```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split, cross_val_score, StratifiedKFold
from sklearn.feature_selection import mutual_info_classif, SelectKBest
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_curve, roc_auc_score, mean_absolut
e_error, accuracy_score, plot_roc_curve, auc
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
from math import sqrt
```

O conjunto de dados apresenta em suma dados numéricos obtidos após transformação PCA (Principal Component Analysis). Não foi possível obter os dados previamente a esta transformação.

Leitura do dataset de entrada com informações referentes a transações de cartão de crédito.

```
In []:

data = pd.read_csv('creditcard.csv')
print('Quantidade de linhas do dataset {}'.format(data.shape[0]))
data.head()
```

Quantidade de linhas do dataset 284807

Out[]:

	Time	V 1	V2	V 3	V 4	V 5	V 6	V 7	V 8	V9	V 10	V 11	1
0	0.0	1.359807	- 0.072781	2.536347	1.378155	0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	0.551600	0.6178
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	0.082361	0.078803	0.085102	0.255425	- 0.166974	1.612727	1.0652
2	1.0	- 1.358354	- 1.340163	1.773209	0.379780	0.503198	1.800499	0.791461	0.247676	- 1.514654	0.207643	0.624501	0.0660
3	1.0	0.966272	- 0.185226	1.792993	0.863291	0.010309	1.247203	0.237609	0.377436	1.387024	0.054952	- 0.226487	0.1782
4	2.0	- 1.158233	0.877737	1.548718	0.403034	0.407193	0.095921	0.592941	0.270533	0.817739	0.753074	0.822843	0.538
4]8								·······································

- Removemos os registros que apresentam features com valores faltantes
- Removemos a feature "time" por achar que a mesma não é relevante para predizer se uma transação é ou não fraudulenta

```
In []:

df = data.dropna()
df = df.drop(columns="Time")
df['ID'] = np.arange(1,len(df.Class)+1)
print('Quantidade de linhas do dataset sem valor Null/NaN/NaT {}'.format(df.shape[0]))
df.head()
```

Quantidade de linhas do dataset sem valor Null/NaN/NaT 284807

Out[]:

V1 V2 V3 V4 V5 V6 V7 V8 V9 V10 V11 V12

```
1.359887 0.072787 2.536343 1.378162 0.338385 0.462388 0.239599 0.098698 0.363783 0.090796 0.551866 0.617867
                                                                   0.085102\\ 0.255425\quad 0.166974
1 1.191857 0.266151 0.166480 0.448154 0.060018
                                                                                               1.612727 1.065235
                                                 0.082361 0.078803
                                                                             1.514654 0.207643 0.624501 0.066084
                     1.773209 0.379780
                                                 1.800499 0.791461 0.247676
                                       0.503198
  1.358354 1.340163
                                                 1.247203 0.237609 0.377436
                                                                                                         0.178228 0.
                              0.863291 0.010309
  0.966272 0.185226
                                                                             1.387024 0.054952 0.226487
                                                                                               0.822843 0.538196 1.
  1.158233 0.877737 1.548718 0.403034
                                                                             0.817739 0.753074
                                                 0.095921 0.592941
```

Particionamos o dataset de entrada em 80% para o conjunto de treino e 20% para o conjunto de teste.

```
In []:

x_train, x_test, y_train, y_test = train_test_split(df.drop(['ID', 'Class'], axis=1), d
f['Class'], test_size=0.20, random_state = 0)
print('Dados de treino {}\n'.format(x_train.shape))
print('Dados de teste {}\n'.format(x_test.shape))

Dados de treino (227845, 29)

Dados de teste (56962, 29)

In []:

df_train = x_train.copy()
df_train['Class'] = y_train
df_test = x_test.copy()
df_test['Class'] = y_test
```

Descrição estatística do conjunto de treino

```
In [ ]:
df train.describe()
```

Out[]:

	V1	V 2	V 3	V4	V 5	V6	V 7	
count	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.000
mean	0.002930	-0.000877	-0.001470	0.001131	-0.001714	-0.001035	-0.000411	-0.001
std	1.955265	1.649672	1.515055	1.416360	1.365962	1.326404	1.225317	1.205
min	-46.855047	-63.344698	-33.680984	-5.683171	-42.147898	-23.496714	-43.557242	-73.216
25%	-0.919898	-0.599013	-0.894424	-0.847412	-0.693585	-0.769201	-0.553573	-0.209
50%	0.021886	0.063972	0.177138	-0.017538	-0.055515	-0.274916	0.039988	0.021
75%	1.316871	0.802516	1.026049	0.744471	0.610153	0.397215	0.569938	0.325
max	2.451888	22.057729	9.382558	16.875344	34.099309	23.917837	44.054461	20.007
1								Þ

