Project : Credit Card Fraud Detection

By

Abdulhadi Abdullah Ayed Alajmi

Dataset:

https://www.kaggle.com/mlg-ulb/creditcardfraud

Data Description:

The dataset contains transactions made by credit cards in September 2013 by European cardholders.

This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions.

It contains only numerical input variables which are the result of a PCA transformation.

Importing Python Libraries

In [1]:

```
import pandas as pd
import numpy as np
import pickle
import matplotlib.pyplot as plt
from scipy import stats
import tensorflow as tf
import seaborn as sns
from pylab import rcParams
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.manifold import TSNE
from sklearn.metrics import classification_report, accuracy_score
from keras.models import Model, load_model
from keras.layers import Input, Dense
from keras.callbacks import ModelCheckpoint, TensorBoard
from keras import regularizers, Sequential
%matplotlib inline
sns.set(style='whitegrid', palette='muted', font_scale=1.5)
rcParams['figure.figsize'] = 14, 8
RANDOM_SEED = 42
LABELS = ["Normal", "Fraud"]
```

- **Importing datasets and printing datasets head:**

In [2]:
```
df = pd.read_csv("downloads/creditcard.csv")
df.head()
```

Out[2]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V2
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.12853
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.16717
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.32764
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.64737
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.20601

5 rows × 31 columns

- **Information about the datasets:**

In [3]:
```
df.shape
```

Out[3]: (284807, 31)

- **Checking and dropping null values:**

In [4]:
```
df.isnull().values.any()
```

Out[4]: False

- **Visualizing all transactions**

```
In [5]: count_classes = pd.value_counts(df['Class'], sort = True)
        count_classes.plot(kind = 'bar', rot=0)
        plt.title("Transaction class distribution")
        plt.xticks(range(2), LABELS)
        plt.xlabel("Class")
        plt.ylabel("Frequency")
```

```
Out[5]: Text(0, 0.5, 'Frequency')
```

- **checking for normal and fraud transactions shapes**

```
In [6]: frauds = df[df.Class == 1]
        normal = df[df.Class == 0]
        frauds.shape

Out[6]: (492, 31)

In [7]: normal.shape

Out[7]: (284315, 31)
```

- **Describing normal and fraud transactions using statistics**

```
In [8]: frauds.Amount.describe()

Out[8]: count     492.000000
        mean      122.211321
        std       256.683288
        min         0.000000
        25%         1.000000
        50%         9.250000
        75%       105.890000
        max      2125.870000
        Name: Amount, dtype: float64
```

In [9]:
```
normal.Amount.describe()
```

Out[9]:
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

- **Visualizing normal and fraud transactions using frequency distribution**

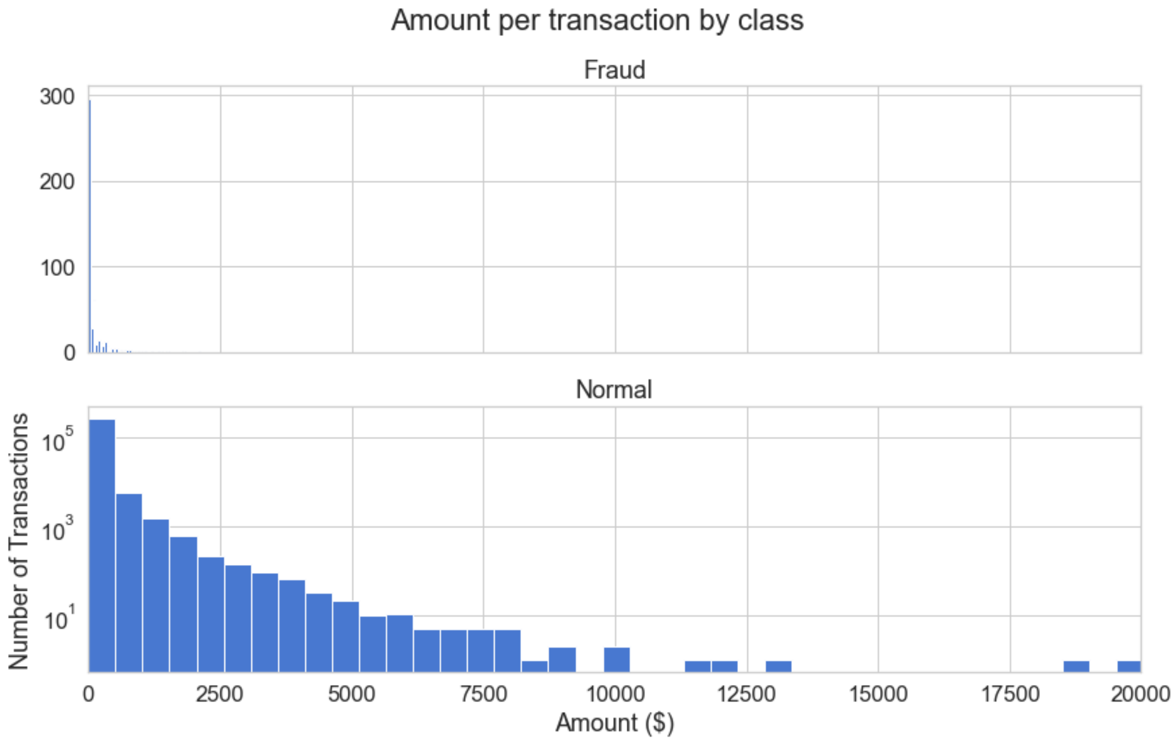
In [10]:
```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Amount per transaction by class')

bins = 50

ax1.hist(frauds.Amount, bins = bins)
ax1.set_title('Fraud')

ax2.hist(normal.Amount, bins = bins)
ax2.set_title('Normal')

plt.xlabel('Amount ($)')
plt.ylabel('Number of Transactions')
plt.xlim((0, 20000))
plt.yscale('log')
plt.show()
```



