Context

BankSim is an agent-based simulator of bank payments based on a sample of aggregated transactional data provided by a bank in Spain. The main purpose of BankSim is the generation of synthetic data that can be used for fraud detection research. Statistical and a Social Network Analysis (SNA) of relations between merchants and customers were used to develop and calibrate the model. Our ultimate goal is for BankSim to be usable to model relevant scenarios that combine normal payments and injected known fraud signatures. The data sets generated by BankSim contain no personal information or disclosure of legal and private customer transactions. Therefore, it can be shared by academia, and others, to develop and reason about fraud detection methods. Synthetic data has the added benefit of being easier to acquire, faster and at less cost, for experimentation even for those that have access to their own data. We argue that BankSim generates data that usefully approximates the relevant aspects of the real data.

Content

We ran BankSim for 180 steps (approx. six months), several times and calibrated the parameters in order to obtain a distribution that get close enough to be reliable for testing. We collected several log files and selected the most accurate. We injected thieves that aim to steal an average of three cards per step and perform about two fraudulent transactions per day. We produced 594643 records in total. Where 587443 are normal payments and 7200 fraudulent transactions. Since this is a randomised simulation the values are of course not identical to original data.

In [12]:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [13]:

```
# Suppressing Warnings
import warnings
warnings.filterwarnings('ignore')
```

In [14]:

```
# Importing Pandas and NumPy
import pandas as pd, numpy as np
```

In [15]:
```
# Importing all datasets
fraud_detection = pd.read_csv("C:/Users/HP/Desktop/Fraud_Detection/fraud_detection.csv")
fraud_detection.head(4)
```

Out[15]:

	step	customer	age	gender	zipcodeOri	merchant	zipMerchant	category	amount	fraud
0	0	'C1093826151'	'4'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	4.55	0
1	0	'C352968107'	'2'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	39.68	0
2	0	'C2054744914'	'4'	'F'	'28007'	'M1823072687'	'28007'	'es_transportation'	26.89	0
3	0	'C1760612790'	'3'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	17.25	0

In [16]:
```
fraud_detection.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 594643 entries, 0 to 594642
Data columns (total 10 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   step         594643 non-null  int64  
 1   customer     594643 non-null  object 
 2   age          594643 non-null  object 
 3   gender       594643 non-null  object 
 4   zipcodeOri   594643 non-null  object 
 5   merchant     594643 non-null  object 
 6   zipMerchant  594643 non-null  object 
 7   category     594643 non-null  object 
 8   amount       594643 non-null  float64
 9   fraud        594643 non-null  int64  
dtypes: float64(1), int64(2), object(7)
memory usage: 45.4+ MB
```

In [17]:
```
fraud_detection.shape
```

Out[17]:
```
(594643, 10)
```

FEATURE ENGINEERING

Treating the `Missing` Values

Data That can be missing can be of two types :

1) Continuous Data

2) Discreate Or Categorical Data

The Types of `missing` can be of mentioned types :

1) **MCAR** - Missing Completely At Random

If the probability of being `missing` is same for all the observations.

2) **MNAR** - Missing Not At Random

There is some relationship between the missing data

3) **MAR** - Missing At Random

In [18]:
```
fraud_detection.isnull().sum()
```

Out[18]:
```
step           0
customer       0
age            0
gender         0
zipcodeOri     0
merchant       0
zipMerchant    0
category       0
amount         0
fraud          0
dtype: int64
```

There is no `missing values` for this data . Incase if there is any missing values , we can use the mentioned below function for imputation

In [19]:
```
def impute_nan(df,variable,median):
    df[variable+"_median"]=df[variable].fillna(median)
    df[variable+"_random"]=df[variable]
    ##It will have the random sample to fill the na
    random_sample=df[variable].dropna().sample(df[variable].isnull().sum(),random_state=0)
    ##pandas need to have same index in order to merge the dataset
    random_sample.index=df[df[variable].isnull()].index
    df.loc[df[variable].isnull(),variable+'_random']=random_sample
```

