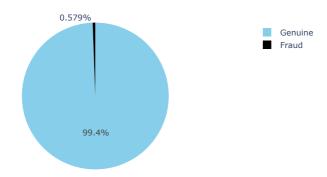
```
In [1]: import numpy as np
          import pandas as pd
          import seaborn as sns
          \textbf{import} \ \texttt{plotly.express} \ \textbf{as} \ \texttt{px}
          {\color{red} \textbf{import}} \ {\color{blue} \textbf{matplotlib.pyplot}} \ {\color{blue} \textbf{as}} \ {\color{blue} \textbf{plt}}
          from sklearn.model_selection import cross_val_score
          from sklearn import metrics
          from collections import Counter
In [2]: import os
          os.chdir("C:\\Users\\kumar\\OneDrive\\Desktop\\Machine Learning")
In [3]: try:
               train_df = pd.read_csv("C:\\Users\\kumar\\OneDrive\\Desktop\\Machine Learning\\fraudTrain.csv")
               test_df = pd.read_csv("C:\\Users\\kumar\\OneDrive\\Desktop\\Machine Learning\\fraudTest.csv")
          except:
              train_df = pd.read_csv('fraudTrain.csv')
test_df = pd.read_csv('fraudTest.csv')
In [4]: train_df.head()
Out[4]:
             Unnamed:
                        trans_date_trans_time
                                                          cc_num
                                                                       merchant
                                                                                       category
                                                                                                   amt
                                                                                                              first
                                                                                                                       last gender
                                                                                                                                       street ...
                                                                                                                                                       lat
                                                                                                                                                                long city_
                                                                     fraud_Rippin,
                                                                                                                                         561
                            2019-01-01 00:00:18 2703186189652095
                                                                                                   4.97
                                                                                                           Jennifer
                                                                                                                                        Perry
                                                                                                                                                  36.0788
                                                                                                                                                            -81.1781
                                                                         Kub and
                                                                                                                      Banks
                                                                                       misc_net
                                                                                                                                        Cove
                                                                                                                                       43039
                                                                     fraud_Heller,
                                                                                                                                        Riley
          1
                      1
                           2019-01-01 00:00:44
                                                    630423337322 Gutmann and
                                                                                    grocery_pos 107.23 Stephanie
                                                                                                                        Gill
                                                                                                                                      Greens
                                                                                                                                                  48.8878 -118.2105
                                                                          Zieme
                                                                                                                                        Suite
                                                                                                                                         393
                                                                                                                                         594
                                                                                                                                       White
                                                                      fraud Lind-
                            2019-01-01 00:00:51
                                                  38859492057661
                                                                                  entertainment 220.11
                                                                                                                                                  42.1808 -112.2620
                                                                                                           Edward Sanchez
                                                                                                                                        Dale
                                                                       Buckridge
                                                                                                                                        Suite
                                                                                                                                         530
                                                                                                                                        9443
                                                                     fraud Kutch,
                                                                                                                                      Cynthia
          3
                           2019-01-01 00:01:16 3534093764340240
                                                                      Hermiston gas_transport 45.00
                                                                                                                                                  46.2306 -112.1138
                                                                                                           Jeremy
                                                                                                                      White
                                                                                                                                  М
                                                                                                                                       Court
                                                                       and Farrell
                                                                                                                                         Apt.
                                                                                                                                         038
                                                                                                                                         408
                                                                   fraud_Keeling-
                           2019-01-01 00:03:06 375534208663984
                                                                                       misc_pos 41.96
                                                                                                                                  M Bradley
                                                                                                                                                  38.4207 -79.4629
                                                                            Crist
                                                                                                                                         Rest
         5 rows × 23 columns
In [5]: fig = px.pie(values=train_df['is_fraud'].value_counts(), names=["Genuine","Fraud"], width=700, height=400, color_discrete_sequence=[
                          ,title="Fraud vs Genuine transactions")
          fig.show()
```

## Fraud vs Genuine transactions



```
In [6]: plt.figure(figsize=(3,4))
    ax = sns.countplot(x='is_fraud',data=train_df,palette="pastel")
    for i in ax.containers:
        ax.bar_label(i,)
```

```
1e6
          L.28917e+06
  1.2
  1.0
  0.8
count
  0.6
  0.4
  0.2
                                 7506
  0.0
                0
                                   1
                      is_fraud
```

```
In [7]: print('Genuine:', round(train_df['is_fraud'].value_counts()[0]/len(train_df) * 100,2), '% of the dataset')
print('Frauds:', round(train_df['is_fraud'].value_counts()[1]/len(train_df) * 100,2), '% of the dataset')
            Genuine: 99.42 % of the dataset
            Frauds: 0.58 % of the dataset
In [8]: train_df.info(),test_df.info()
            <class 'pandas.core.frame.DataFrame'>
           RangeIndex: 1296675 entries, 0 to 1296674 Data columns (total 23 columns):
             #
                  Column
                                                  Non-Null Count
                                                                           Dtype
                  Unnamed: 0
                                                  1296675 non-null int64
```

1 trans\_date\_trans\_time 1296675 non-null object cc\_num 1296675 non-null 3 merchant 1296675 non-null object 4 category 1296675 non-null object 1296675 non-null float64 5 amt 1296675 non-null object 6 first 1296675 non-null object last 1296675 non-null object gender 1296675 non-null street object 10 city 1296675 non-null 11 state 1296675 non-null 12 zip 1296675 non-null int64 13 lat 1296675 non-null float64 1296675 non-null 14 long float64 1296675 non-null int64 15 city\_pop 1296675 non-null object 16 job 17 dob 1296675 non-null object trans\_num 1296675 non-null object unix\_time 1296675 non-null int64 20 merch\_lat 1296675 non-null float64 merch\_long 21 1296675 non-null float64 22 is\_fraud 1296675 non-null int64 dtypes: float64(5), int64(6), object(12)

memory usage: 227.5+ MB <class 'pandas.core.frame.DataFrame'> RangeIndex: 555719 entries, 0 to 555718

Data columns (total 23 columns):

Column Non-Null Count a Unnamed: 0 555719 non-null int64 1 trans\_date\_trans\_time 555719 non-null object 2 cc\_num 555719 non-null int64 merchant 555719 non-null object 4 category 555719 non-null object 555719 non-null float64 amt 6 first 555719 non-null object 555719 non-null object last 555719 non-null gender 9 street 555719 non-null 10 city 555719 non-null 11 state 555719 non-null object 12 zip 555719 non-null int64 555719 non-null float64 13 lat 555719 non-null float64 14 long 555719 non-null int64 city\_pop 15 555719 non-null 16 job object 17 dob 555719 non-null object trans\_num 555719 non-null object 19 unix\_time 555719 non-null 20 merch\_lat 555719 non-null float64 21 merch\_long 555719 non-null float64 22 is\_fraud 555719 non-null int64 dtypes: float64(5), int64(6), object(12)
memory usage: 97.5+ MB

Out[8]: (None, None)

```
Out[9]: (Unnamed: 0
           trans_date_trans_time
           cc_num
                                      0
           merchant
           category
           amt
           first
           last
           gender
           street
                                       0
           city
           state
                                       0
                                       0
           zin
                                      0
           lat
                                      0
           long
           city_pop
           iob
           dob
           trans num
           unix_time
           merch lat
                                       0
           merch long
                                       0
           is fraud
                                      0
           dtvpe: int64.
           Unnamed: 0
           trans_date_trans_time
           cc num
           merchant
           category
           amt
                                       0
           first
           last
                                      a
           gender
           street
           city
                                       0
           state
           zip
           lat
                                       0
           long
           city_pop
           iob
           dob
                                      0
           trans num
                                      0
           unix time
                                      0
           merch_lat
                                       0
           merch_long
           is_fraud
           dtype: int64)
In [10]: drop_columns = ['Unnamed: 0','cc_num','merchant','trans_num','unix_time','first','last','street','zip']
          train_df.drop(columns=drop_columns,inplace=True)
          test_df.drop(columns=drop_columns,inplace=True)
In [11]: print(train_df.shape)
          print(test df.shape)
          (1296675, 14)
          (555719, 14)
In [12]: train_df['trans_date_trans_time']=pd.to_datetime(train_df['trans_date_trans_time'])
    train_df['trans_date']=train_df['trans_date_trans_time'].dt.strftime('%Y-%m-%d')
    train_df['trans_date']=pd.to_datetime(train_df['trans_date'])
          train_df['dob']=pd.to_datetime(train_df['dob'])
In [13]: test_df['trans_date_trans_time']=pd.to_datetime(test_df['trans_date_trans_time'])
test_df['trans_date']=test_df['trans_date_trans_time'].dt.strftime('%Y-%m-%d')
          test_df['trans_date']=pd.to_datetime(test_df['trans_date'])
          test_df['dob']=pd.to_datetime(test_df['dob'])
In [14]: train_df["age"] = train_df["trans_date"]-train_df["dob"]
          train_df["age"]=train_df["age"].astype('timedelta64[Y]')
In [15]: test_df["age"] = test_df["trans_date"]-test_df["dob"]
          test_df["age"]=test_df["age"].astype('timedelta64[Y]')
In [16]: train_df['trans_month'] = pd.DatetimeIndex(train_df['trans_date']).month
          train_df['trans_year'] = pd.DatetimeIndex(train_df['trans_date']).year
In [17]: train_df['latitudinal_distance'] = abs(round(train_df['merch_lat']-train_df['lat'],3))
          train_df['longitudinal_distance'] = abs(round(train_df['merch_long']-train_df['long'],3))
In [18]: test_df['latitudinal_distance'] = abs(round(test_df['merch_lat']-test_df['lat'],3))
          test_df['longitudinal_distance'] = abs(round(test_df['merch_long']-test_df['long'],3))
In [19]: drop_columns = ['trans_date_trans_time','city','lat','long','job','dob','merch_lat','merch_long','trans_date','state']
          train_df.drop(columns=drop_columns,inplace=True)
          test_df.drop(columns=drop_columns,inplace=True)
In [20]: train_df.gender=train_df.gender.apply(lambda x: 1 if x=="M" else 0)
          test_df.gender=test_df.gender.apply(lambda x: 1 if x=="M" else \theta)
In [21]: train_df = pd.get_dummies(train_df, columns=['category'], prefix='category')
          test_df = pd.get_dummies(test_df, columns=['category'], prefix='category')
```

```
test_df = test_df.reindex(columns=train_df.columns, fill_value=0)
In [22]: train_df.head()
Out[22]:
              amt gender city_pop is_fraud age trans_month trans_year latitudinal_distance longitudinal_distance category_entertainment ... category_grocery_i
          0 4.97
                        0
                              3495
                                         0 30.0
                                                                  2019
                                                                                   0.068
                                                                                                      0.870
                                                                                                                               0
          1 107.23
                        0
                               149
                                         0 40.0
                                                                  2019
                                                                                   0.271
                                                                                                      0.024
                                                                                                                               0 ...
          2 220.11
                              4154
                                         0 56.0
                                                                  2019
                                                                                   0.970
                                                                                                      0.108
          3 45.00
                              1939
                                         0 51.0
                                                                  2019
                                                                                   0.804
                                                                                                      0.447
                                                                                                                               0 ...
          4 41.96
                                99
                                         0 32.0
                                                                  2019
                                                                                   0.254
                                                                                                      0.830
                                                                                                                               0 ...
         5 rows × 23 columns
In [23]: test_df.head()
Out[23]:
             amt gender city_pop is_fraud age trans_month trans_year latitudinal_distance longitudinal_distance category_entertainment ... category_grocery_pr
          0 2.86
                           333497
                                                         0
                                                                   0
                                                                                  0.020
                                                                                                      0.265
                                                                                                                               0 ...
                                        0 52.0
         1 29.84
                       0
                                                         0
                                                                   0
                                                                                  0.870
                                                                                                     0.476
                                                                                                                               0 ...
                              302
                                        0 30.0
          2 41.28
                            34496
                                        0 49.0
                                                         0
                                                                   0
                                                                                  0.177
                                                                                                      0.660
                                                                                                                               0 ...
                                                                                                     0.064
          3 60.05
                       1
                            54767
                                        0 32.0
                                                         0
                                                                   0
                                                                                  0.243
                                                                                                                              0 ...
          4 3.19
                             1126
                                        0 64.0
                                                                                  0.706
                                                                                                      0.868
                                                                                                                               0 ...
         5 rows × 23 columns
In [24]: X_train = train_df.drop('is_fraud', axis=1)
          y_train = train_df['is_fraud']
          X_test = test_df.drop('is_fraud', axis=1)
          y_test = test_df['is_fraud']
In [25]: from imblearn.over_sampling import SMOTE
          smote = SMOTE(random state=42)
          X_train, y_train = smote.fit_resample(X_train, y_train)
In [26]: from sklearn.preprocessing import StandardScaler
          scaler = StandardScaler()
          scaler.fit(X_train)
          X_train = scaler.transform(X_train)
          X_test = scaler.transform(X_test)
In [27]: from sklearn.tree import DecisionTreeClassifier
          from sklearn.metrics import classification_report
In [28]: clf = DecisionTreeClassifier(random_state=42)
          clf.fit(X_train, y_train)
         DecisionTreeClassifier(random_state=42)
Out[28]:
In [29]: y_pred = clf.predict(X_test)
In [30]: report = classification_report(y_test, y_pred)
          print(report)
                        precision
                                     recall f1-score support
                     0
                              1.00
                                        0.99
                                                  1.00
                                                           553574
                              0.33
                                        0.72
                                                  0.45
                                                             2145
              accuracy
                                                  9.99
                                                           555719
                             0.67
                                        0.86
                                                           555719
             macro avg
                                                  0.73
         weighted avg
                             1.00
                                        0.99
                                                  0.99
                                                           555719
In [31]: from sklearn.ensemble import RandomForestClassifier
In [32]: clf = RandomForestClassifier(n_estimators=100, random_state=42)
          clf.fit(X_train, y_train)
Out[32]: RandomForestClassifier(random_state=42)
In [33]: y_pred = clf.predict(X_test)
In [34]: report = classification_report(y_test, y_pred)
          print(report)
```

```
553574
                              1.00
                                        1.00
                                                  1.00
                     0
                     1
                              0.56
                                        0.79
                                                  0.65
                                                             2145
                                                   1.00
                                                           555719
              accuracy
                              0.78
                                                   0.83
                                                            555719
             macro avg
          weighted avg
                                        1.00
                                                   1.00
                                                           555719
In [35]: import xgboost as xgb
In [36]: clf = xgb.XGBClassifier(
              learning_rate=0.1,
              n_estimators=100,
              max_depth=3,
              objective='binary:logistic',
              random_state=42
In [37]: clf.fit(X_train, y_train)
Out[37]: XGBClassifier(base_score=None, booster=None, callbacks=None,
                         {\tt colsample\_bylevel=None,\ colsample\_bynode=None,}
                         \verb|colsample_bytree=None|, | device=None|, | early_stopping_rounds=None|, |
                        enable_categorical=False, eval_metric=None, feature_types=None,
gamma=None, grow_policy=None, importance_type=None,
                         interaction_constraints=None, learning_rate=0.1, max_bin=None,
                         max_cat_threshold=None, max_cat_to_onehot=None,
                         max_delta_step=None, max_depth=3, max_leaves=None,
                         min_child_weight=None, missing=nan, monotone_constraints=None,
                         multi_strategy=None, n_estimators=100, n_jobs=None,
                         num_parallel_tree=None, random_state=42, ...)
In [38]: y_pred = clf.predict(X_test)
In [39]: report = classification_report(y_test, y_pred)
          print(report)
                                     recall f1-score support
                        precision
                     0
                              1.00
                                        0.98
                                                   0.99
                                                           553574
                              0.16
                                                   0.27
                                                             2145
              accuracy
                                                   0.98
                                                           555719
             macro avg
                              0.58
                                        0.92
                                                   0.63
                                                            555719
          weighted avg
                              1.00
                                        0.98
                                                   0.99
                                                           555719
```

precision

In [ ]:

recall f1-score

support