Descrição estatística do conjunto de teste

V1

V2

V3

```
In []:
df_test.describe()
Out[]:
```

V4

V5

V6

V7

V8

count	56962.0000 00	56962.0000 00	56962.0000 09	56962.000000	56962.0000 09	56962.000000	56962.0000 09	56962.0000 08	569
mean	-0.011720	0.003508	0.005881	-0.004524	0.006858	0.004139	0.001644	0.005440	
std	1.972334	1.657848	1.521044	1.413903	1.435957	1.355490	1.283130	1.148643	
min	-56.407510	-72.715728	-48.325589	-5.600607	-113.743307	-26.160506	-23.189397	-50.943369	
25%	-0.921972	-0.595792	-0.874649	-0.853267	-0.683487	-0.765653	-0.555542	-0.206208	
50%	-0.002761	0.072712	0.191364	-0.028170	-0.050472	-0.271310	0.040576	0.025516	
75%	1.309289	0.809015	1.031690	0.739049	0.619408	0.403661	0.572788	0.332808	
max	2.454930	14.845545	4.079168	16.491217	34.801666	73.301626	120.589494	17.573712	
4		188							◎ ▶

Contagem dos valores de cada classe. 0 indicando uma transação onde não há fraude e 1 indicando uma fraude.

Gráficos com a quantidade de cada classe nos conjuntos de dados

Class

```
In [ ]:
```

ò

40000

₹ 30000

```
ax = sns.countplot(x="Class", data=df_train)

200000 - 150000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 500000 - 50000 - 50000 - 500000 - 50000 - 500000 - 500000 - 50000 - 50
```

```
In [ ]:
bx = sns.countplot(x="Class", data=df_test)
```

```
0 Class
```

In []:

```
n_fraudulent_transactions = df_train['Class'].value_counts()[1]
print('Quantidade de transações fraudulentas no dataset de treino ({}) representando um t
otal de ({})% do dataset'.format(n_fraudulent_transactions, (n_fraudulent_transactions/d
f_train.shape[0])*100))
n_fraudulent_transactions = df_test['Class'].value_counts()[1]
print('Quantidade de transações fraudulentas no dataset de teste ({}) representando um to
tal de ({})% do dataset'.format(n_fraudulent_transactions, (n_fraudulent_transactions/df_
test.shape[0])*100))
```

Quantidade de transações fraudulentas no dataset de treino (391) representando um total de (0.171607891329632)% do dataset Quantidade de transações fraudulentas no dataset de teste (101) representando um total de (0.1773111899160844)% do dataset

Utilizamos o mutual_info_classif para estimar informações através de testes estatísticos, auxiliando na seleção de atributos que possuem forte relacionamento com a variável que estamos tentando prever.

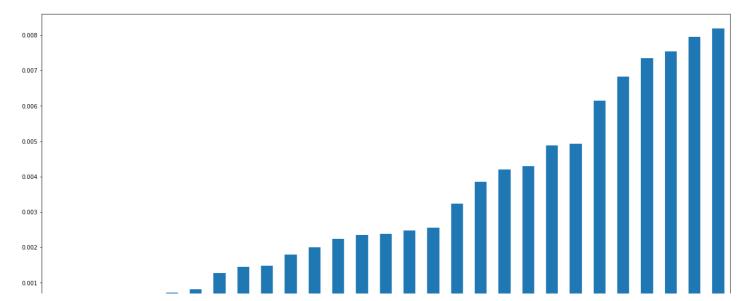
```
In [ ]:
```

In []:

```
mic = pd.Series(mic)
mic.index = x_train.columns
mic = mic.sort_values(ascending = True)
mic.plot.bar(figsize=(22,10))
```

Out[]:

 ${\tt <matplotlib.axes._subplots.AxesSubplot}$ at ${\tt 0x7f63922f6fd0>}$



Selecionamos as K variáveis que mais se relacionam com a coluna que indica a classificação da transação.

```
In []:
selection = SelectKBest(mutual_info_classif, k= 22).fit(x_train, y_train)
X_train = x_train[x_train.columns[selection.get_support()]]
X_test = x_test[x_test.columns[selection.get_support()]]
```