In [20]:
```
fraud_detection.head(4)
```

Out[20]:

	step	customer	age	gender	zipcodeOri	merchant	zipMerchant	category	amount	fraud
0	0	'C1093826151'	'4'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	4.55	0
1	0	'C352968107'	'2'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	39.68	0
2	0	'C2054744914'	'4'	'F'	'28007'	'M1823072687'	'28007'	'es_transportation'	26.89	0
3	0	'C1760612790'	'3'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	17.25	0

In [21]:
```
fraud_detection.gender = fraud_detection.gender.astype('category').cat.codes
```

In [22]:
```
fraud_detection.category = fraud_detection.category.astype('category').cat.codes
```

In [23]:
```
fraud_detection.customer = fraud_detection.customer.astype('category').cat.codes
fraud_detection.merchant = fraud_detection.merchant.astype('category').cat.codes
```

In [24]:
```
fraud_detection.head(3)
```

Out[24]:

	step	customer	age	gender	zipcodeOri	merchant	zipMerchant	category	amount	fraud
0	0	210	'4'	2	'28007'	30	'28007'	12	4.55	0
1	0	2753	'2'	2	'28007'	30	'28007'	12	39.68	0
2	0	2285	'4'	1	'28007'	18	'28007'	12	26.89	0

In [25]:
```
fraud_detection.age = fraud_detection.age.str.replace('[\'\,]', '', regex=True)
```

In [26]:
```
fraud_detection.zipcodeOri = fraud_detection.zipcodeOri.str.replace('[\'\,]', '', regex=True)
```

In [27]:
```
fraud_detection.zipMerchant = fraud_detection.zipMerchant.str.replace('[\'\,]', '', regex=True)
```

In [28]:
```
fraud_detection.dtypes
```

Out[28]:
```
step             int64
customer         int16
age             object
gender            int8
zipcodeOri      object
merchant          int8
zipMerchant     object
category          int8
amount         float64
fraud            int64
dtype: object
```

In [29]:
```
fraud_detection["age"] = pd.to_numeric(fraud_detection["age"], errors='ignore')
```

In [30]:
```
fraud_detection["zipcodeOri"] = pd.to_numeric(fraud_detection["zipcodeOri"], errors='coerce')
```

In [31]:
```
fraud_detection["zipMerchant"] = pd.to_numeric(fraud_detection["zipMerchant"], errors='coerce')
```

In [32]:
```
fraud_detection.head(3)
```

Out[32]:

	step	customer	age	gender	zipcodeOri	merchant	zipMerchant	category	amount	fraud
0	0	210	4	2	28007	30	28007	12	4.55	0
1	0	2753	2	2	28007	30	28007	12	39.68	0
2	0	2285	4	1	28007	18	28007	12	26.89	0

In [33]:
```
fraud_detection.age.value_counts()
```

Out[33]:
```
2    187310
3    147131
4    109025
5     62642
1     58131
6     26774
0      2452
U      1178
Name: age, dtype: int64
```

HERE 'U' and '0' stands for error data. Drop the data

In [34]:
```
fraud_detection = fraud_detection[~(fraud_detection.age == '0')]
```

In [35]:
```
fraud_detection = fraud_detection[~(fraud_detection.age == 'U')]
```

In [36]:
```
fraud_detection.age.value_counts()
```

Out[36]:
```
2    187310
3    147131
4    109025
5     62642
1     58131
6     26774
Name: age, dtype: int64
```

In [37]:
```
X = fraud_detection.drop(columns="fraud")
```

In [38]:
```
Y = fraud_detection["fraud"]
```

In [39]:
```
fraud_detection.columns
```

Out[39]:
```
Index(['step', 'customer', 'age', 'gender', 'zipcodeOri', 'merchant',
       'zipMerchant', 'category', 'amount', 'fraud'],
      dtype='object')
```

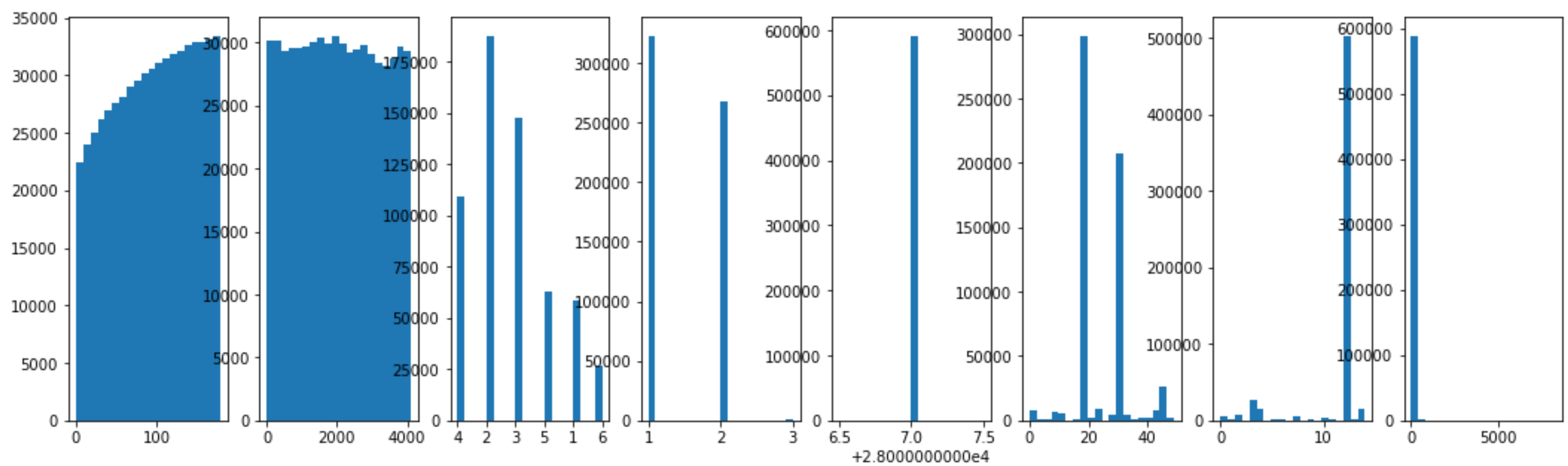
In [40]:
```
fraud_detection.isnull().sum()
```

Out[40]:
```
step           0
customer       0
age            0
gender         0
zipcodeOri     0
merchant       0
zipMerchant    0
category       0
amount         0
fraud          0
dtype: int64
```

In [41]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(18,5))
plt.subplot(1,8,1)
plt.hist(fraud_detection['step'],bins=20)
plt.subplot(1,8,2)
plt.hist(fraud_detection['customer'],bins=20)
plt.subplot(1,8,3)
plt.hist(fraud_detection['age'],bins=20)
plt.subplot(1,8,4)
plt.hist(fraud_detection['gender'],bins=20)
plt.subplot(1,8,5)
plt.hist(fraud_detection['zipcodeOri'],bins=20)
plt.subplot(1,8,6)
plt.hist(fraud_detection['merchant'],bins=20)
plt.subplot(1,8,7)
plt.hist(fraud_detection['category'],bins=20)
plt.subplot(1,8,8)
plt.hist(fraud_detection['amount'],bins=20)

plt.show()
```



In [42]:
```
# choosing all the numerical variables as independent variables (classifier can only take numerical input)
# dropping two variable funded_amnt as we have created new variable transformation based on it
X = fraud_detection.drop(columns = "fraud")
Y = fraud_detection["fraud"]

#splitting the dataset in train and test datasets using a split ratio of 70:30

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=10)
```

In [43]:
```
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(413709, 9) (413709,) (177304, 9) (177304,)
```

FEATURE SELECTION

In [44]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
```

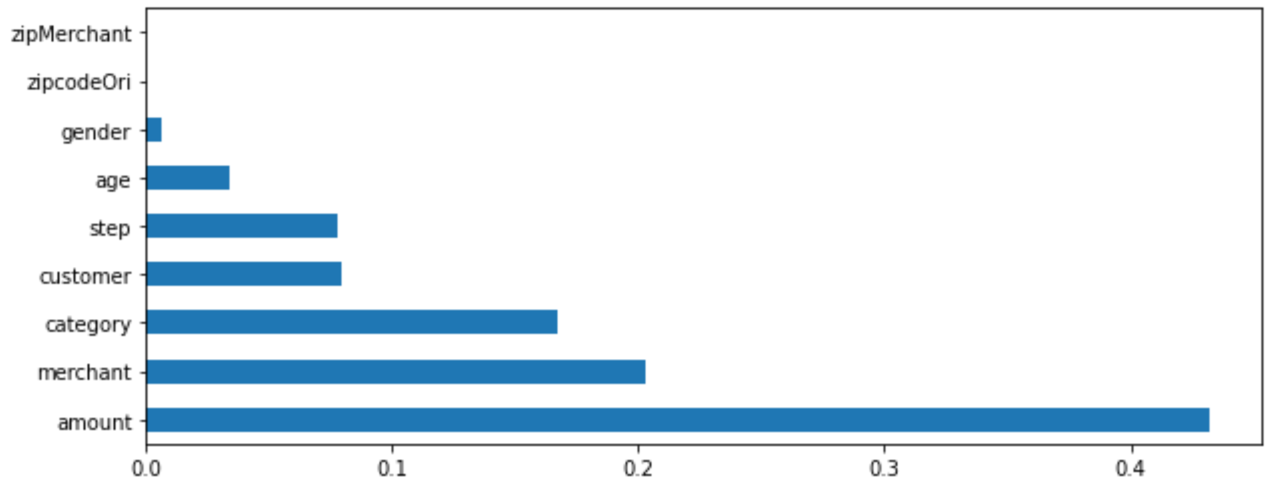
In [45]:
```
from sklearn.ensemble import ExtraTreesClassifier
import matplotlib.pyplot as plt
model=ExtraTreesClassifier()
model.fit(X_train,y_train)
```

Out[45]:
```
▾ ExtraTreesClassifier
ExtraTreesClassifier()
```

In [46]:
```
print(model.feature_importances_)
```

```
[0.07790335 0.07974806 0.03347501 0.00642493 0.         0.20321823
 0.         0.16733023 0.43190019]
```

In [47]:
```
plt.figure(figsize = [10,4])
ranked_features=pd.Series(model.feature_importances_,index=X_train.columns)
ranked_features.nlargest(10).plot(kind='barh')
plt.show()
```



Correlation - To Check `Multicollinearity`

In [48]:
```
X_train.corr()
```

Out[48]:

	step	customer	gender	zipcodeOri	merchant	zipMerchant	category	amount
step	1.000000	0.002905	0.000545	NaN	-0.155699	NaN	-0.018231	-0.007801
customer	0.002905	1.000000	-0.007449	NaN	0.013391	NaN	0.000175	0.004658
gender	0.000545	-0.007449	1.000000	NaN	-0.007365	NaN	0.006780	-0.012025
zipcodeOri	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
merchant	-0.155699	0.013391	-0.007365	NaN	1.000000	NaN	-0.247635	0.066526
zipMerchant	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
category	-0.018231	0.000175	0.006780	NaN	-0.247635	NaN	1.000000	-0.095956
amount	-0.007801	0.004658	-0.012025	NaN	0.066526	NaN	-0.095956	1.000000

In [49]:
```
import seaborn as sns
corr=X_train.corr()
top_features=corr.index
plt.figure(figsize=(10,7))
sns.heatmap(X_train[top_features].corr(),annot=True)
```

Out[49]: <AxesSubplot:>

Reduction Of `Multi Collinearity`

In [50]:
```
threshold=0.6
```

In [51]:
```
# find and remove correlated features
def correlation(dataset, threshold):
    col_corr = set()  # Set of all the names of correlated columns
    corr_matrix = dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) > threshold: # we are interested in absolute coeff value
                colname = corr_matrix.columns[i]  # getting the name of column
                col_corr.add(colname)
    return col_corr
```

In [52]:
```
correlation(X_train,threshold)
```

Out[52]:
```
set()
```

In [53]:
```
X.columns
```

Out[53]:
```
Index(['step', 'customer', 'age', 'gender', 'zipcodeOri', 'merchant',
       'zipMerchant', 'category', 'amount'],
      dtype='object')
```

In [54]:
```
X.drop(columns="zipcodeOri", inplace=True)
```

In [55]:
```
X.drop(columns="zipMerchant", inplace=True)
```

In [56]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=10)
```

In [57]:
```
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(413709, 7) (413709,) (177304, 7) (177304,)
```

PIPELINE CREATION

In [58]:
```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
```

In [59]:
```
###! pip install xgboost
```

In [60]:
```
from sklearn.preprocessing import StandardScaler,MinMaxScaler,MaxAbsScaler,RobustScaler
```

In [61]:
```
pipeline_randomforest=Pipeline([('scalar3',RobustScaler()),
                     ('pca3',PCA(n_components=2)),
                     ('rf_classifier',RandomForestClassifier())])
```

In [62]:
```
pipeline_gradient_boost=Pipeline([('scalar4',RobustScaler()),
                     ('pca4',PCA(n_components=2)),
                     ('gb_classifier',GradientBoostingClassifier())])
```

In [63]:
```
pipeline_XGboost=Pipeline([('scalar5',RobustScaler()),
                          ('pca5',PCA(n_components=2)),
                          ('xgb_classifier',XGBClassifier())])
```

In [64]:
```
## LEts make the list of pipelines
pipelines = [pipeline_randomforest,pipeline_gradient_boost,pipeline_XGboost]
```

In [65]:
```
best_accuracy=0.0
best_classifier=0
best_pipeline=""
```

In [66]:
```
# Dictionary of pipelines and classifier types for ease of reference
pipe_dict = {0: 'RandomForest', 1: 'Gradient Boost', 2: 'Extreme Gradient Boost'}

# Fit the pipelines
for pipe in pipelines:
        pipe.fit(X_train, y_train)
```

```
[13:57:54] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/src/learner.cc:1095: Starting in XG
Boost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'lo
gloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

In [67]:

```
for i,model in enumerate(pipelines):
    print("{} Test Accuracy: {}".format(pipe_dict[i],model.score(X_test,y_test)))
```

```
RandomForest Test Accuracy: 0.9952341740739069
Gradient Boost Test Accuracy: 0.9948562920182286
Extreme Gradient Boost Test Accuracy: 0.9955612958534494
```

In [68]:

```
y_test.value_counts()
```

Out[68]:

```
0    175227
1      2077
Name: fraud, dtype: int64
```

In [69]:

```
gb = GradientBoostingClassifier(n_estimators=100)
gb.fit(X_train, y_train)
preds = gb.predict(X_test)
```

In [70]:

```
from sklearn import metrics
```

In [71]:

```
# Confusion matrix
confusion = metrics.confusion_matrix(y_test, preds)
print(confusion)
```

```
[[175060    167]
 [   578   1499]]
```

In [72]:

```
random_grid = {'bootstrap': [True, False],
               'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None],
               'max_features': ['auto', 'sqrt'],
               'min_samples_leaf': [1, 2, 4],
               'min_samples_split': [2, 5, 10],
               'n_estimators': [130, 180, 230]}
```

In [73]:

```
from sklearn.model_selection import RandomizedSearchCV
```

In [74]:
```
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
rf_random = RandomizedSearchCV(estimator = rf,
                               param_distributions = random_grid,
                               n_iter = 5,
                               cv = 4,
                               verbose=2,
                               random_state=42,
                               n_jobs = -1)
```

In [75]:
```
# Fit the random search model
rf_random.fit(X_train, y_train)
```

```
Fitting 4 folds for each of 5 candidates, totalling 20 fits
```

Out[75]:

RandomizedSearchCV

estimator: RandomForestClassifier

RandomForestClassifier

In [76]:
```
rf_random.best_params_
```

Out[76]:
```
{'n_estimators': 130,
 'min_samples_split': 10,
 'min_samples_leaf': 2,
 'max_features': 'auto',
 'max_depth': 90,
 'bootstrap': False}
```

In [77]:
```
best_random_grid=rf_random.best_estimator_
```

In [78]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
y_pred=best_random_grid.predict(X_test)
print(confusion_matrix(y_test,y_pred))
print("Accuracy Score {}".format(accuracy_score(y_test,y_pred)))
print("Classification report: {}".format(classification_report(y_test,y_pred)))
```

```
[[175057    170]
 [   537   1540]]
Accuracy Score 0.9960124983079908
Classification report:               precision    recall  f1-score   support

           0       1.00      1.00      1.00    175227
           1       0.90      0.74      0.81      2077

    accuracy                           1.00    177304
   macro avg       0.95      0.87      0.91    177304
weighted avg       1.00      1.00      1.00    177304
```

In [ ]:

In [ ]: