synthetic detecting fraud

October 14, 2020

[1]:
```
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.lines as mlines
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
from sklearn.model_selection import train_test_split, learning_curve
from sklearn.metrics import average_precision_score
from xgboost.sklearn import XGBClassifier
from xgboost import plot_importance, to_graphviz
```

[2]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

[3]:
```
df = pd.read_csv('PS_20174392719_1491204439457_log.csv')
df = df.rename(columns={'oldbalanceOrg':'oldBalanceOrig', 'newbalanceOrig':
 ↪'newBalanceOrig', \
                        'oldbalanceDest':'oldBalanceDest', 'newbalanceDest':
 ↪'newBalanceDest'})
```

[4]:
```
df.head()
```

[4]:

	step	type	amount	nameOrig	oldBalanceOrig	newBalanceOrig	\
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	

	nameDest	oldBalanceDest	newBalanceDest	isFraud	isFlaggedFraud
0	M1979787155	0.0	0.0	0	0
1	M2044282225	0.0	0.0	0	0
2	C553264065	0.0	0.0	1	0
3	C38997010	21182.0	0.0	1	0
4	M1230701703	0.0	0.0	0	0

[5]:
```
df.isnull().sum()
```

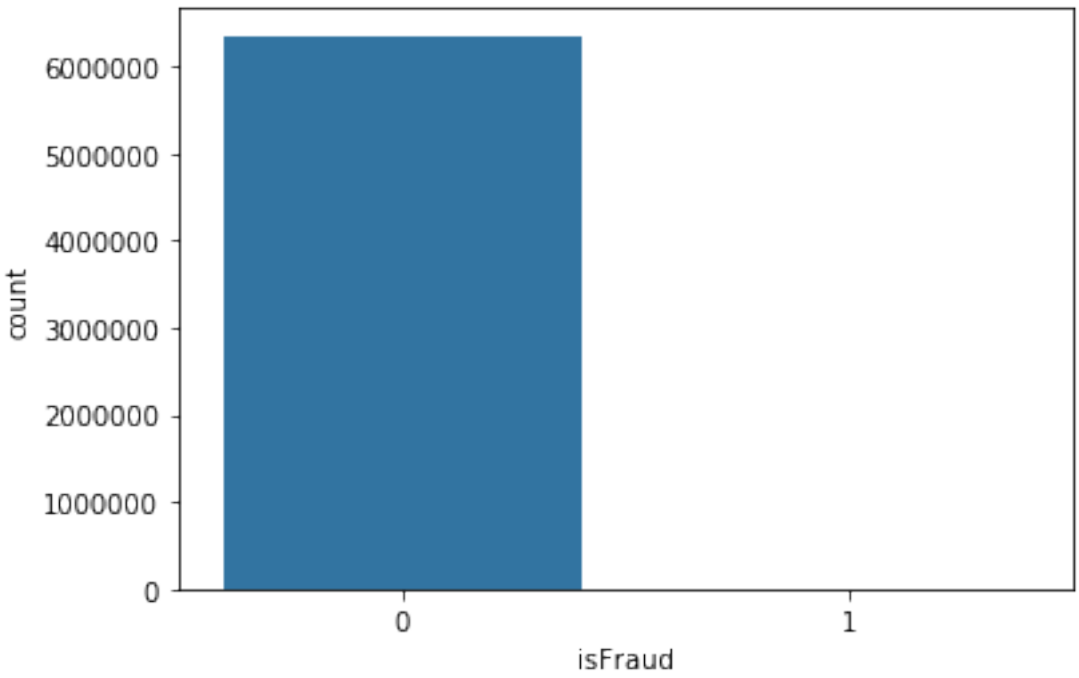
[5]:
```
step              0
type              0
amount            0
nameOrig          0
oldBalanceOrig    0
newBalanceOrig    0
nameDest          0
oldBalanceDest    0
newBalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

[6]:
```
df.shape
```

[6]:
```
(6362620, 11)
```

[7]:
```
### distribution of fradulent transaction
sns.countplot(df.isFraud)
```

[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fcdadab98d0>
```

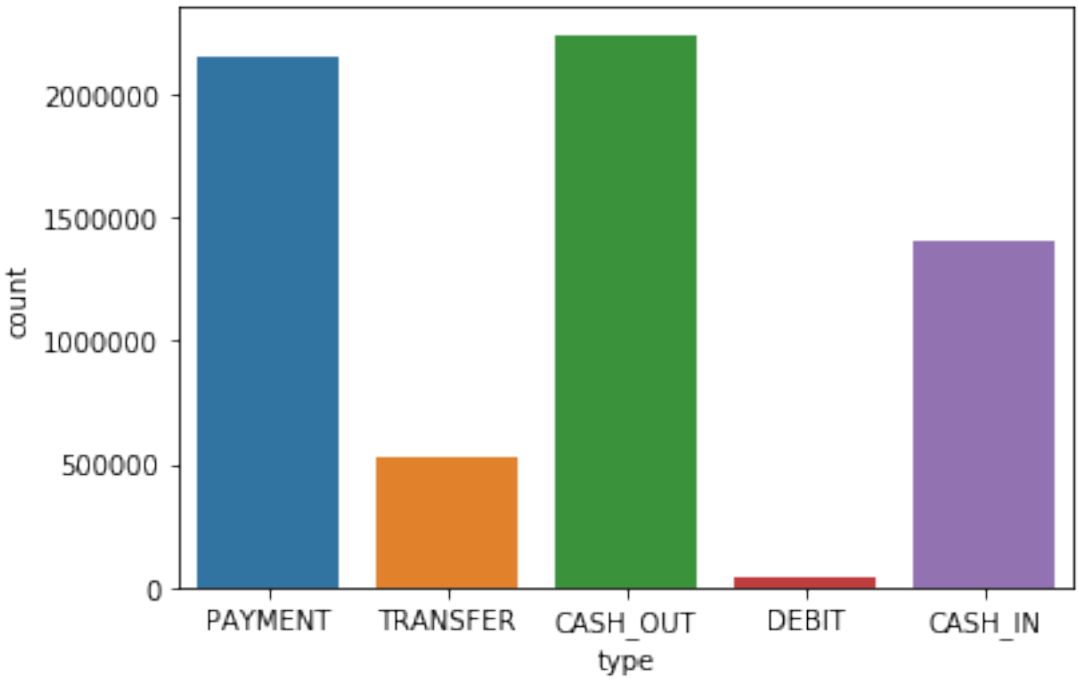


[8]:
```
print('Percentage of fradulent transactions is {}%'.format(sum(df.isFraud)/
↪len(df)*100))
```

```
Percentage of fradulent transactions is 0.12908204481801522%
```

