Baseline gradient boosted decision tree model trained using LightGBM

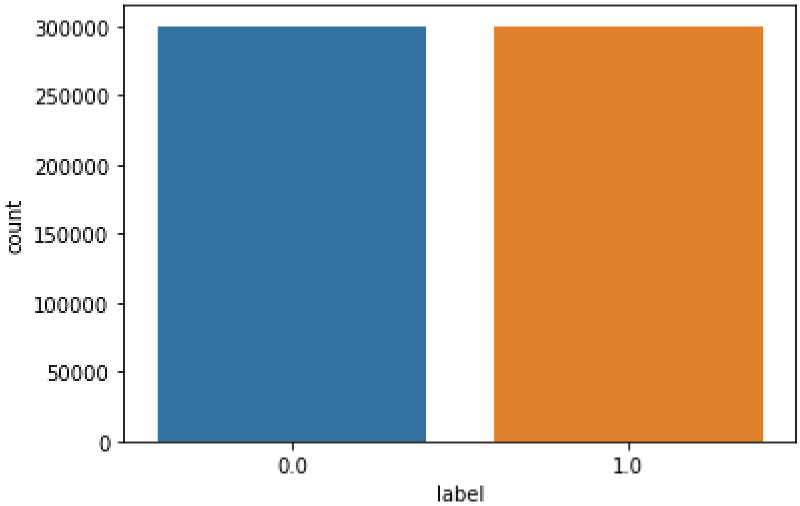
In [4]:
```
import os
import numpy as np
from matplotlib import pyplot as plt
import lightgbm as lgb
import pandas as pd
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report
from tabulate import tabulate
```

In [5]:
```
ember2018 = '../Dataset/ember_zip/ember2018'
```

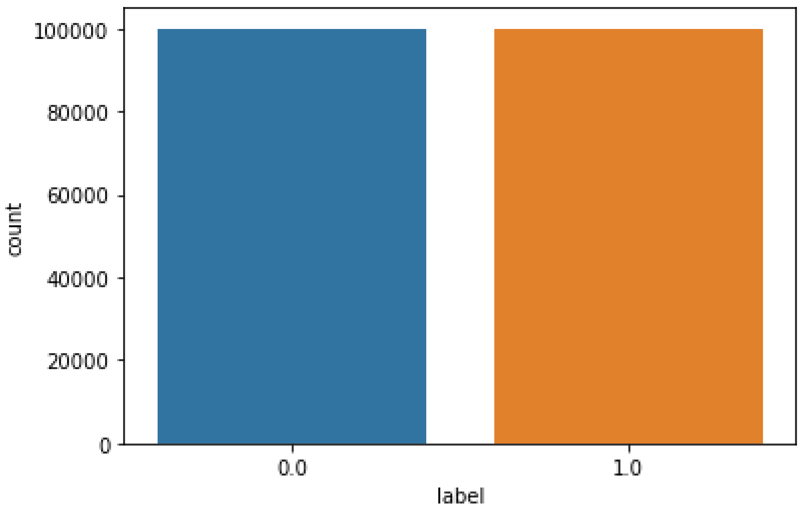
Train and Test Datset loaded

In [6]:
```
train_dataset = np.load(os.path.join(ember2018,'ember2018_train_data.npz'),allow_pic
X_train, y_train= train_dataset['arr_0'],train_dataset['arr_1']
test_dataset = np.load(os.path.join(ember2018,'ember2018_test_data.npz'),allow_pickl
X_test,y_test = test_dataset['arr_0'],test_dataset['arr_1']
```

In [7]:
```
df = pd.DataFrame(data=y_train, columns=["label"])
sns.countplot(x = 'label', data=df);
```



In [8]:
```
df = pd.DataFrame(data=y_test, columns=["label"])
sns.countplot(x = 'label', data=df);
```



A simple LightGBM model is trained and tested with default params </h4

In [ ]:
```
params = {
    "boosting": "gbdt",
}
lgbm_dataset = lgb.Dataset(X_train, y_train)
lgbm_model = lgb.train(params, lgbm_dataset)
lgbm_model.save_model(os.path.join(ember2018, "model2018.txt"))
```

In [9]:
```
lgbm_model = lgb.Booster(model_file=os.path.join(ember2018,"model2018.txt"))
```

In [10]:
```
y_test_pred = lgbm_model.predict(X_test)
y_train_pred1 = lgbm_model.predict(X_train)
print (y_test_pred[:10])
```

```
[ 1.00337967  0.17395378  1.0968505   0.11058255  0.00546004  1.01191492
  0.06304254 -0.07678607  0.95925355  0.29313985]
```

It can be observed that with simple model with default params 100 trees and number of leaves 31

train accuarcy was 100% , test accuracy obtained was 93% it took very less time to train

The corresponding Confusion matrix and classification reports shown below

In [11]:
```
y_test_pred1 = np.where(y_test_pred > 0.5, 1, 0)
y_train_pred = np.where(y_train_pred1 > 0.5, 1, 0)
confusion_matrix_df = pd.DataFrame(confusion_matrix(y_test, y_test_pred1))
# sns.heatmap(confusion_matrix_df, annot=True);
confusion_matrix_df
```

Out[11]:

	0	1
0	91323	8677
1	5436	94564

In [12]:
```
print(classification_report(y_test, y_test_pred1))
```

```
              precision    recall  f1-score   support

         0.0       0.94      0.91      0.93    100000
         1.0       0.92      0.95      0.93    100000

    accuracy                           0.93    200000
   macro avg       0.93      0.93      0.93    200000
weighted avg       0.93      0.93      0.93    200000
```

In [13]:
```
confusion_matrix_df = pd.DataFrame(confusion_matrix(y_train, y_train_pred))

# sns.heatmap(confusion_matrix_df, annot=True);
confusion_matrix_df
```

Out[13]:

	0	1
0	284127	15873
1	15338	284662

In [14]:
```
print(classification_report(y_train, y_train_pred))
```

```
              precision    recall  f1-score   support
```

```
         0.0       0.95      0.95      0.95    300000
         1.0       0.95      0.95      0.95    300000

    accuracy                           0.95    600000
   macro avg       0.95      0.95      0.95    600000
weighted avg       0.95      0.95      0.95    600000
```

ember_model_2018.txt is a pretrained model provided by ember

It was trained using the parameters params = { "boosting": "gbdt", "objective": "binary", "num_iterations": 1000, "learning_rate": 0.05, "num_leaves": 2048, "max_depth": 15, "min_data_in_leaf": 50, "feature_fraction": 0.5 }

we can observe the model sizes below, model with deafult params having size 380kB where as model with higher params having size 121MB

In [15]:
```
ls -l ../Dataset/ember_zip/ember2018/*.txt
```

```
-rw-r--r-- 1 mcs192792 mcs19 127284141 Jul 30  2019 ../Dataset/ember_zip/ember2018/e
mber_model_2018.txt
-rw-r--r-- 1 mcs192792 mcs19    389298 May 15 12:39 ../Dataset/ember_zip/ember2018/m
odel2018.txt
```

After parameter tuning and by increasing the capacity of the dtree test accuracy was improved to 98%

The corresponding Confusion matrix and classification reports shown below

In [16]:
```
lgbm_model = lgb.Booster(model_file=os.path.join(ember2018,"ember_model_2018.txt"))
```

In [17]:
```
y_test_pred = lgbm_model.predict(X_test)
y_train_pred1 = lgbm_model.predict(X_train)
y_test_pred1 = np.where(y_test_pred > 0.5, 1, 0)
y_train_pred = np.where(y_train_pred1 > 0.5, 1, 0)

confusion_matrix_df = pd.DataFrame(confusion_matrix(y_test, y_test_pred1))

# sns.heatmap(confusion_matrix_df, annot=True);
confusion_matrix_df
```

Out[17]:

	0	1
0	98314	1686
1	2710	97290

In [18]:
```
print(classification_report(y_test, y_test_pred1))
```

```
              precision    recall  f1-score   support

         0.0       0.97      0.98      0.98    100000
         1.0       0.98      0.97      0.98    100000

    accuracy                           0.98    200000
   macro avg       0.98      0.98      0.98    200000
weighted avg       0.98      0.98      0.98    200000
```

In [19]:
```
confusion_matrix_df = pd.DataFrame(confusion_matrix(y_train, y_train_pred))

# sns.heatmap(confusion_matrix_df, annot=True);
confusion_matrix_df
```

Out[19]:

	0	1

	0	1
0	300000	0
1	1	299999

In [20]:
```
print(classification_report(y_train, y_train_pred))
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00    300000
         1.0       1.00      1.00      1.00    300000

    accuracy                           1.00    600000
   macro avg       1.00      1.00      1.00    600000
weighted avg       1.00      1.00      1.00    600000
```

Experiment With Packer:

Generally Packers are used to compress the PEfiles. But the same are being used for encoding the PE files to Obfuscate Malware detectors. To check the perormance of the model aginst packers I have taken 26 clean files from windows and created varients of them using UPX packer. when tested against the model, it is observed that all the original files classified as benign. but one packed file detected as malware which is packed verison standard cmd.exe in windows

In [21]:
```
original_binaries_dir =   '../Dataset/executables/original'
packed_binaries_dir =   '../Dataset/executables/packed'
```

In [22]:
```
!ls '../Dataset/executables/packed'
```

```
CheckNetIsolation_pack.exe  fixmapi_pack.exe
chglogon_pack.exe           fltMC_pack.exe
chgport_pack.exe            help_pack.exe
chgusr_pack.exe             icacls_pack.exe
chkdsk_pack.exe             IcsEntitlementHost_pack.exe
chkntfs_pack.exe            icsunattend_pack.exe
choice_pack.exe             InfDefaultInstall_pack.exe
CIDiag_pack.exe             iscsicpl_pack.exe
cipher_pack.exe             ktmutil_pack.exe
cmd_pack.exe                label_pack.exe
find_pack.exe               Locator_pack.exe
findstr_pack.exe            upx.exe
finger_pack.exe             upx_pack.exe
```

In [23]:
```
!ls '../Dataset/executables/original'
```

```
CheckNetIsolation.exe  CIDiag.exe   fltMC.exe               iscsicpl.exe
chglogon.exe           cipher.exe   help.exe                ktmutil.exe
chgport.exe            cmd.exe      HOSTNAME.EXE            label.exe
chgusr.exe             find.exe     icacls.exe              Locator.exe
chkdsk.exe             findstr.exe  IcsEntitlementHost.exe  upx.exe
chkntfs.exe            finger.exe   icsunattend.exe
choice.exe             fixmapi.exe  InfDefaultInstall.exe
```

In [24]:
```
from extract_binary_features import extract_features
from ember_dataset import create_data,read_metadata,read_vectorized_features
```

In [25]:
```
original_features = extract_features(original_binaries_dir,feature_version=2)
packed_features = extract_features(packed_binaries_dir,feature_version=2)
```

In [26]:
```
original_features.shape, packed_features.shape
```

Out[26]:
```
((26, 2381), (26, 2381))
```

In [27]:
```
y_orig_pred = lgbm_model.predict(original_features)
y_orig_pred = np.where(y_orig_pred > 0.5, 1, 0)
print (y_orig_pred)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

In [28]:
```
y_packed_pred = lgbm_model.predict(packed_features)
y_packed_pred = np.where(y_packed_pred > 0.5, 1, 0)
print (y_packed_pred)
```

```
[0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

Experiment With Sorel Datset on model trained using ember Dataset

test-features.npz and validation-features.npz are the files obtained from sorel datset which combinely contains 20 lakh malware features and 45 lakh beningn samples.

When tested 98% accuracy was obtained aginst these datasets. It is good to see that the model which was trained using 3 lakh samples was able to detect 20 lakh malwares well with 98% accuarcy. which means the model is generaizing well with all classes of the malwares. Results and confusion matrix can be seen below

In [29]:
```
sorel_dir = '../Dataset/sorel'
```

In [30]:
```
data = np.load(os.path.join(sorel_dir,'test-features.npz'))

data['arr_0'].shape
```

Out[30]:
```
(4195042, 2381)
```

In [31]:
```
train = data['arr_0']
y_true= data['arr_1']
y_pred = lgbm_model.predict(train)
y_pred = np.where(y_pred > 0.5, 1, 0)
confusion_matrix_df = pd.DataFrame(confusion_matrix(y_true, y_pred))
# sns.heatmap(confusion_matrix_df, annot=True);
confusion_matrix_df
```

Out[31]:

	0	1
0	2821166	13262
1	66793	1293821

In [32]:
```
print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99   2834428
           1       0.99      0.95      0.97   1360614

    accuracy                           0.98   4195042
   macro avg       0.98      0.97      0.98   4195042
weighted avg       0.98      0.98      0.98   4195042
```

In [33]:
```
data = np.load(os.path.join(sorel_dir,'validation-features.npz'))
data['arr_0'].shape
```

Out[33]:
```
(2495822, 2381)
```

In [34]:
```
train = data['arr_0']
y_true= data['arr_1']
y_pred = lgbm_model.predict(train)
y_pred = np.where(y_pred > 0.5, 1, 0)
confusion_matrix_df = pd.DataFrame(confusion_matrix(y_true, y_pred))
# sns.heatmap(confusion_matrix_df, annot=True);
confusion_matrix_df
```

Out[34]:

	0	1
0	1522998	10594
1	36850	925380

In [35]:
```
print(classification_report(y_true, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.98   1533592
           1       0.99      0.96      0.98    962230

    accuracy                           0.98   2495822
   macro avg       0.98      0.98      0.98   2495822
weighted avg       0.98      0.98      0.98   2495822
```

Experiment with differrrent classes of malwares on model trained using ember Dataset

Tested the model with 11 classes of the malwares, it is observed that for the classes crypto_miner and downloader the detection ration is very less compared to others around 60% the distribution of the malware sample from each class and the corressponding accuracies shown below.

In [27]:
```
data = np.load(os.path.join(sorel_dir,'sorel_data.npz'),allow_pickle=True)
data['arr_0'].shape,data['arr_1'].shape,
```

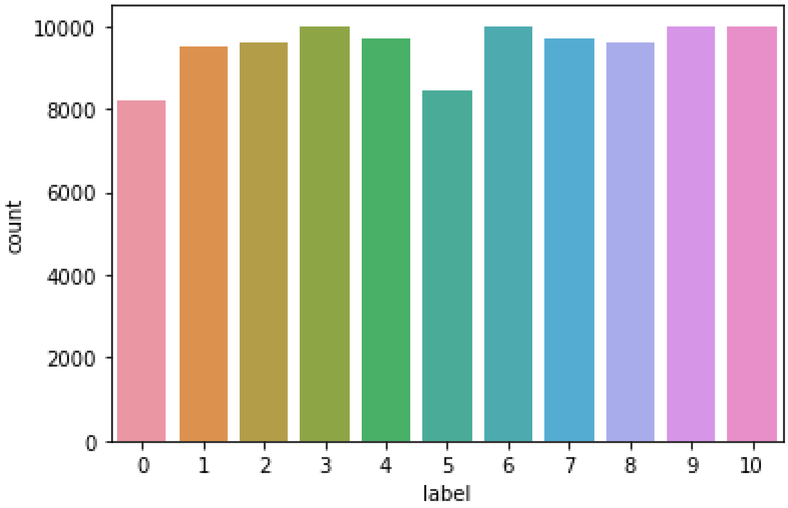
Out[27]: ((104746, 2381), (104746, 13))

In [28]:
```
y_pred = lgbm_model.predict(data['arr_0'])
y_pred = np.where(y_pred > 0.5, 1, 0)
print("accuracy is: ", np.sum(y_pred)/len(y_pred))
```

```
accuracy is:  0.9209420884807057
```

In [29]:
```
df = pd.DataFrame(data=data['arr_1'][:,-1], columns=["label"])
sns.countplot(x = 'label', data=df)
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x2b63cad7af98>



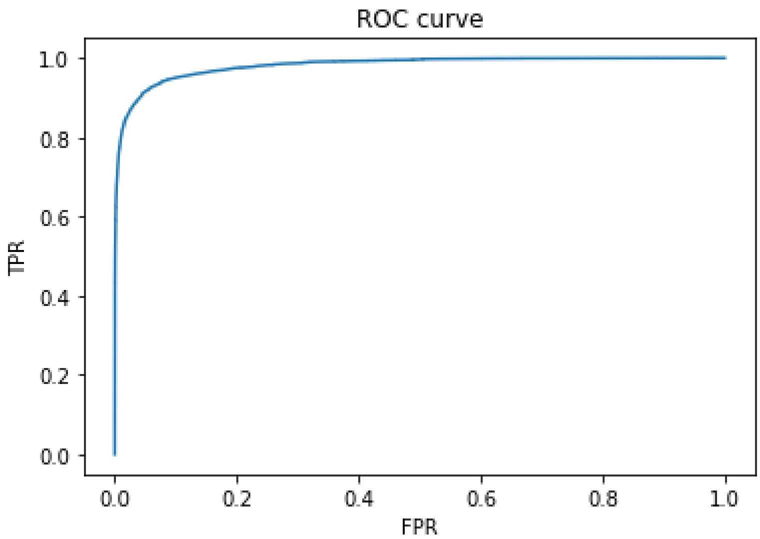
In [30]:
```
def per_label_detection(labels,y_pred):
    D = [[0,0] for range in np.unique(labels)]
    for l,y in zip(labels,y_pred):
        D[l][0] += 1
        D[l][1] += y
    return D
P = per_label_detection(data['arr_1'][:,-1],y_pred)


labels = ['adware', 'flooder', 'ransomware', 'dropper',
   'spyware', 'packed', 'crypto_miner', 'file_infector', 'installer',
   'worm', 'downloader']

table = []
for i,l in zip(P,labels):

    table.append([l,i[0],i[1], i[1]/i[0]])
print (tabulate(table,headers=['label', 'sample_count','samples_detected','accuracy'
```

label	sample_count	samples_detected	accuracy
adware	8211	7151	0.870905
flooder	9481	9480	0.999895
ransomware	9607	9585	0.99771
dropper	9997	9942	0.994498
spyware	9717	9557	0.983534
packed	8465	7776	0.918606
crypto_miner	9988	8655	0.86654
file_infector	9709	9067	0.933876
installer	9595	5533	0.576655
worm	10000	9969	0.9969
downloader	9976	9750	0.977346

In [12]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score
from matplotlib import pyplot as plt



print (roc_auc_score(y_test, y_test_pred))

fpr, tpr, _ = roc_curve(y_test, y_test_pred)

plt.clf()
plt.plot(fpr, tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
```

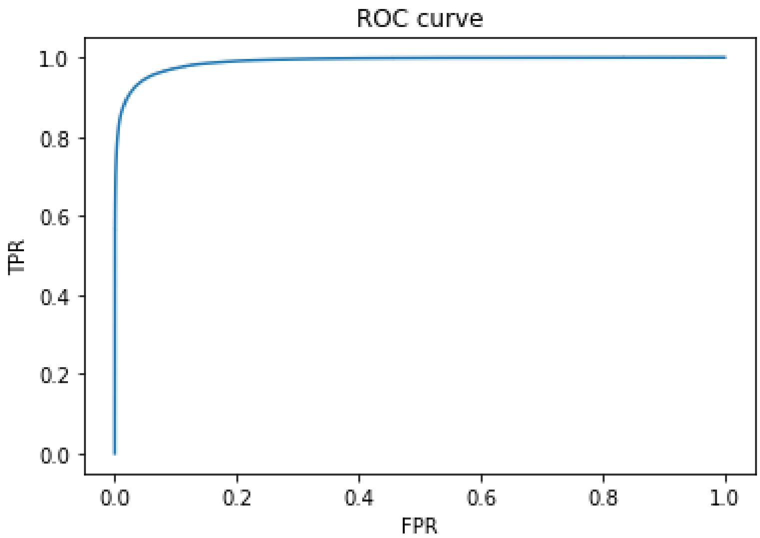
```
plt.title('ROC curve')
plt.show()
```

0.9812892095



In [13]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score
from matplotlib import pyplot as plt



print (roc_auc_score(y_train, y_train_pred1))

fpr, tpr, _ = roc_curve(y_train, y_train_pred1)

plt.clf()
plt.plot(fpr, tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC curve')
plt.show()
```

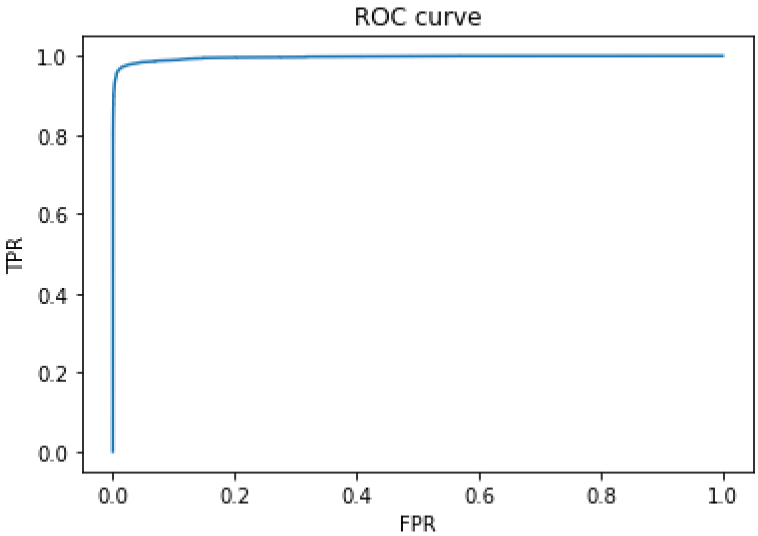
0.9894951144



In [23]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score
from matplotlib import pyplot as plt
```

```
print (roc_auc_score(y_test, y_test_pred))

fpr, tpr, _ = roc_curve(y_test, y_test_pred)

plt.clf()
plt.plot(fpr, tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC curve')
plt.show()
```

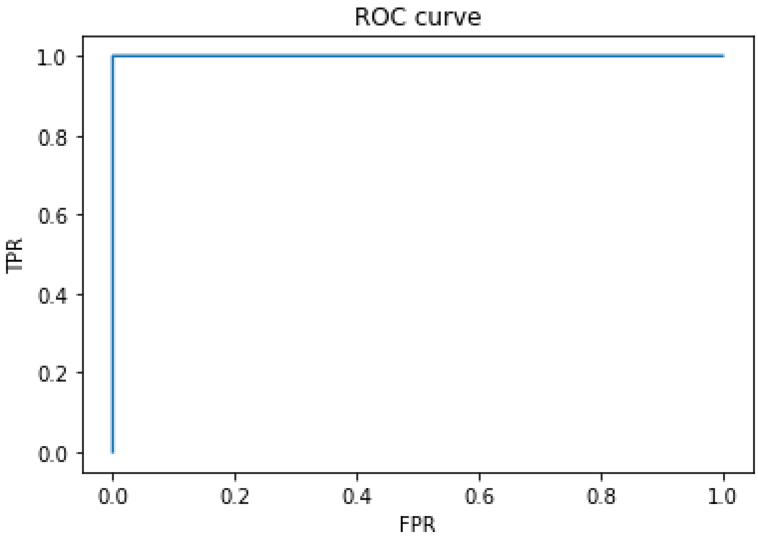
0.9964289467999999



In [24]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score
from matplotlib import pyplot as plt



print (roc_auc_score(y_train, y_train_pred1))

fpr, tpr, _ = roc_curve(y_train, y_train_pred1)

plt.clf()
plt.plot(fpr, tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC curve')
plt.show()
```

0.9999999999944444


ROC curve
1.0
0.8
0.6
0.4
0.2
0.0
TPR
0.0
0.2
0.4
0.6
0.8
1.0
FPR