Session Length vs. Data Transfer -- Anomaly Detection with Python

This notebook demonstrates use of the Python Outlier Detection (PyOD) module to detect anomalies in users session lengths (in seconds) and data transferred (in MB).

See pypi.org for more information on PyOD

[https://pypi.org/project/pyod/ (https://pypi.org/project/pyod/)](https://pypi.org/project/pyod/)

In [1]:

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from scipy import stats
import matplotlib.pyplot as plt
import matplotlib.font_manager
%matplotlib inline

# Anomaly detection models
from pyod.models.cblof import CBLOF
from pyod.models.hbos import HBOS
from pyod.models.iforest import IForest
from pyod.models.knn import KNN
```

In [2]:

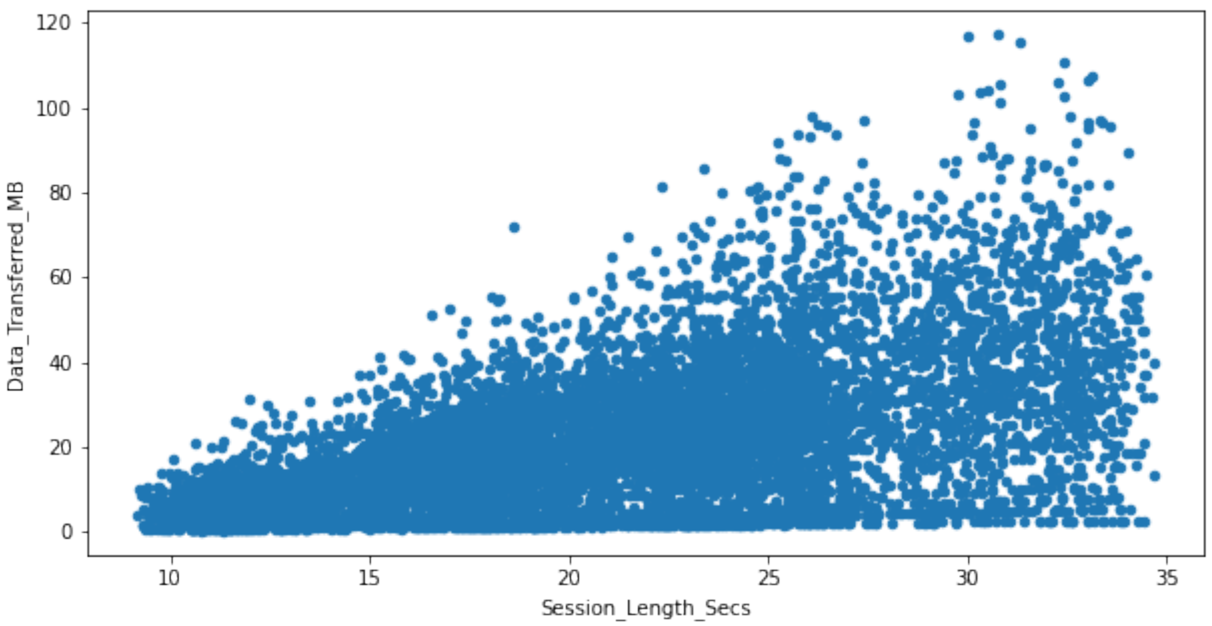
```
# read the cyber data
df = pd.read_excel("cyberdata.xlsx")
```

In [3]:

```
# Create a scatter plot of Session_Length_Secs vs. Data_Transferred
df.plot.scatter( 'Session_Length_Secs', 'Data_Transferred_MB', figs
```

Out[3]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1212b7cf8>
```



In [4]:

```
# Scale down the data to aid in visualization creation.
scaler = MinMaxScaler( feature_range=(0, 1) )
df[ ['Session_Length_Secs', 'Data_Transferred_MB'] ] = \
    scaler.fit_transform(df[ ['Session_Length_Secs', 'Data_Transfer
```

In [5]:

```
# Save the values for later usage in calls to classifier fit().
X1 = df['Session_Length_Secs'].values.reshape(-1,1)
X2 = df['Data_Transferred_MB'].values.reshape(-1,1)
X = np.concatenate( (X1, X2), axis=1 )
```