[9]:
```
# type of payments
sns.countplot(df.type)
```

[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fccfd2c4f98>
```



[10]:
```
print('The types of fraudulent transactions are {}'.format(list(np.
 ↪unique(df[df['isFraud'] == 1]['type']))))
```

```
The types of fraudulent transactions are ['CASH_OUT', 'TRANSFER']
```

[11]:
```
### number of 'Cash out' payment and 'transfer' fraud payment
print('The number of fraudulent TRANSFERs is {}'.format(len(df[(df['type'] ==␣
 ↪'TRANSFER')&(df['isFraud'] == 1)])))
print('The number of cash out TRANSFERs is {}'.format(len(df[(df['type'] ==␣
 ↪'CASH_OUT')&(df['isFraud'] == 1)])))
```

```
The number of fraudulent TRANSFERs is 4097
The number of cash out TRANSFERs is 4116
```

[12]:
```
### the variable isFlaggedFraud is vaguely described, we need more explore of␣
 ↪it. It has been said that isFlaggedFraud
### will be labeled 1 if the transaction amount is larger than 200,000
len(df[df['isFlaggedFraud']==1])
```

[12]:
```
16
```

[13]:
```
### only 16 records
print('Type of transactions is 1 in isFlaggedFraud are {}'.format(list(np.
 ↪unique(df[df['isFlaggedFraud']==1]['type']))))
print('Minimal transactions that is labeled as isFlaggedFraud = {}'.
 ↪format(min(df[df['isFlaggedFraud']==1]['amount'])))
print('Maximal transactions that is labeled as isFlaggedFraud = {}'.
 ↪format(max(df[df['isFlaggedFraud']==1]['amount'])))
```

```
Type of transactions is 1 in isFlaggedFraud are ['TRANSFER']
Minimal transactions that is labeled as isFlaggedFraud = 353874.22
Maximal transactions that is labeled as isFlaggedFraud = 10000000.0
```

[14]:
```
### how about the records are not labeled 1 in isFlaggedFraud
print('Minimal transactions that is labeled as isFlaggedFraud = {}'.
 ↪format(min(df[df['isFlaggedFraud']==0]['amount'])))
print('Maximal transactions that is labeled as isFlaggedFraud = {}'.
 ↪format(max(df[df['isFlaggedFraud']==0]['amount'])))
```

```
Minimal transactions that is labeled as isFlaggedFraud = 0.0
Maximal transactions that is labeled as isFlaggedFraud = 92445516.64
```

[15]:
```
### seem like the standard used to tell whether isFlaggedFraud or not is not␣
 ↪consistent with what we have been told
### in the data description, so there must be some other factors
```

[16]:
```
df.head()
```

[16]:

	step	type	amount	nameOrig	oldBalanceOrig	newBalanceOrig	\
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	

	nameDest	oldBalanceDest	newBalanceDest	isFraud	isFlaggedFraud
0	M1979787155	0.0	0.0	0	0
1	M2044282225	0.0	0.0	0	0
2	C553264065	0.0	0.0	1	0
3	C38997010	21182.0	0.0	1	0
4	M1230701703	0.0	0.0	0	0

[17]:
```
### data cleaning
X = df.loc[(df.type == 'TRANSFER')|(df.type == 'CASH_OUT')]
Y = X['isFraud']
del X['isFraud']

X = X.drop(['nameOrig', 'nameDest', 'isFlaggedFraud'], axis = 1)
X.head()
```

[17]:
```
     step      type     amount  oldBalanceOrig  newBalanceOrig  oldBalanceDest  \
2       1  TRANSFER     181.00           181.0             0.0             0.0
3       1  CASH_OUT     181.00           181.0             0.0         21182.0
15      1  CASH_OUT  229133.94         15325.0             0.0          5083.0
19      1  TRANSFER  215310.30           705.0             0.0         22425.0
24      1  TRANSFER  311685.89         10835.0             0.0          6267.0

    newBalanceDest
2             0.00
3             0.00
15        51513.44
19            0.00
24      2719172.89
```

[18]:
```
X.loc[X.type == 'TRANSFER', 'type'] = 0
X.loc[X.type == 'CASH_OUT', 'type'] = 1
X.type = X.type.astype(int)
X.head()
```

[18]:
```
     step  type     amount  oldBalanceOrig  newBalanceOrig  oldBalanceDest  \
2       1     0     181.00           181.0             0.0             0.0
3       1     1     181.00           181.0             0.0         21182.0
15      1     1  229133.94         15325.0             0.0          5083.0
19      1     0  215310.30           705.0             0.0         22425.0
24      1     0  311685.89         10835.0             0.0          6267.0

    newBalanceDest
2             0.00
3             0.00
15        51513.44
19            0.00
24      2719172.89
```

[19]:
```
Xfraud = X.loc[Y == 1]
XnonFraud = X.loc[Y == 0]

print("The fraction of fraudulent transactions with 'oldBalanceDest' =␣
 ↪'newBalanceDest' = 0 \
although the transacted amount \nis non-zero is: {}".
format(len(Xfraud.loc[(Xfraud.oldBalanceDest == 0) & (Xfraud.newBalanceDest ==␣
 ↪0)]) / (len(Xfraud))))

print("\nThe fraction of genuine transactions with 'oldBalanceDest' = \
'newBalanceDest' = 0 although the transacted amount is \nnon-zero is: {}".\
format(len(XnonFraud.loc[(XnonFraud.oldBalanceDest == 0) & \
(XnonFraud.newBalanceDest == 0) & (XnonFraud.amount)]) / (1.0 *␣
 ↪len(XnonFraud))))
```