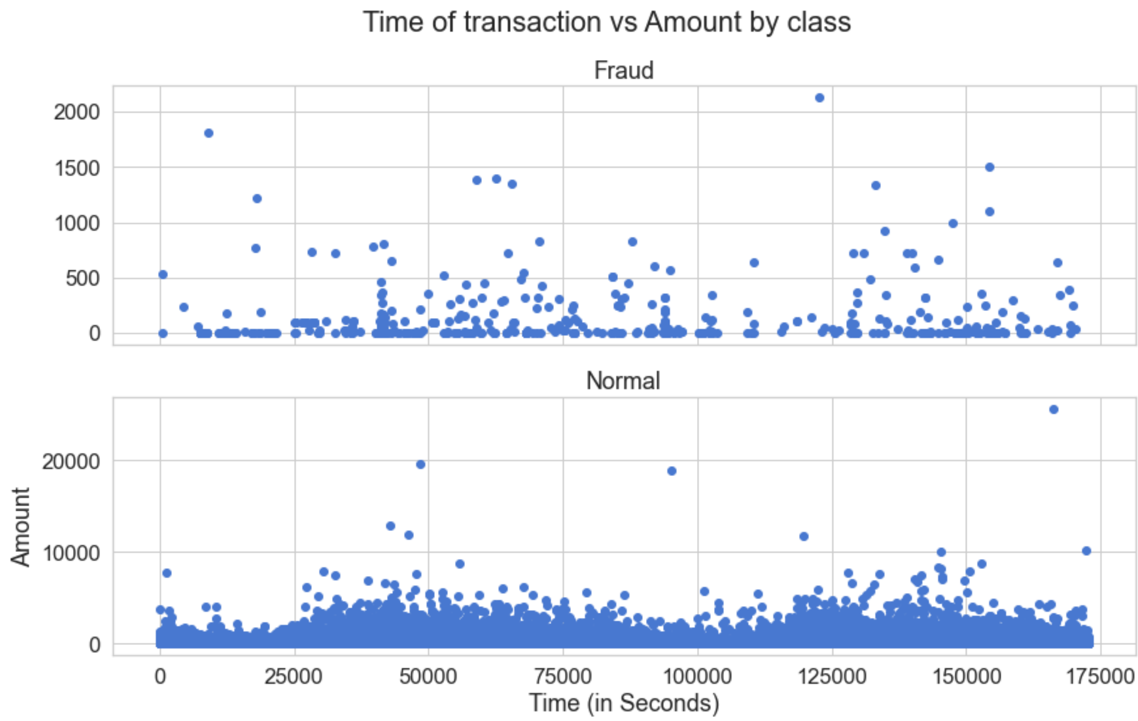
- **visualizing time of transactions vs number of transactions by class using scatter plot**

In [11]:
```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Time of transaction vs Amount by class')

ax1.scatter(frauds.Time, frauds.Amount)
ax1.set_title('Fraud')

ax2.scatter(normal.Time, normal.Amount)
ax2.set_title('Normal')

plt.xlabel('Time (in Seconds)')
plt.ylabel('Amount')
plt.show()
```



- **Dropping Time column**

```
In [12]: data = df.drop(['Time'], axis=1)
```

- **Scaling the Amount using Standard Scaler and building machine learning model**

```
In [13]: from sklearn.preprocessing import StandardScaler

         data['Amount'] = StandardScaler().fit_transform(data['Amount'].values.reshape(-1, 1))
```

```
In [14]: non_fraud = data[data['Class'] == 0] #.sample(1000)
         fraud = data[data['Class'] == 1]

         df = non_fraud.append(fraud).sample(frac=1).reset_index(drop=True)
         X = df.drop(['Class'], axis = 1).values
         Y = df["Class"].values
```

- **spiting the data into 80% training and 20% testing**

```
In [15]: X_train, X_test = train_test_split(data, test_size=0.2, random_state=RANDOM_SEED)
         X_train_fraud = X_train[X_train.Class == 1]
         X_train = X_train[X_train.Class == 0]
         X_train = X_train.drop(['Class'], axis=1)
         y_test = X_test['Class']
         X_test = X_test.drop(['Class'], axis=1)
         X_train = X_train.values
         X_test = X_test.values
         X_train.shape

Out[15]: (227451, 29)
```

- **Autoencoder model**

```
In [16]: input_layer = Input(shape=(X.shape[1],))

         ## encoding part
         encoded = Dense(100, activation='tanh', activity_regularizer=regularizers.l1(10e-5))(input_layer)
         encoded = Dense(50, activation='relu')(encoded)

         ## decoding part
         decoded = Dense(50, activation='tanh')(encoded)
         decoded = Dense(100, activation='tanh')(decoded)

         ## output layer
         output_layer = Dense(X.shape[1], activation='relu')(decoded)
```

```
In [17]: autoencoder = Model(input_layer, output_layer)
         autoencoder.compile(optimizer="adadelta", loss="mse")
```

- **Training the credit card fraud detection model**


```
In [17]: autoencoder = Model(input_layer, output_layer)
         autoencoder.compile(optimizer="adadelta", loss="mse")
```


- **Scaling the values**

```
In [18]: x = data.drop(["Class"], axis=1)
         y = data["Class"].values

         x_scale = MinMaxScaler().fit_transform(x.values)
         x_norm, x_fraud = x_scale[y == 0], x_scale[y == 1]

         autoencoder.fit(x_norm[0:2000], x_norm[0:2000],
                         batch_size = 256, epochs = 10,
                         shuffle = True, validation_split = 0.20);
```

- **Obtaining the Hidden Representation**

```
In [19]: hidden_representation = Sequential()
         hidden_representation.add(autoencoder.layers[0])
         hidden_representation.add(autoencoder.layers[1])
         hidden_representation.add(autoencoder.layers[2])
```

- **Model Prediction**

```
In [20]: norm_hid_rep = hidden_representation.predict(x_norm[:3000])
         fraud_hid_rep = hidden_representation.predict(x_fraud)
```

- **Getting the representation data**

```
In [21]: rep_x = np.append(norm_hid_rep, fraud_hid_rep, axis = 0)
         y_n = np.zeros(norm_hid_rep.shape[0])
         y_f = np.ones(fraud_hid_rep.shape[0])
         rep_y = np.append(y_n, y_f)
```

- **Train, test, split**

```
In [22]: train_x, val_x, train_y, val_y = train_test_split(rep_x, rep_y, test_size=0.25)
```

- **Credit Card Fraud Detection Prediction model**

```
In [23]: clf = LogisticRegression(solver="lbfgs").fit(train_x, train_y)
         pred_y = clf.predict(val_x)

         print ("")
         print ("Classification Report: ")
         print (classification_report(val_y, pred_y))

         print ("")
         print ("Accuracy Score: ", accuracy_score(val_y, pred_y))
```

```
Classification Report:
              precision    recall  f1-score   support

         0.0       0.96      1.00      0.98       766
         1.0       0.99      0.70      0.82       107

    accuracy                           0.96       873
   macro avg       0.97      0.85      0.90       873
weighted avg       0.96      0.96      0.96       873


Accuracy Score:  0.9621993127147767
```