In [6]:

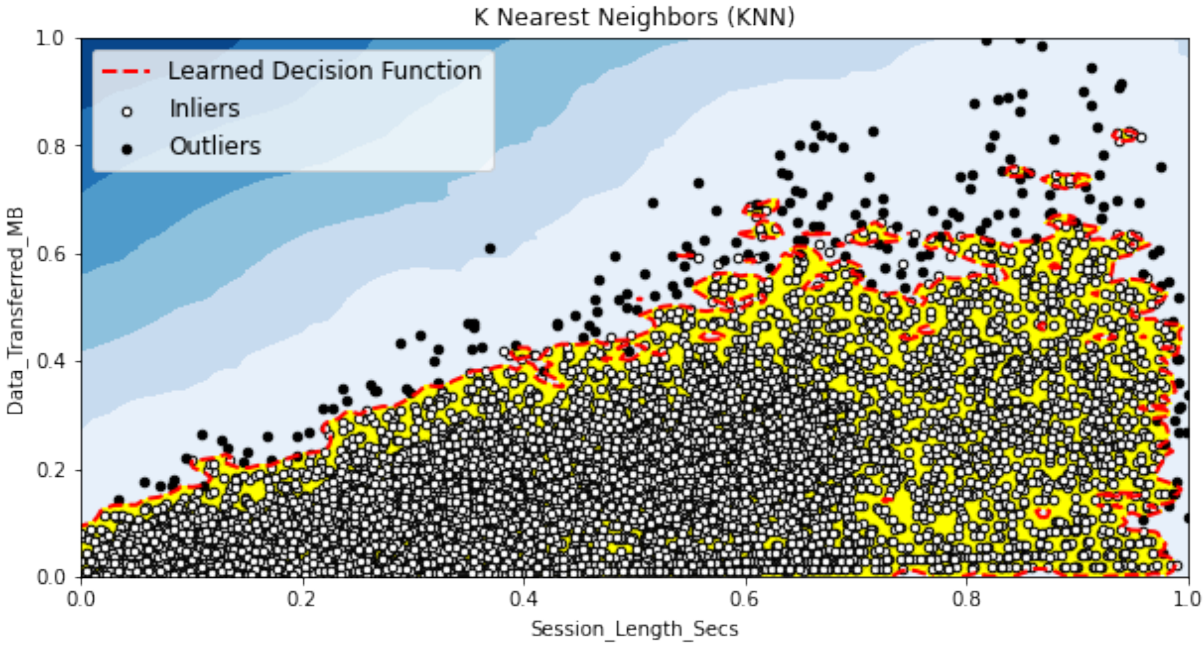
```
rand_value = 3  #  for randomization
random_state = np.random.RandomState( rand_value )

# Set the desired outlier detection fraction (i.e., % observations
outlier_fraction = 0.03

# The dictionary of outlier detection models
classifiers = {
        'K Nearest Neighbors (KNN)': KNN(contamination=outlier_frac
        'Isolation Forest': IForest(contamination=outlier_fraction,
        'Cluster-based Local Outlier Factor (CBLOF)':CBLOF(contamin
        'Histogram-base Outlier Detection (HBOS)': HBOS(contaminati
}
```

In [7]:

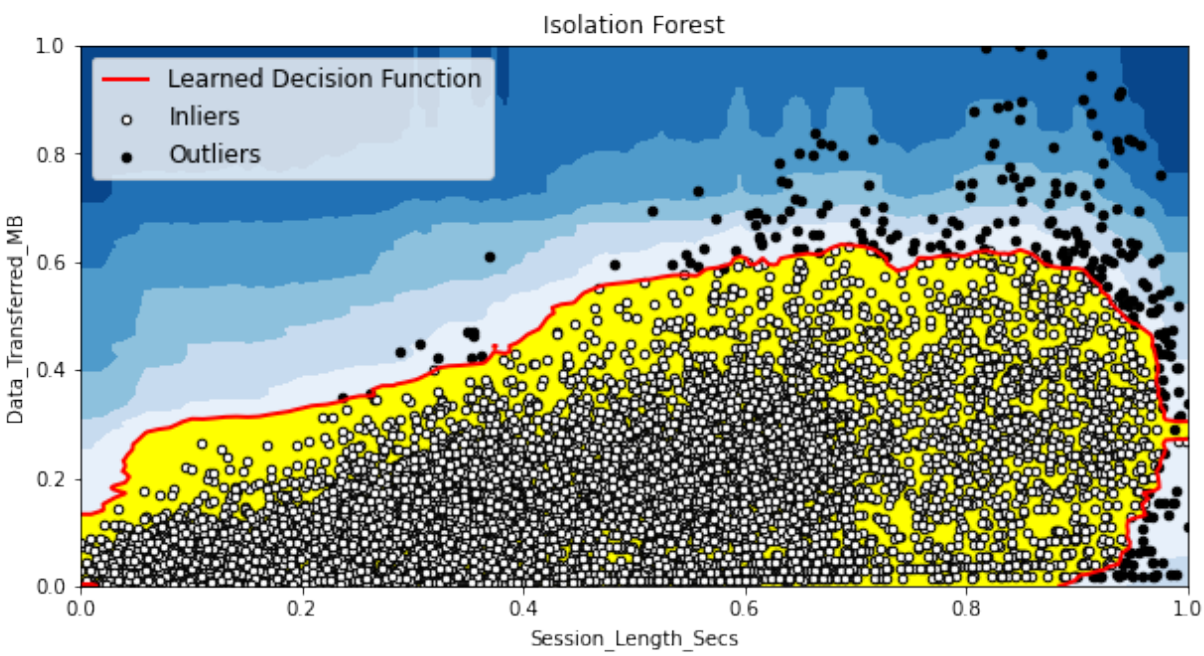
```
# Run the anomaly detection models and compare results.
# 1. Fit the data to each model to see how each model predicts the
# 2. Plot the results for each model
xx, yy = np.meshgrid( np.linspace(0,1 , 100), np.linspace(0, 1, 100
comp_results = pd.DataFrame(columns=['model', 'outliers', 'inliers'

print("\n NOTE: This cell may take a while to finish (depending on

for i, (clf_name, clf) in enumerate(classifiers.items()):
    # fit the data and tag outliers
    clf.fit(X)

    # predict raw anomaly score
    scores_pred = clf.decision_function(X) * -1

    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, 5))

    xtitle = 'Session_Length_Secs'
    ytitle = 'Data_Transferred_MB'

    dfx = df
    dfx['outlier'] = y_pred.tolist()
```

```
    # InX1: inlier feature #1,  InX2: inlier feature 2
    InX1 =  np.array(dfx[ xtitle ][dfx['outlier'] == 0]).reshape(-1
    InX2 =  np.array(dfx[ ytitle ][dfx['outlier'] == 0]).reshape(-1

    # OutX1: outlier feature #1, OutX2: outlier feature 2
    OutX1 = dfx[ xtitle ][dfx['outlier'] == 1].values.reshape(-1,1)
    OutX2 = dfx[ ytitle ][dfx['outlier'] == 1].values.reshape(-1,1)

    print('\n\n{} --> # Outliers detected: {},  # Inliers: {} '.for
    comp_results = comp_results.append( {'model': clf_name,
                                         'outliers': n_outliers,
                                         'inliers': n_inliers,
                                         'ratio: out/in': (n_outlie

    threshold = stats.scoreatpercentile(scores_pred, 100 * outlier_
    Z = clf.decision_function(np.c_[xx.ravel(), yy.ravel()]) * -1
    Z = Z.reshape(xx.shape)

    # color the map and contour lines
    plt.contourf(xx, yy, Z, levels=np.linspace(Z.min(), threshold,
    a = plt.contour(xx, yy, Z, levels=[threshold],linewidths=2, col
    plt.contourf(xx, yy, Z, levels=[threshold, Z.max()],colors='yel

    b = plt.scatter(InX1, InX2, c='white',s=20, edgecolor='k')
    c = plt.scatter(OutX1, OutX2, c='black',s=20, edgecolor='k')

    plt.axis('tight')
    plt.legend(
        [a.collections[0], b, c],
        ['Learned Decision Function', 'Inliers','Outliers'],
        prop=matplotlib.font_manager.FontProperties(size = 12), loc
    plt.xlim((0, 1))
    plt.ylim((0, 1))
    plt.xlabel( xtitle )
    plt.ylabel( ytitle )
    plt.title(clf_name)
    plt.show()
```

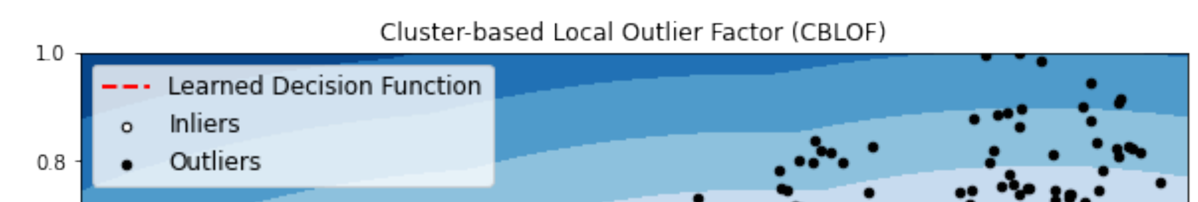
```
 NOTE: This cell may take a while to finish (depending
on your hardware).



K Nearest Neighbors (KNN) --> # Outliers detected: 192
,  # Inliers: 8331
```

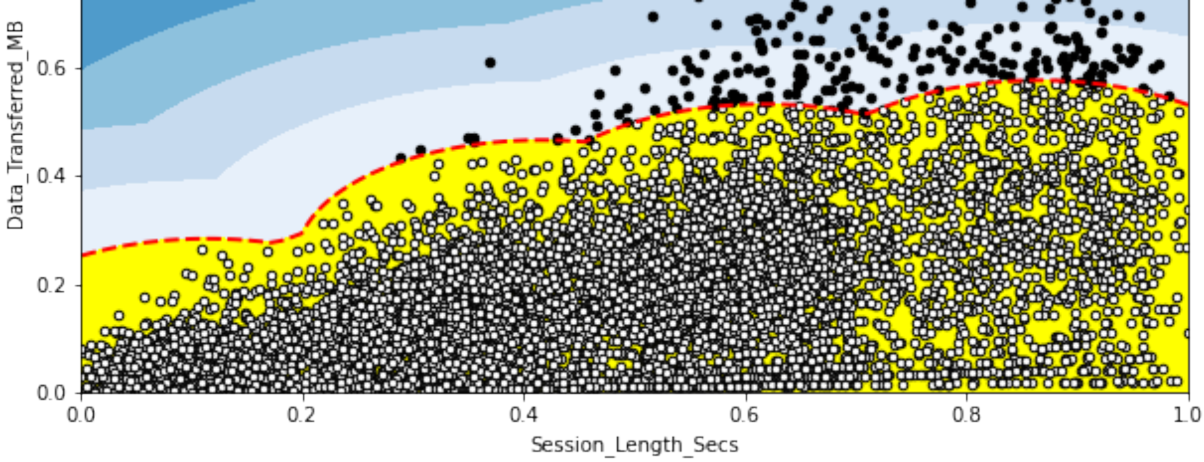



```
Isolation Forest --> # Outliers detected: 256,  # Inli
ers: 8267
```

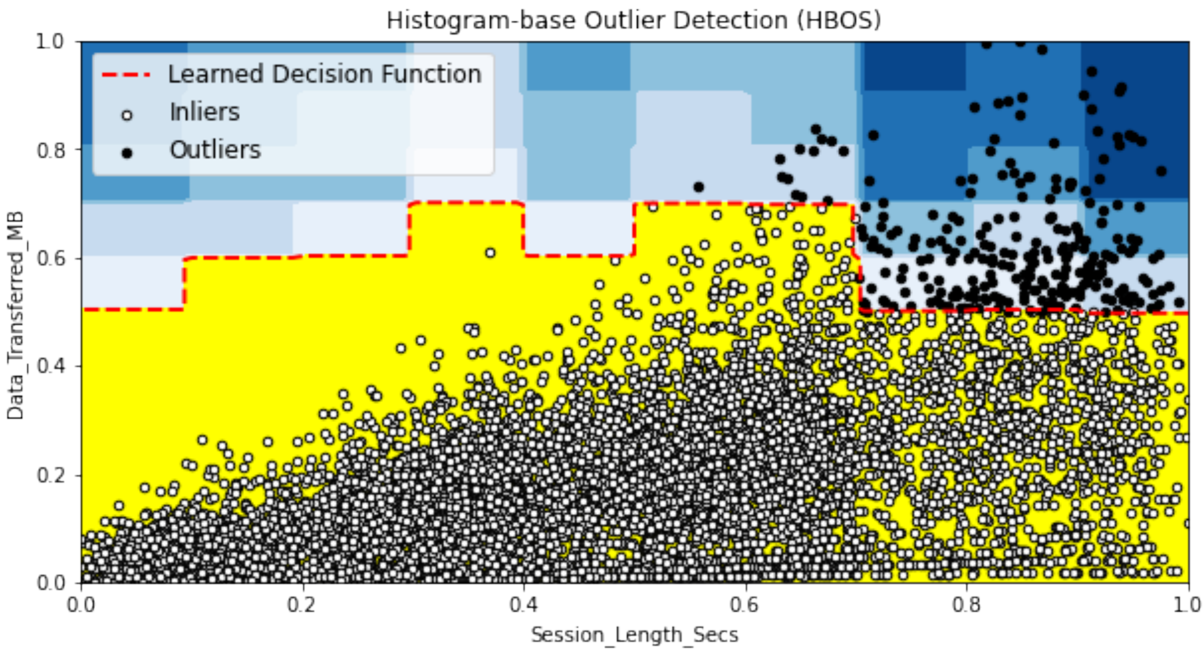



```
Cluster-based Local Outlier Factor (CBLOF) --> # Outli
ers detected: 256,  # Inliers: 8267
```






```
Histogram-base Outlier Detection (HBOS) --> # Outliers
detected: 256,  # Inliers: 8267
```



In [8]:

```
print("\n Summary of model comparision results:")
comp_results
```

```
 Summary of model comparision results:
```

Out[8]:

	model	outliers	inliers	ratio: out/in
0	K Nearest Neighbors (KNN)	192	8331	0.023046
1	Isolation Forest	256	8267	0.030966
2	Cluster-based Local Outlier Factor (CBLOF)	256	8267	0.030966
3	Histogram-base Outlier Detection (HBOS)	256	8267	0.030966

In [ ]:

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Out[3]:

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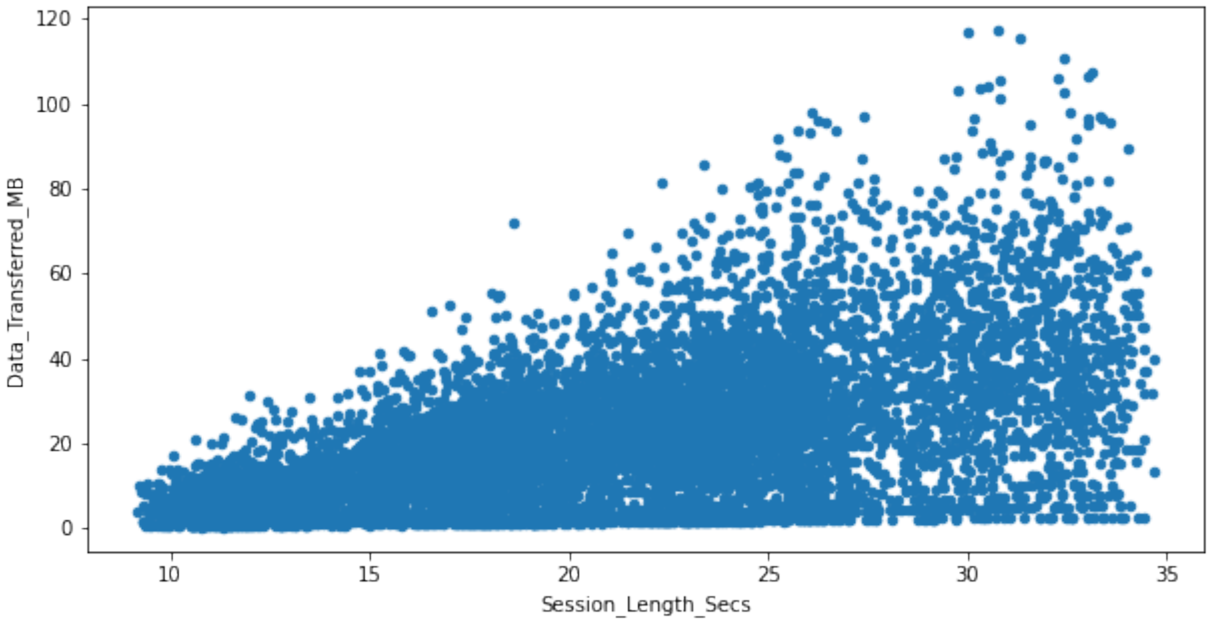

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In [5]:

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In [7]:

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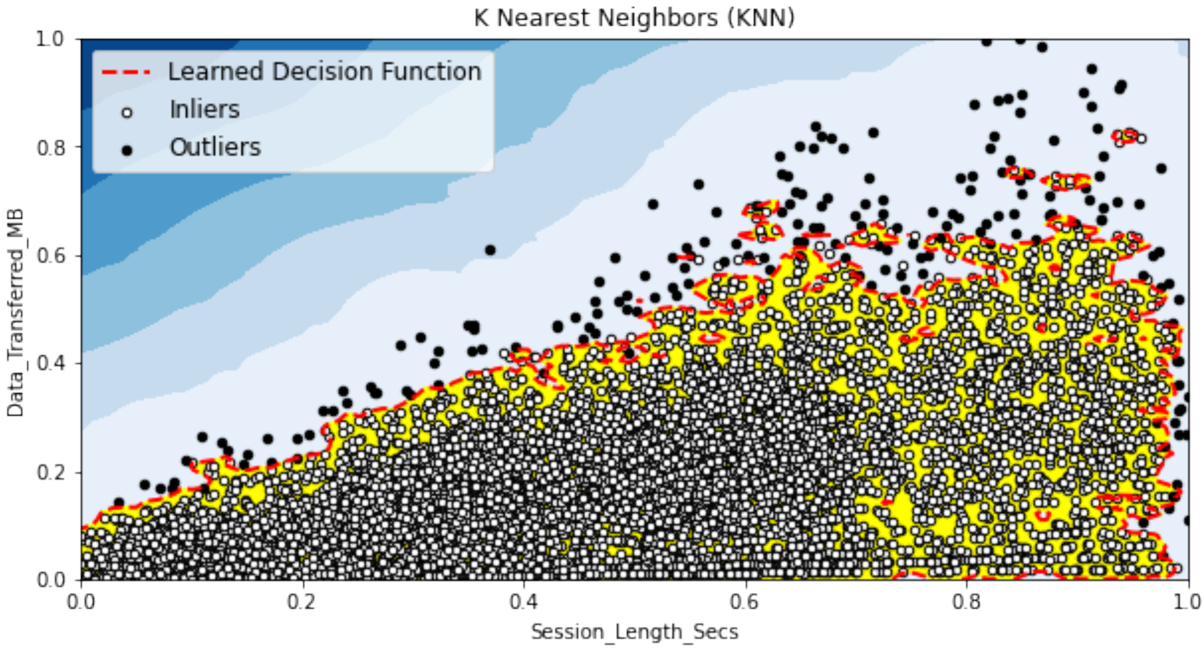


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ers: 8267
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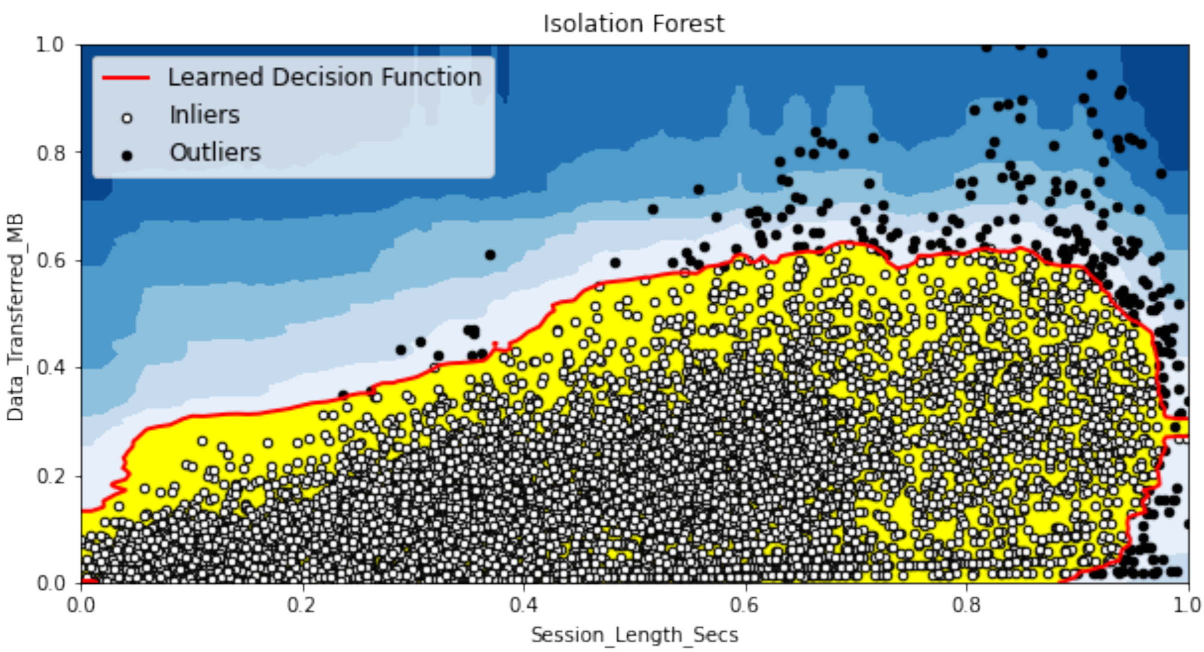
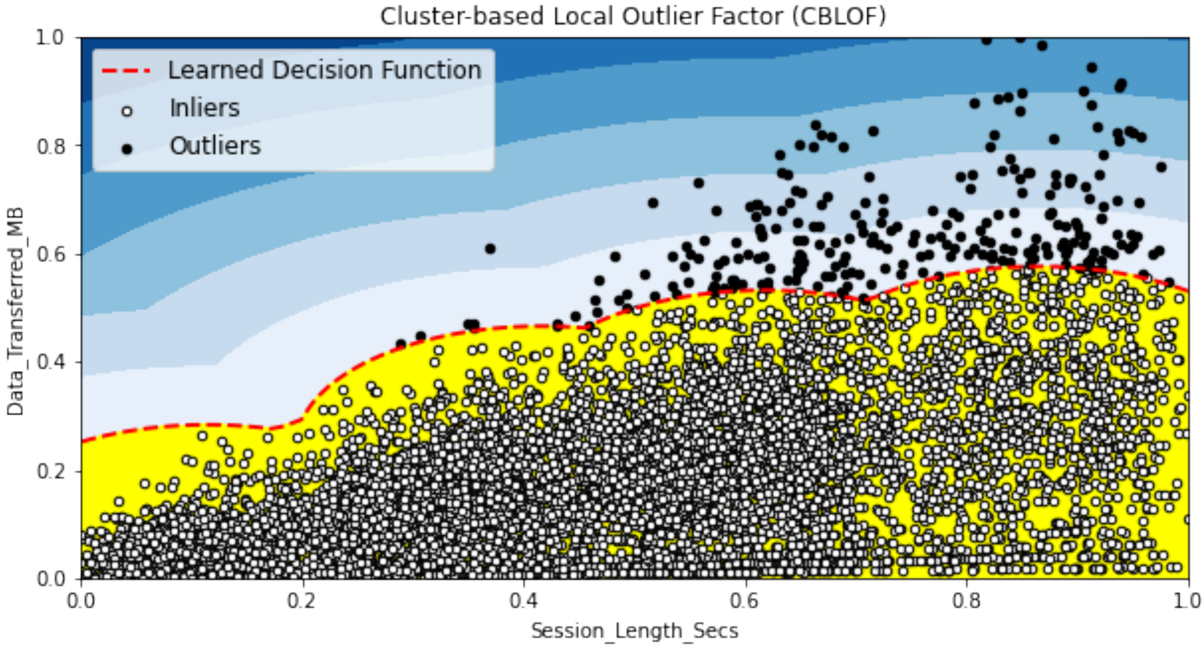
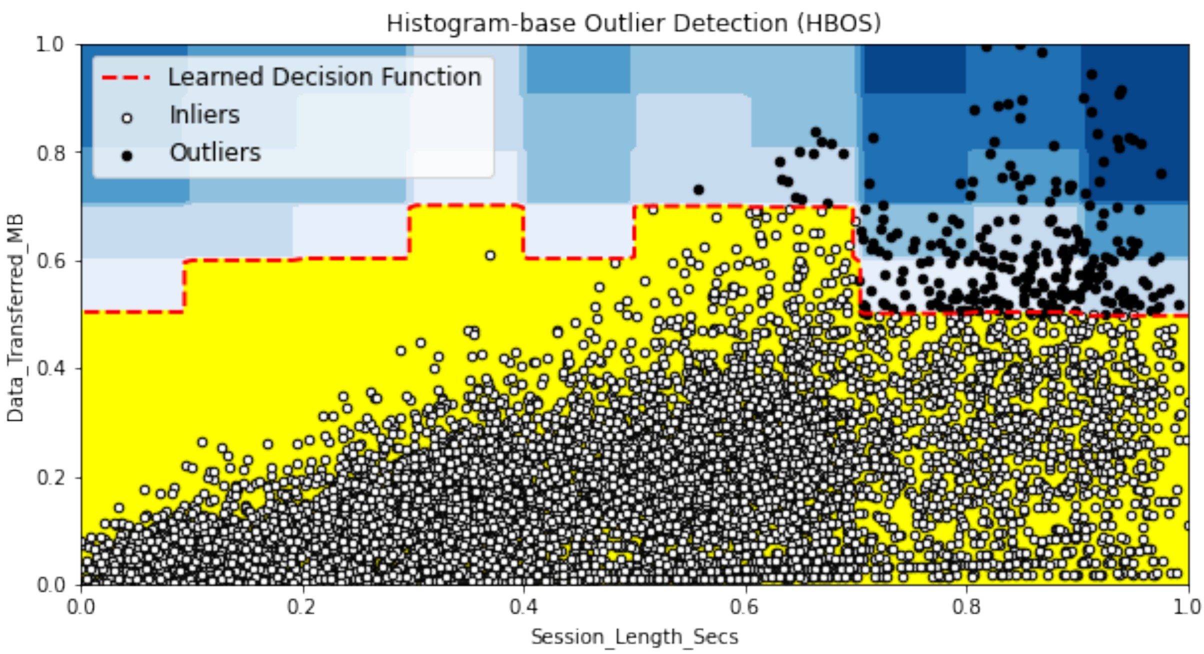



```
Cluster-based Local Outlier Factor (CBLOF) --> # Outli
ers detected: 256,  # Inliers: 8267
```




```
Histogram-base Outlier Detection (HBOS) --> # Outliers
detected: 256,  # Inliers: 8267
```



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Summary of model comparision results:
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In [ ]: