learned decision function ', ' inliers ', ' outliers '],
        prop = matplotlib.font_manager.FontProperties ( size =20),
        location =2)

    plt.xlim ((0, 1))
    plt.ylim ((0, 1))
    plt.title ( clf_name )
    plt.show ()
```

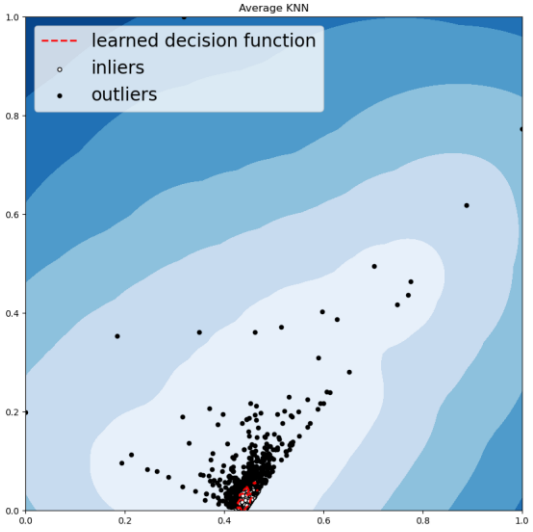
Results:


Cluster-based Local Outlier Factor (CBLOF)
learned decision function
inliers
outliers


Feature Bagging
learned decision function
inliers
outliers


Isolation Forest
learned decision function
inliers
outliers


K Nearest Neighbors (KNN)
learned decision function
inliers
outliers


Average KNN
learned decision function
inliers
outliers