```
The fraction of fraudulent transactions with 'oldBalanceDest' = 'newBalanceDest'
```

```
= 0 although the transacted amount
is non-zero is: 0.49628637525873615

The fraction of genuine transactions with 'oldBalanceDest' = 'newBalanceDest' =
0 although the transacted amount is
non-zero is: 0.0006176245277308345
```

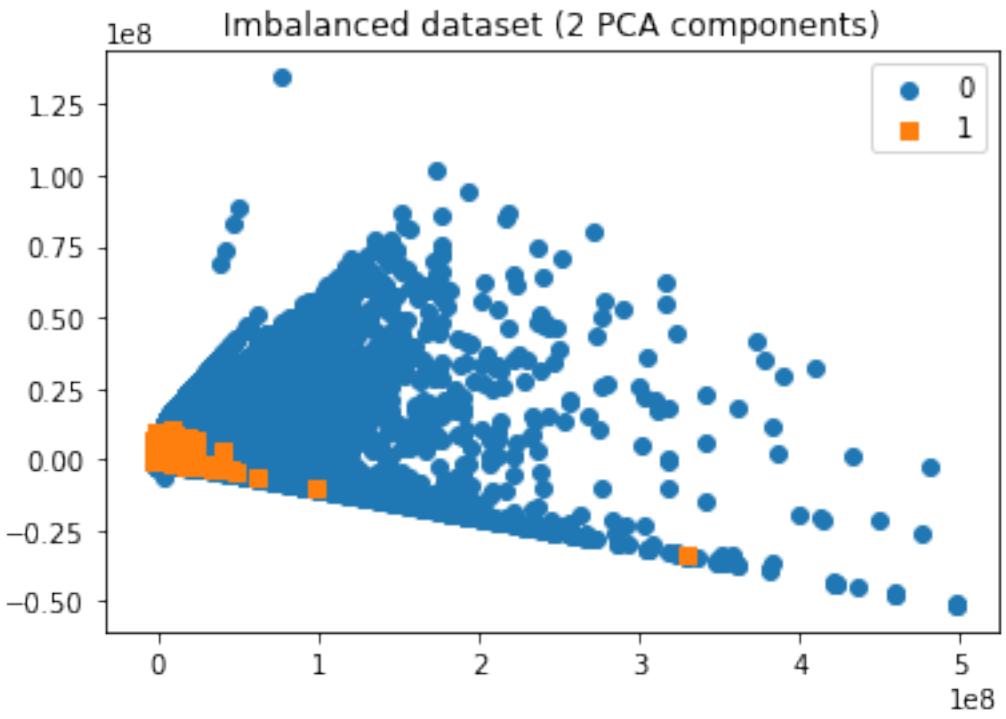
[20]:
```
X['errorBalanceOrig'] = X.newBalanceOrig + X.amount - X.oldBalanceOrig
X['errorBalanceDest'] = X.oldBalanceDest + X.amount - X.newBalanceDest
X.head()
```

[20]:

	step	type	amount	oldBalanceOrig	newBalanceOrig	oldBalanceDest	\
2	1	0	181.00	181.0	0.0	0.0	
3	1	1	181.00	181.0	0.0	21182.0	
15	1	1	229133.94	15325.0	0.0	5083.0	
19	1	0	215310.30	705.0	0.0	22425.0	
24	1	0	311685.89	10835.0	0.0	6267.0	

	newBalanceDest	errorBalanceOrig	errorBalanceDest
2	0.00	0.00	181.0
3	0.00	0.00	21363.0
15	51513.44	213808.94	182703.5
19	0.00	214605.30	237735.3
24	2719172.89	300850.89	-2401220.0

[21]:
```
### scatter plot of the distribution of fraud and genuine transaction
# we will use pca to shrink the multi-dimentional data into 2 dimentions.

from sklearn.decomposition import PCA

pca = PCA(n_components = 2)
X_pca = pca.fit_transform(X)

def plot_2d_space(X, Y, label='Classes'):
    colors = ['#1F77B4', '#FF7F0E']
    markers = ['o', 's']
    for l, c, m in zip(np.unique(Y), colors, markers):
        plt.scatter(
            X[Y==l, 0],
            X[Y==l, 1],
            c=c, label=l, marker=m
        )
    plt.title(label)
    plt.legend(loc='upper right')
    plt.show()


plot_2d_space(X_pca, Y, 'Imbalanced dataset (2 PCA components)')
```



[22]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import␣
 ↪confusion_matrix,accuracy_score,classification_report
from sklearn.metrics import roc_curve, auc
```