Função utilizada para gerar as curvas do K fold cross validation

```
In [ ]:
```

k = 22

```
def plot Kfold cross validation curves(md, x data, y data):
 cv = StratifiedKFold(n splits=5)
 tprs = []
 aucs = []
 mean fpr = np.linspace(0, 1, 100)
  fig, ax = plt.subplots()
  for i, (train, test) in enumerate(cv.split(x_data, y_data)):
     md.fit(x data.iloc[train], y data.iloc[train])
      viz = plot_roc_curve(md, x_data.iloc[test], y_data.iloc[test],
                          name='ROC fold {}'.format(i),
                          alpha=0.3, lw=1, ax=ax)
      interp tpr = np.interp(mean fpr, viz.fpr, viz.tpr)
      interp tpr[0] = 0.0
     tprs.append(interp_tpr)
      aucs.append(viz.roc auc)
  ax.plot([0, 1], [0, 1], linestyle='--', lw=2, color='r',
          label='Chance', alpha=.8)
 mean tpr = np.mean(tprs, axis=0)
 mean tpr[-1] = 1.0
 mean auc = auc(mean fpr, mean_tpr)
  std auc = np.std(aucs)
  ax.plot(mean fpr, mean tpr, color='b',
          label=r'Mean ROC (AUC = %0.2f $\pm$ %0.2f)' % (mean auc, std auc),
          lw=2, alpha=.8)
  std tpr = np.std(tprs, axis=0)
  tprs upper = np.minimum(mean tpr + std tpr, 1)
  tprs lower = np.maximum(mean tpr - std tpr, 0)
  ax.fill between (mean fpr, tprs lower, tprs upper, color='grey', alpha=.2,
                  label=r'$\pm$ 1 std. dev.')
  ax.set(xlim=[-0.05, 1.05], ylim=[-0.05, 1.05],
        title="ROC for K fold cross-validation curves")
  ax.legend(loc="lower right")
  plt.show()
```

Random Forest

Utilizaremos a classe padrão do classificador Random Forest, não utilizamos variações na parametrização da classe devido a obtenção de um resultado satisfatório com os parâmetros padrões.

```
In [ ]:

rf = RandomForestClassifier()
rf.fit(X train, y train)
```

Treino

Relatório de classificação da predição com o modelo Random forest com o sample de treino

```
In [ ]:
```

```
predictions = rf.predict(X_train)
print(classification_report(y_train, predictions))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	227454 391
accuracy macro avg weighted avg	1.00	1.00	1.00 1.00 1.00	227845 227845 227845

Matriz de confusão dos valores preditos com o conjunto de treino

```
In [ ]:
```

```
pd.crosstab(y_train, predictions, rownames=['Real'],colnames=['Predito'],margins=True)
Out[]:
```

```
        Predito
        0
        1
        All

        Real
        0
        227454
        0
        227454

        1
        1
        390
        391

        All
        227455
        390
        227845
```

Scores das validações cruzadas

```
In [ ]:
```

```
scores = cross_val_score(rf, X_train, y_train, cv=5, scoring='accuracy')
scores

Out[]:
array([0.99958305, 0.99940749, 0.99962694, 0.99956111, 0.99949527])
```

Media dos scores obtidos das validações cruzadas

```
In [ ]:
```

```
scores.mean()
```

Out[]:

0.9995347714455003

Acurácia das predições com base no conjunto de treino

```
In [ ]:
accuracy_score(y_train, predictions)
```

Out[]:

0.9999956110513727

Erro absoluto com base no conjunto de treino

```
In [ ]:

e = mean_absolute_error(y_train, predictions)
e
```

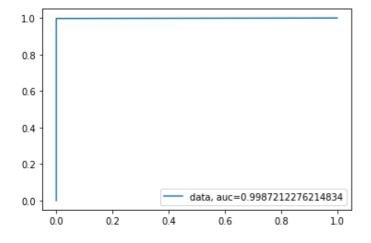
Out[]:

4.388948627356317e-06

Curva ROC

In []:

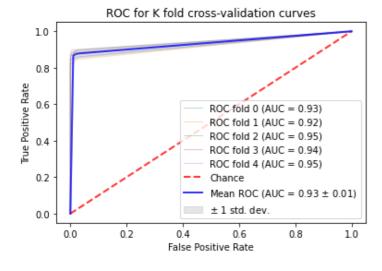
```
fpr, tpr, _ = roc_curve(y_train, predictions)
roc_auc_scr = roc_auc_score(y_train, predictions)
plt.plot(fpr,tpr,label="data, auc="+str(roc_auc_scr))
plt.legend(loc=4)
plt.show()
```



Curvas da K fold cross-validation

In []:

```
plot_Kfold_cross_validation_curves(rf, X_train, y_train)
```



Teste

Predição com o sample de teste

```
In [ ]:
```

```
predictions_test = rf.predict(X_test)
```

Relatório de classificação da predição com o modelo Random forest com o sample de teste

In []:

```
print(classification_report(y_test, predictions_test))
           precision recall f1-score
                                      support
                                      56861
         0
              1.00
                      1.00
                               1.00
         1
              0.93
                       0.77
                               0.84
                                        101
                                      56962
   accuracy
                                1.00
              0.96 0.89
                               0.92
                                       56962
  macro avg
              1.00
                       1.00
                               1.00
                                       56962
weighted avg
```

Matriz de confusão dos valores preditos com o conjunto de teste

```
In [ ]:
```

```
pd.crosstab(y_test, predictions_test, rownames=['Real'],colnames=['Predito'],margins=Tru
e)
```

Out[]:

Predito	0	1	All
Real			
0	56855	6	56861
1	23	78	101
All	56878	84	56962

Validação cruzada utilizando 5 pastas com conjunto de teste

```
In [ ]:
```

```
scores = cross_val_score(rf, X_test, predictions_test, cv=5, scoring='accuracy')
scores
```

```
Out[]:
```

```
array([0.99973668, 0.99964891, 0.99982444, 0.99947331, 0.99982444])
```

Media dos scores obtidos com o conjunto de teste

```
In [ ]:
```

```
scores.mean()
```

Out[]:

0.9997015557305542

Acurácia do modelo

```
In [ ]:
```

```
accuracy_score(y_test, predictions_test)
```

Out[]:

0.9994908886626171

Mean Absolute Error

```
In [ ]:
```

```
e = mean_absolute_error(y_test, predictions_test)
e
```

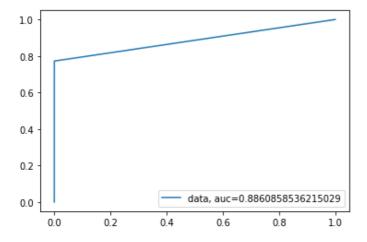
Out[]:

0.0005091113373828166

Curva ROC com o conjunto de teste

In []:

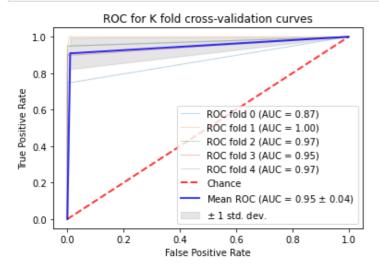
```
fpr, tpr, _ = roc_curve(y_test, predictions_test)
roc_auc_scr = roc_auc_score(y_test, predictions_test)
plt.plot(fpr,tpr,label="data, auc="+str(roc_auc_scr))
plt.legend(loc=4)
plt.show()
```



Curvas da K fold cross-validation com os dados de teste

In []:

plot_Kfold_cross_validation_curves(rf, X_test, y_test)





Utilizaremos a classe padrão do K Neighbors Classifier, utilizaremos apenas o parâmetro n_neighbors=3 pois o mesmo demonstrou um aumento na acurácia do modelo. Para descobrir isso executamos i execuções com i variando de 1 até 25 e a execução com 3 vizinhos mostrou a melhor acurácia.

```
In [ ]:
```

```
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
Out[]:
```

Treino

Predição da classificação dos dados de treino com base no modelo treinado

weights='uniform')

```
In [ ]:

y_pred = knn.predict(X_train)
```

Relatório de classificação da predição com o modelo K Neighbors classifier com o sample de treino

In []:

```
print(classification report(y train, y pred))
            precision recall f1-score support
                                1.00
                 1.00
                          1.00
                                         227454
                 0.96
                          0.76
                                             391
                                   0.85
                                   1.00
                                           227845
   accuracy
                 0.98
                         0.88
                                  0.92
                                         227845
  macro avg
weighted avg
                 1.00
                          1.00
                                  1.00
                                           227845
```

Matriz de confusão dos valores preditos com o conjunto de treino

```
In [ ]:
```

```
pd.crosstab(y_train, y_pred, rownames=['Real'],colnames=['Predito'],margins=True)
Out[]:
```

```
        Predito
        0
        1
        All

        Real

        0
        227442
        12
        227454

        1
        94
        297
        391

        All
        227536
        309
        227845
```

Scores das validações cruzadas

```
In []:
scores = cross_val_score(knn, X_train, y_train, cv=5, scoring='accuracy')
scores
Out[]:
array([0.9993636 , 0.99927582, 0.99945138, 0.99934166, 0.99912221])
```

Media dos scores obtidos das validações cruzadas

```
In []:
scores.mean()
Out[]:
0.9993109350655051
```

Acurácia das predições com base no conjunto de treino

```
In []:
accuracy_score(y_train, y_pred)
Out[]:
```

Erro absoluto médio

0.9995347714455002

```
In [ ]:
e = mean_absolute_error(y_train, y_pred)
e
Out[ ]:
```

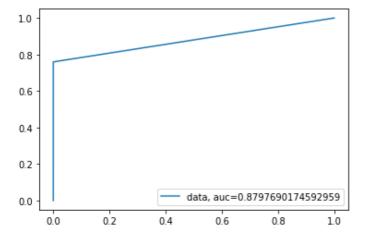
Curva ROC dos dados de treino

0.0004652285544997696

In []:

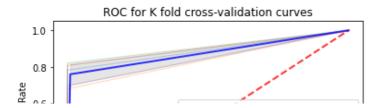
In []:

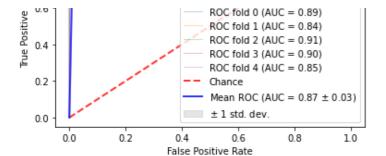
```
fpr, tpr, _ = roc_curve(y_train, y_pred)
roc_auc_scr = roc_auc_score(y_train, y_pred)
plt.plot(fpr,tpr,label="data, auc="+str(roc_auc_scr))
plt.legend(loc=4)
plt.show()
```



Curvas da K fold cross-validation

plot_Kfold_cross_validation_curves(knn, X_train, y_train)





Teste

Predição com base no modelo treinado utilizando o sample de teste

```
In [ ]:
```

```
y_pred = knn.predict(X_test)
```

Relatório de classificação da predição com o modelo KNN com o sample de teste

In []:

```
print(classification_report(y_test, y_pred))
                          recall f1-score
              precision
                                               support
           0
                   1.00
                             1.00
                                        1.00
                                                 56861
                   0.92
                             0.72
                                        0.81
           1
                                                   101
   accuracy
                                        1.00
                                                 56962
  macro avg
                   0.96
                             0.86
                                        0.91
                                                 56962
weighted avg
                   1.00
                             1.00
                                        1.00
                                                 56962
```

Matriz de confusão dos valores preditos com o conjunto de teste

```
In [ ]:
```

```
pd.crosstab(y_test, y_pred, rownames=['Real'], colnames=['Predito'], margins=True)
Out[]:
```

```
        Predito
        0
        1
        All

        Real
        6
        56855
        6
        56861

        1
        28
        73
        101

        All
        56883
        79
        56962
```

Scores das validações cruzadas

```
In [ ]:
```

```
scores = cross_val_score(knn, X_test, y_test, cv=5, scoring='accuracy')
scores
```

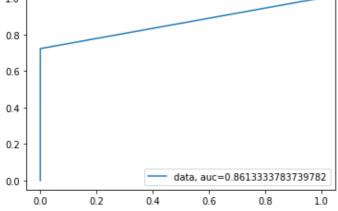
```
Out[]:
```

```
array([0.99938559, 0.99912227, 0.99894663, 0.99894663, 0.99920997])
```

Media dos scores obtidos com o conjunto de teste

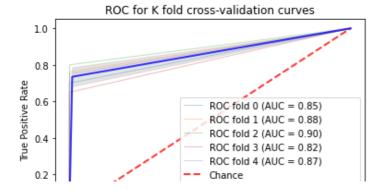
```
In [ ]:
```

```
scores.mean()
Out[]:
0.9991222172075895
Acurácia do modelo com base nos dados preditos do conjunto de teste
In [ ]:
accuracy score(y test, y pred)
Out[]:
0.999403110845827
Erro absoluto do modelo com base no conjunto de teste
In [ ]:
e = mean_absolute_error(y_test, y_pred)
Out[]:
0.0005968891541729574
Curva ROC com o conjunto de teste
In [ ]:
fpr, tpr, _ = roc_curve(y_test, y_pred)
roc_auc_scr = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data, auc="+str(roc auc scr))
plt.legend(loc=4)
plt.show()
 1.0
 0.8
 0.6
 0.4
 0.2
```



Curvas da K fold cross-validation com os dados de teste

```
In [ ]:
plot Kfold cross validation curves(knn, X test, y test)
```





MLPClassifier

Utilizaremos a classe do MLP Classifier com algumas alterações dos parâmetros default, pois principalmente relacionado ao número de iterações acaba fazendo com que o tempo de execução se torne algo muito custoso principalmente para executar as k validações cruzadas. Optamos por diminuir o número de layers como o número de neurônios da rede neural para 2 camadas com 50 neurônios cada e um número máximo de iterações igual a 5. Importante deixar claro que o modelo apresenta uma acurácia superor utizando a parametrização padrão da classe.

Treino

Treino e predição com o modelo treinado utilizando o MLP classifier

```
In []:
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_train)

Iteration 1, loss = inf
Iteration 2, loss = 0.02712378
Iteration 3, loss = inf
Iteration 4, loss = 0.01661020
Iteration 5, loss = 0.01060315

/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the optimization hasn't converged yet.
    % self.max_iter, ConvergenceWarning)
```

Relatório de classificação da predição com o modelo MLPClassifier com o sample de treino

In []:

Predito

```
print(classification_report(y_train, y_pred))
              precision
                            recall f1-score
                                                support
           0
                    1.00
                              1.00
                                         1.00
                                                 227454
           1
                    0.87
                              0.64
                                         0.74
                                                    391
    accuracy
                                         1.00
                                                 227845
                    0.93
                              0.82
                                        0.87
                                                 227845
   macro avq
weighted avg
                   1.00
                              1.00
                                        1.00
                                                 227845
```

Matriz de confusão dos valores preditos com o conjunto de treino

ΔII

```
In []:
pd.crosstab(y_train, y_pred, rownames=['Real'],colnames=['Predito'],margins=True)
Out[]:
```

```
Predito Real

Real

0 227416 38 227454

1 141 250 391

All 227557 288 227845
```

Out[]:

```
Scores das validações cruzadas com conjunto de treino
In [ ]:
scores = cross val score(clf, X train, y train, cv=5, scoring='accuracy')
scores
Iteration 1, loss = inf
Iteration 2, loss = 0.02722532
Iteration 3, loss = 0.02695025
Iteration 4, loss = 0.02307299
Iteration 5, loss = 0.01372564
/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max iter, ConvergenceWarning)
Iteration 1, loss = \inf
Iteration 2, loss = 0.02913047
Iteration 3, loss = 0.03468142
Iteration 4, loss = 0.01834889
Iteration 5, loss = 0.01344923
/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
Iteration 1, loss = \inf
Iteration 2, loss = 0.02834564
Iteration 3, loss = \inf
Iteration 4, loss = 0.02769228
Iteration 5, loss = 0.01786017
/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
Iteration 1, loss = inf
Iteration 2, loss = 0.02960014
Iteration 3, loss = \inf
Iteration 4, loss = 0.01987128
Iteration 5, loss = 0.01891146
/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
Iteration 1, loss = \inf
Iteration 2, loss = 0.03324739
Iteration 3, loss = \inf
Iteration 4, loss = 0.01918058
Iteration 5, loss = 0.01250826
/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max iter, ConvergenceWarning)
```

array([0.99918804, 0.99929777, 0.99881498, 0.99899054, 0.99870526])

Media dos scores obtidos das validações cruzadas

```
In [ ]:
scores.mean()
Out[]:
0.9989993197129629
```

Acurácia das predições com base no conjunto de treino

```
In [ ]:
accuracy score(y train, y pred)
Out[]:
0.9992143781957032
```

Erro absoluto com base no conjunto de treino

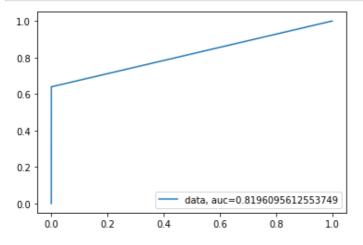
```
In [ ]:
e = mean absolute error(y train, y pred)
Out[]:
```

Curva ROC com os dados de treino

0.0007856218042967807

```
In [ ]:
```

```
fpr, tpr, _
           = roc_curve(y_train, y_pred)
roc_auc_scr = roc_auc_score(y_train, y_pred)
plt.plot(fpr,tpr,label="data, auc="+str(roc auc scr))
plt.legend(loc=4)
plt.show()
```



Curvas da K fold cross-validation com os dados de treino

```
In [ ]:
plot Kfold cross validation curves(clf, X train, y train)
Iteration 1, loss = inf
Iteration 2, loss = 0.02722532
Iteration 3, loss = 0.02695025
Iteration 4, loss = 0.02307299
Iteration 5, loss = 0.01372564
```

/usr/local/lib/pvthon3.7/dist-packages/sklearn/neural network/ multilaver perceptron.pv:5

71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the optimization hasn't converged yet.
% self.max_iter, ConvergenceWarning)

Iteration 1, loss = inf
Iteration 2, loss = 0.02913047
Iteration 3, loss = 0.03468142
Iteration 4, loss = 0.01834889
Iteration 5, loss = 0.01344923

/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5 71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti mization hasn't converged yet.

% self.max_iter, ConvergenceWarning)

Iteration 1, loss = inf
Iteration 2, loss = 0.02834564
Iteration 3, loss = inf
Iteration 4, loss = 0.02769228
Iteration 5, loss = 0.01786017

/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5 71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti mization hasn't converged yet.

% self.max_iter, ConvergenceWarning)

Iteration 1, loss = inf
Iteration 2, loss = 0.02960014
Iteration 3, loss = inf
Iteration 4, loss = 0.01987128
Iteration 5, loss = 0.01891146

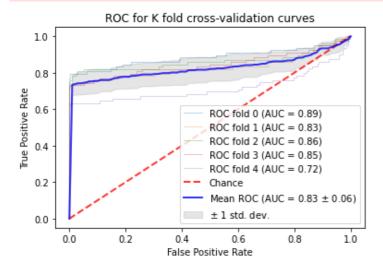
/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5 71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti mization hasn't converged yet.

% self.max iter, ConvergenceWarning)

Iteration 1, loss = inf
Iteration 2, loss = 0.03324739
Iteration 3, loss = inf
Iteration 4, loss = 0.01918058
Iteration 5, loss = 0.01250826

/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5 71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti mization hasn't converged yet.

% self.max iter, ConvergenceWarning)



Teste

Predição dos dados de teste com o modelo treinado utilizando o MLP classifier

```
y_pred = clf.predict(X_test)
```

Relatório de classificação da predição com o modelo MLPClassifier com o sample de teste

```
In [ ]:
```

```
print(classification report(y test, y pred))
             precision recall f1-score
                                             support
                  1.00
                            1.00
                                      1.00
                                               56861
                            0.56
                                      0.69
                  0.88
                                                101
                                      1.00
                                               56962
   accuracy
                  0.94
                          0.78
                                     0.84
                                              56962
  macro avg
weighted avg
                  1.00
                            1.00
                                     1.00
                                              56962
```

Matriz de confusão dos valores preditos com o conjunto de teste

```
In [ ]:
```

```
pd.crosstab(y_test, y_pred, rownames=['Real'],colnames=['Predito'],margins=True)
```

Out[]:

Predito	0	1	All
Real			
0	56853	8	56861
1	44	57	101
All	56897	65	56962

Scores das validações cruzadas com conjunto de treino

```
In [ ]:
```

```
scores = cross_val_score(clf, X_test, y_test, cv=5, scoring='accuracy')
scores
```

```
Iteration 1, loss = inf
Iteration 2, loss = 0.10979617
Iteration 3, loss = 0.07809046
Iteration 4, loss = 0.05709109
Iteration 5, loss = 0.04128277
```

/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5 71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti mization hasn't converged yet.

% self.max iter, ConvergenceWarning)

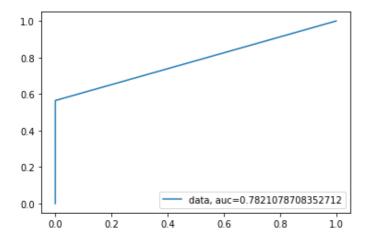
```
Iteration 1, loss = inf
Iteration 2, loss = 0.10426688
Iteration 3, loss = 0.07710955
Iteration 4, loss = 0.05767491
Iteration 5, loss = 0.04334860
```

/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5 71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti mization hasn't converged yet.

% self.max_iter, ConvergenceWarning)

```
Iteration 1, loss = inf
Iteration 2, loss = 0.10734112
Iteration 3, loss = 0.07366163
Iteration 4, loss = 0.05507909
Iteration 5, loss = 0.03982645
```

```
/usr/local/lib/python3.//dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max iter, ConvergenceWarning)
Iteration 1, loss = inf
Iteration 2, loss = 0.11081528
Iteration 3, loss = 0.07684522
Iteration 4, loss = 0.05440205
Iteration 5, loss = 0.03938074
/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max iter, ConvergenceWarning)
Iteration 1, loss = inf
Iteration 2, loss = 0.10059844
Iteration 3, loss = 0.07369080
Iteration 4, loss = 0.05428945
Iteration 5, loss = 0.03891028
/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
Out[]:
array([0.99877118, 0.99850786, 0.99868329, 0.99885885, 0.99868329])
Média dos scores obtidos das k validações cruzadas
In [ ]:
scores.mean()
Out[]:
0.9987008904664505
Acurácia das predições com base no conjunto de teste
In [ ]:
accuracy score(y test, y pred)
Out[]:
0.9990871107053826
Erro absoluto com base no conjunto de teste
In [ ]:
e = mean absolute error(y test, y pred)
Out[]:
0.0009128892946174643
Curva ROC utilizando os dados de teste
In [ ]:
fpr, tpr, _ = roc_curve(y_test, y_pred)
roc auc scr = roc_auc_score(y_test, y_pred)
plt.plot(fpr,tpr,label="data, auc="+str(roc_auc_scr))
plt.legend(loc=4)
plt.show()
```



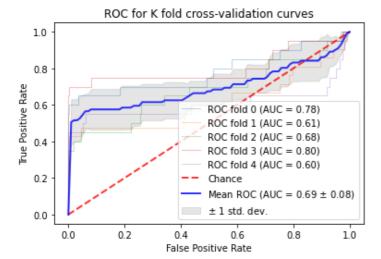
Curvas da K fold cross-validation com os dados de teste

Iteration 5, loss = 0.03891028

```
In [ ]:
plot Kfold cross validation curves(clf, X test, y test)
Iteration 1, loss = inf
Iteration 2, loss = 0.10979617
Iteration 3, loss = 0.07809046
Iteration 4, loss = 0.05709109
Iteration 5, loss = 0.04128277
/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max iter, ConvergenceWarning)
Iteration 1, loss = inf
Iteration 2, loss = 0.10426688
Iteration 3, loss = 0.07710955
Iteration 4, loss = 0.05767491
Iteration 5, loss = 0.04334860
/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
Iteration 1, loss = inf
Iteration 2, loss = 0.10734112
Iteration 3, loss = 0.07366163
Iteration 4, loss = 0.05507909
Iteration 5, loss = 0.03982645
/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max iter, ConvergenceWarning)
Iteration 1, loss = inf
Iteration 2, loss = 0.11081528
Iteration 3, loss = 0.07684522
Iteration 4, loss = 0.05440205
Iteration 5, loss = 0.03938074
/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5
71: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti
mization hasn't converged yet.
  % self.max iter, ConvergenceWarning)
Iteration 1, loss = \inf
Iteration 2, loss = 0.10059844
Iteration 3, loss = 0.07369080
Iteration 4, loss = 0.05428945
```

/usr/local/lib/python3.7/dist-packages/sklearn/neural network/ multilayer perceptron.py:5

/1: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (5) reached and the opti mization hasn't converged yet. % self.max iter, ConvergenceWarning)



É uma pena para a execução do trabalho com base nesse tema não ter o dataset pré processamento para identificar um possível overfit nos modelos criados, haja vista a grande acurácia apresentada. Apesar da incógnita perando as features dos dados pré processamento podemos concluir que o objetivo foi alcançado com sucesso. Podemos fazer esta afirmação olhando para as taxas de falso positivo e falso negativo já que os dados em si apresentam em ampla maioria registros de transações não fraudulentas, logo o peso de marcar uma transação como fraudulenda ou não sem que a mesma tenha realmente esta classificação adquire um peso maior.