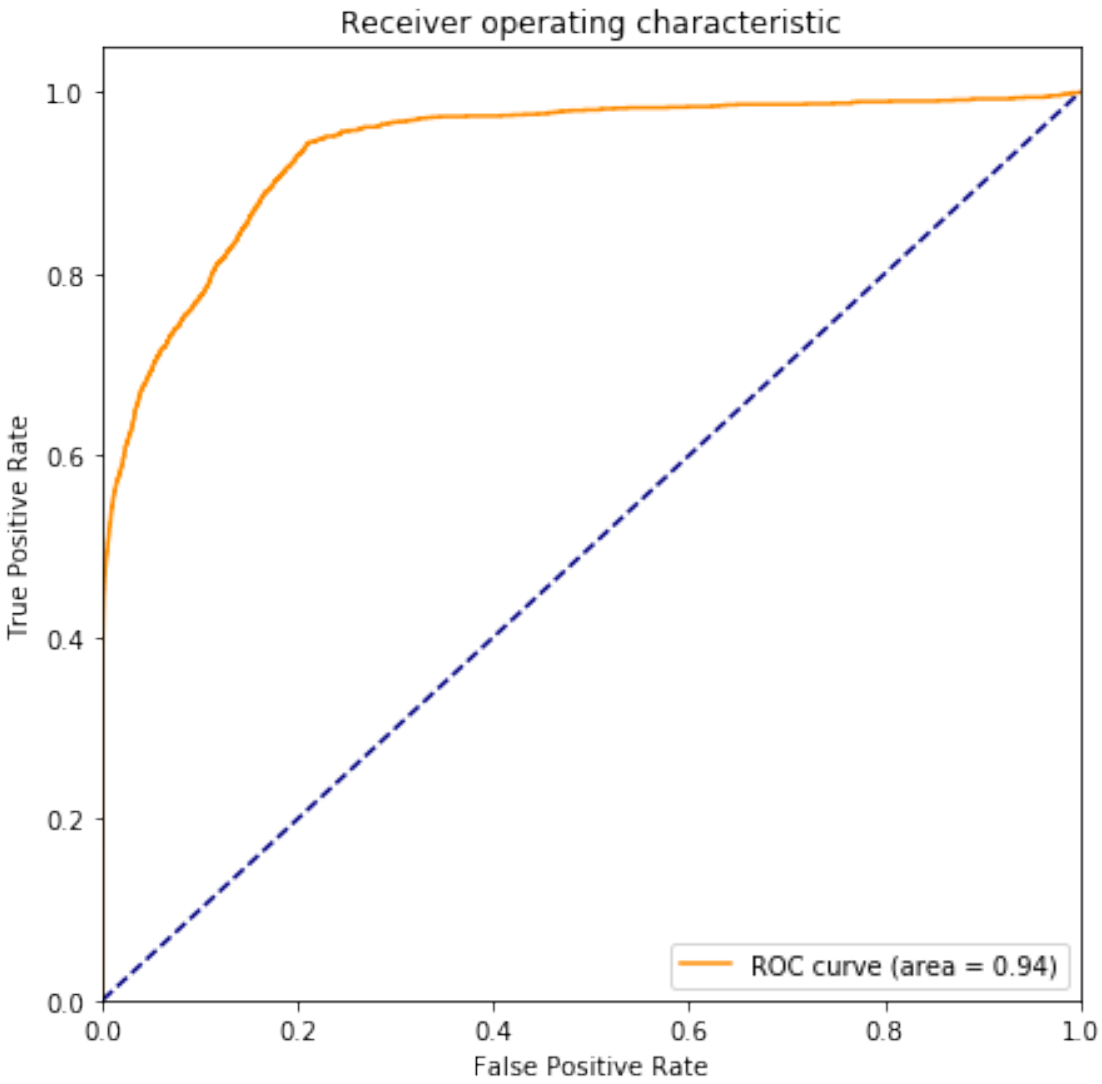
[23]:
```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.20,␣
 ↪random_state=42)
```

[24]:
```
log = LogisticRegression()
log.fit(X_train, y_train)
y_pred = log.predict(X_test)
print(classification_report(y_test, y_pred))
```

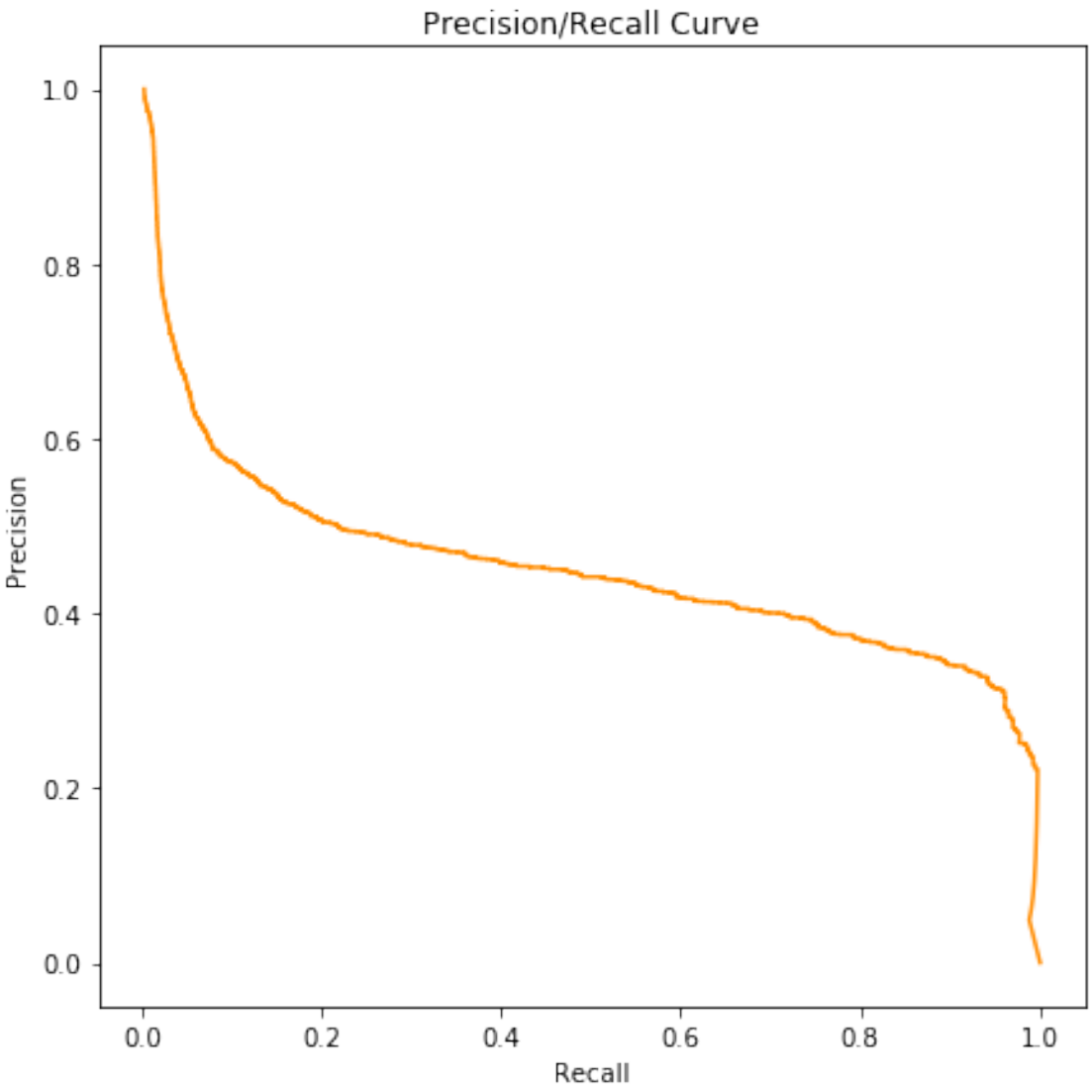
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    552436
           1       0.49      0.44      0.47      1646

    accuracy                           1.00    554082
   macro avg       0.75      0.72      0.73    554082
weighted avg       1.00      1.00      1.00    554082
```

[25]:
```
# Compute ROC curve and ROC area

fpr,tpr,threshold = roc_curve(y_test, log.predict_proba(X_test)[:,1])
roc_auc = auc(fpr,tpr)

plt.figure()
plt.figure(figsize=(7,7))
plt.plot(fpr, tpr, color='darkorange', label='ROC curve (area = %0.2f)' %␣
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



[26]:
```
from sklearn.metrics import precision_recall_curve

precision, recall, thresholds = precision_recall_curve(y_test, log.
 ↪predict_proba(X_test)[:,1])
plt.figure(figsize=(7,7))
plt.title('Precision/Recall Curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.plot(precision, recall,color='darkorange')
plt.show()
```

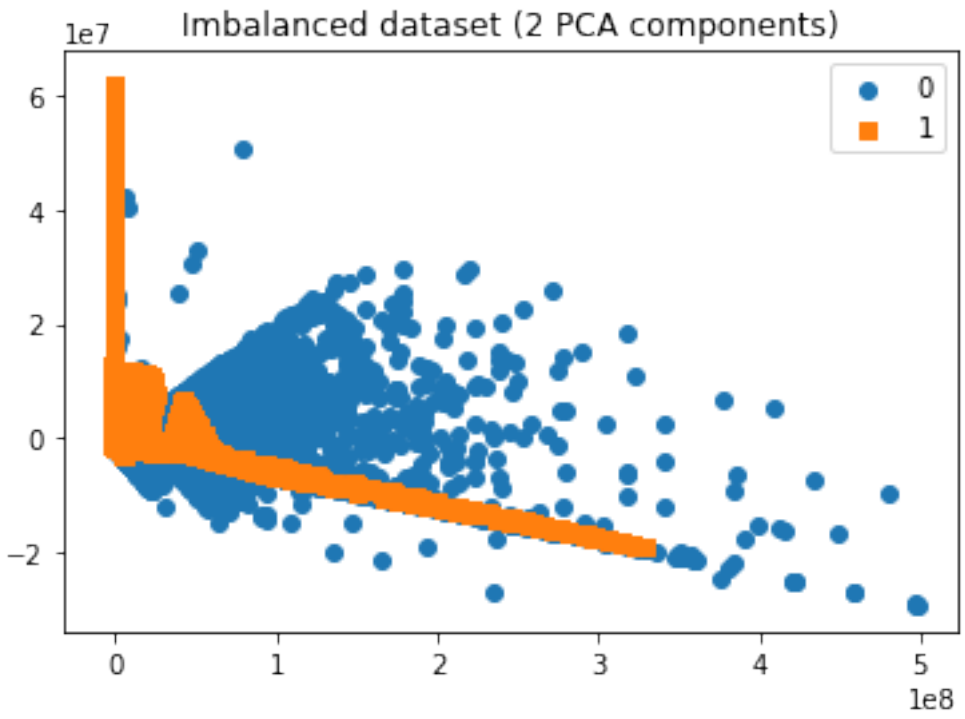


[27]:
```
### recall is what we really care about but we have 0.44 recall in logistic␣
↪model
```

[28]:
```
from imblearn.over_sampling import SMOTE

os = SMOTE(sampling_strategy = 'minority', random_state = 0, )
X_train_os, y_train_os = os.fit_sample(X_train, y_train)
```

```
Using TensorFlow backend.
```

[29]:
```
X_pca = pca.fit_transform(X_train_os)

plot_2d_space(X_pca, y_train_os, 'Imbalanced dataset (2 PCA components)')
```



[30]:
```
log = LogisticRegression()
log.fit(X_train_os, y_train_os)
y_pred = log.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.89      0.94    552436
           1       0.03      0.97      0.05      1646

    accuracy                           0.89    554082
   macro avg       0.51      0.93      0.50    554082
weighted avg       1.00      0.89      0.94    554082
```

[31]:
```
def perf_measure(y_actual, y_hat):
    TP = 0
    FP = 0
    TN = 0
    FN = 0

    for i in range(len(y_hat)):
        if y_actual[i]==y_hat[i]==1:
           TP += 1
```

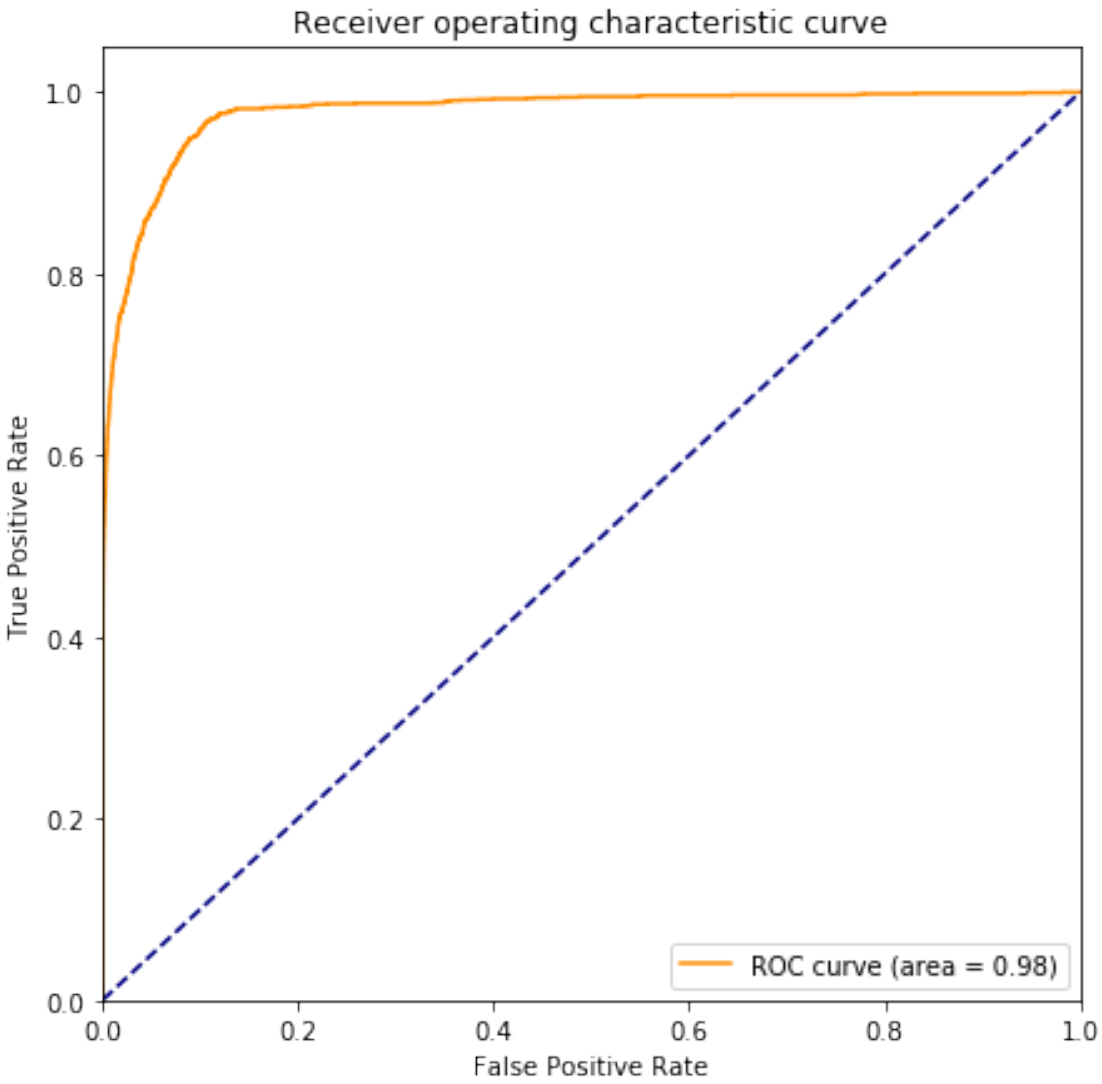
```
        if y_hat[i]==1 and y_actual[i]!=y_hat[i]:
           FP += 1
        if y_actual[i]==y_hat[i]==0:
           TN += 1
        if y_hat[i]==0 and y_actual[i]!=y_hat[i]:
           FN += 1

    return TP, FP, TN, FN
```

[43]:
```
TP, FP, TN, FN = perf_measure(np.array(y_test), y_pred)
```

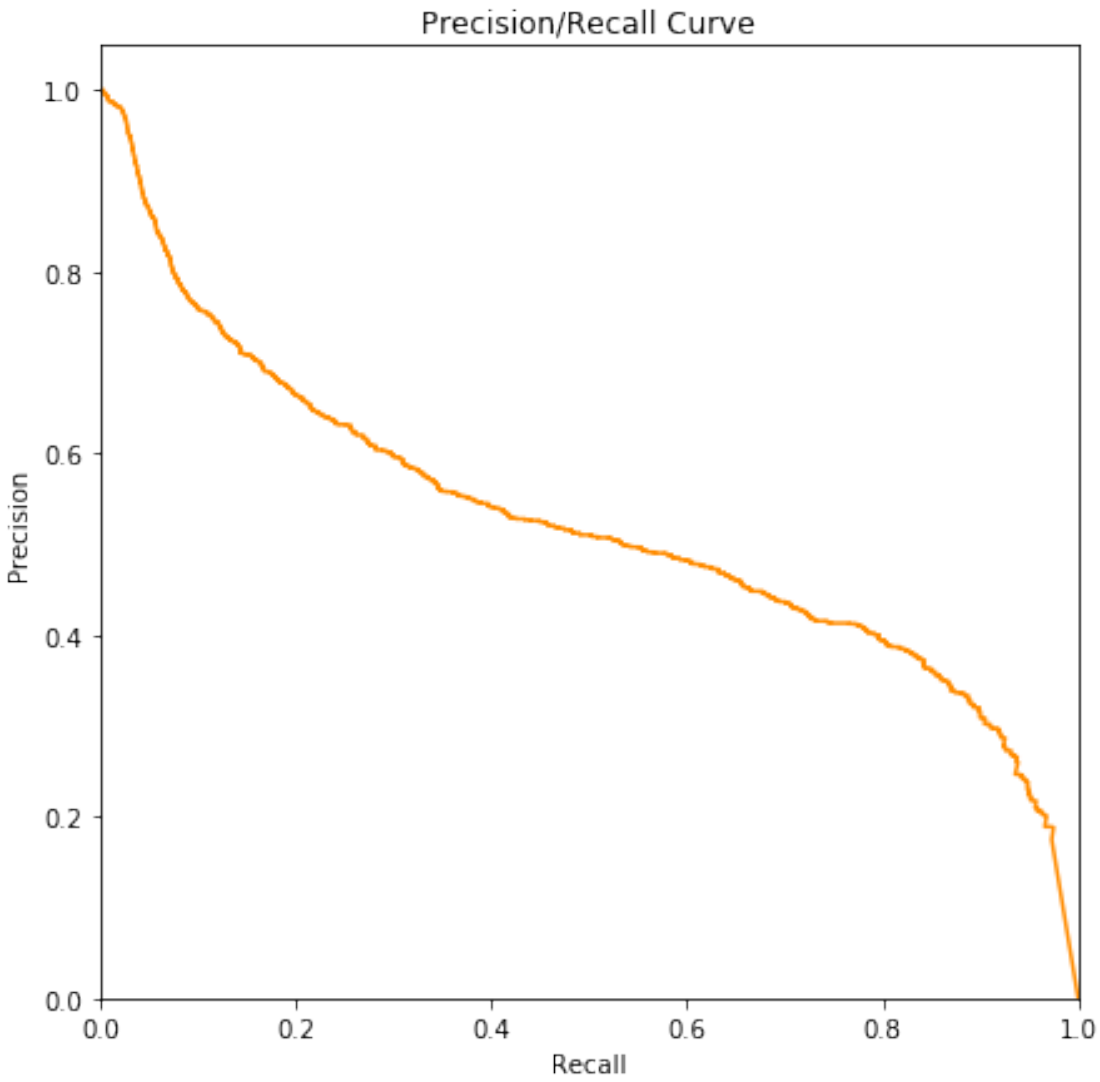
[44]:
```
precision = TP/(TP+FP)
recall = TP/(TP+FN)

F2_score = (1+2**2)*(precision*recall)/(2**2*precision+recall)
print('F2_score is {}'.format(F2_score))
```

```
F2_score is 0.11509744003690038
```

[45]:
```
fpr,tpr,threshold = roc_curve(y_test, log.predict_proba(X_test)[:,1])
roc_auc = auc(fpr,tpr)

plt.figure(figsize=(7,7))
plt.plot(fpr, tpr, color='darkorange', label='ROC curve (area = %0.2f)' %␣
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic curve')
plt.legend(loc="lower right")
plt.show()
```



[46]:
```
### because the distribution of classes are highly skewed, using pr curve would␣
 ↪probably be a better idea.
precision, recall, thresholds = precision_recall_curve(y_test, log.
 ↪predict_proba(X_test)[:,1])
plt.figure(figsize=(7,7))
plt.title('Precision/Recall Curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.plot(precision, recall,color='darkorange')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.show()
```



[47]:
```
import warnings
warnings.filterwarnings("ignore")
```

[48]:
```
#from sklearn.model_selection import GridSearchCV

#log = LogisticRegression()

#c_values = [10, 1, 0.1]
#penalty = ['l2']
#solver = ['sag', 'saga']

#param = dict(solver = solver, penalty = penalty, C = c_values)
```

```
#lg_grid = GridSearchCV(estimator=log, param_grid=param, cv=5,␣
 ↪scoring='accuracy',error_score=0)
#lg_grid.fit(X_train_os, y_train_os)
```

[49]:
```
#lg_grid.best_params_
```

[50]:
```
#params = {'C': 10, 'penalty': 'l2', 'solver': 'sag'}
#log = LogisticRegression(**params)
#log.fit(X_train_os, y_train_os)
#y_pred = log.predict(X_test)
#print(classification_report(y_test, y_pred))
```

[51]:
```
from sklearn.ensemble import RandomForestClassifier , GradientBoostingClassifier
from xgboost import XGBClassifier
```

[53]:
```
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
print(classification_report(y_test, y_pred))
```

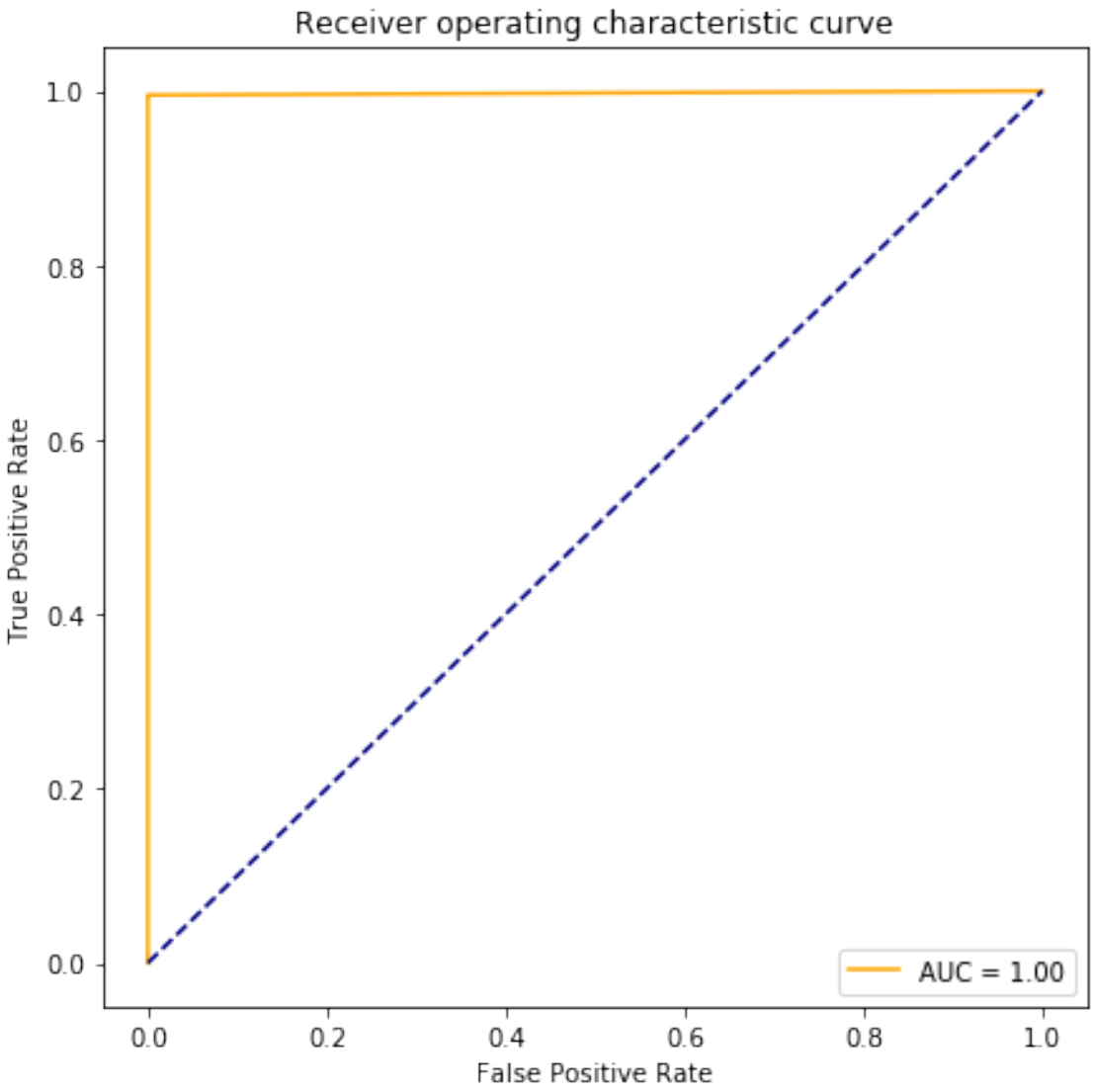
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    552436
           1       1.00      0.99      1.00      1646

    accuracy                           1.00    554082
   macro avg       1.00      1.00      1.00    554082
weighted avg       1.00      1.00      1.00    554082
```

[54]:
```
TP, FP, TN, FN = perf_measure(np.array(y_test), y_pred)
precision = TP/(TP+FP)
recall = TP/(TP+FN)

F2_score = (1+2**2)*(precision*recall)/(2**2*precision+recall)
print('F2_score is {}'.format(F2_score))
```

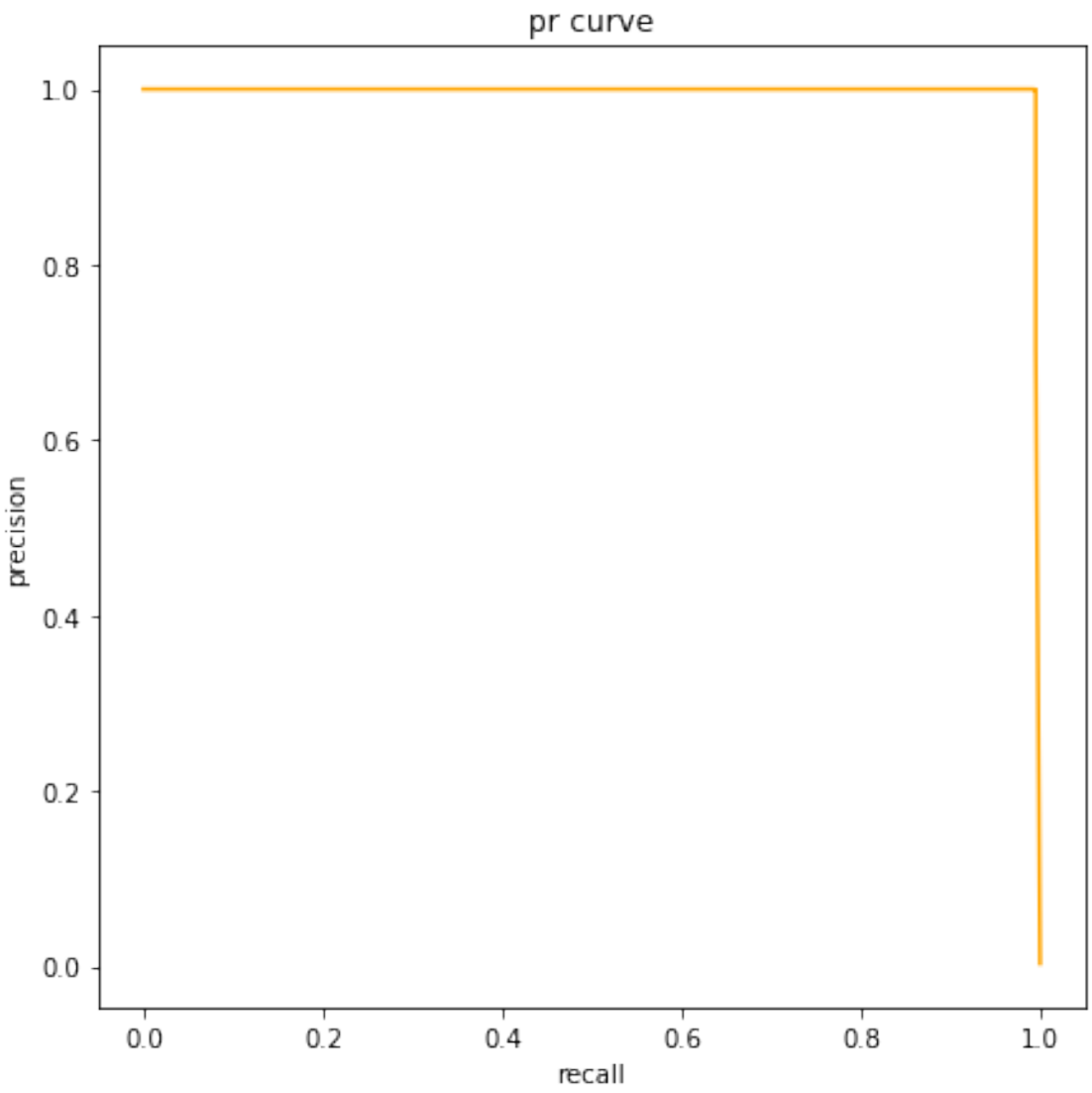
```
F2_score is 0.9946465506752648
```

[55]:
```
fpr, tpr, threshold = roc_curve(y_test, rf.predict_proba(X_test)[:, 1])
roc_auc = auc(fpr, tpr)

plt.figure(figsize = (7, 7))
plt.plot(fpr, tpr, color = 'orange', label = 'AUC = %0.2f' % roc_auc)
plt.plot([0,1], [0,1], color = 'navy', linestyle = '--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic curve')
```

```
plt.legend(loc="lower right")
plt.show()
```



[56]:
```
precision, recall, thresholds = precision_recall_curve(y_test, rf.
 ↪predict_proba(X_test)[:,1])

plt.figure(figsize = (7, 7))
plt.plot(recall, precision, color = 'orange')
plt.xlabel('recall')
plt.ylabel('precision')
plt.title('pr curve')
plt.show()
```



[57]:
```
rf = RandomForestClassifier()
rf.fit(X_train_os, y_train_os)
y_pred = rf.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    552436
           1       0.98      1.00      0.99      1646

    accuracy                           1.00    554082
   macro avg       0.99      1.00      0.99    554082
weighted avg       1.00      1.00      1.00    554082
```

[ ]: