```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import missingno as msno
import datetime as dt
```

```
/opt/conda/lib/python3.10/site-packages/scipy/__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for thi
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

```
csv_path_train="/kaggle/input/fraud-detection/fraudTrain.csv"
data=pd.read_csv(csv_path_train)
df_train=pd.DataFrame(data)
df_train.head(2)
```

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt
0	0	2019-01-01 00:00:18	2703186189652095	fraud_Rippin, Kub and Mann	misc_net	4.97
1	1	2019-01-01 00:00:44	630423337322	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23

2 rows × 23 columns

```
csv_path_test="/kaggle/input/fraud-detection/fraudTrain.csv"
data=pd.read_csv(csv_path_test)
df_test=pd.DataFrame(data)
df_test.head(2)
```

	Unnamed: 0	trans_date_trans_time	cc_num	merchant	category	amt
0	0	2019-01-01 00:00:18	2703186189652095	fraud_Rippin, Kub and Mann	misc_net	4.97
1	1	2019-01-01 00:00:44	630423337322	fraud_Heller, Gutmann and Zieme	grocery_pos	107.23

2 rows × 23 columns

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   Unnamed: 0             1296675 non-null  int64  
 1   trans_date_trans_time  1296675 non-null  object 
 2   cc_num                 1296675 non-null  int64  
 3   merchant               1296675 non-null  object 
 4   category               1296675 non-null  object 
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object 
 7   last                   1296675 non-null  object 
 8   gender                 1296675 non-null  object 
 9   street                 1296675 non-null  object 
 10  city                   1296675 non-null  object 
 11  state                  1296675 non-null  object 
 12  zip                    1296675 non-null  int64  
 13  lat                    1296675 non-null  float64
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64  
 16  job                    1296675 non-null  object 
 17  dob                    1296675 non-null  object 
 18  trans_num              1296675 non-null  object 
 19  unix_time              1296675 non-null  int64  
 20  merch_lat              1296675 non-null  float64
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64  
```

```
dtypes: float64(5), int64(6), object(12)
memory usage: 227.5+ MB
```

```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Non-Null Count    Dtype  
---  ------                 --------------    -----  
 0   Unnamed: 0             1296675 non-null  int64  
 1   trans_date_trans_time  1296675 non-null  object 
 2   cc_num                 1296675 non-null  int64  
 3   merchant               1296675 non-null  object 
 4   category               1296675 non-null  object 
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object 
 7   last                   1296675 non-null  object 
 8   gender                 1296675 non-null  object 
 9   street                 1296675 non-null  object 
 10  city                   1296675 non-null  object 
 11  state                  1296675 non-null  object 
 12  zip                    1296675 non-null  int64  
 13  lat                    1296675 non-null  float64
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64  
 16  job                    1296675 non-null  object 
 17  dob                    1296675 non-null  object 
 18  trans_num              1296675 non-null  object 
 19  unix_time              1296675 non-null  int64  
 20  merch_lat              1296675 non-null  float64
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64  
dtypes: float64(5), int64(6), object(12)
memory usage: 227.5+ MB
```

Exploratory Data Analysis (EDA)

```
df_train.isnull().sum()
```

```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
dob                      0
trans_num                0
unix_time                0
merch_lat                0
merch_long               0
is_fraud                 0
dtype: int64
```

```
df_test.isnull().sum()
```

```
Unnamed: 0               0
trans_date_trans_time    0
cc_num                   0
merchant                 0
category                 0
amt                      0
first                    0
last                     0
gender                   0
street                   0
city                     0
state                    0
zip                      0
lat                      0
long                     0
city_pop                 0
job                      0
```

```
dob                 0
trans_num           0
unix_time           0
merch_lat           0
merch_long          0
is_fraud            0
dtype: int64
```

```
df_train.describe()
```

	Unnamed: 0	cc_num	amt	zip	lat	lo
count	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e
mean	6.483370e+05	4.171920e+17	7.035104e+01	4.880067e+04	3.853762e+01	-9.022634e
std	3.743180e+05	1.308806e+18	1.603160e+02	2.689322e+04	5.075808e+00	1.375908e
min	0.000000e+00	6.041621e+10	1.000000e+00	1.257000e+03	2.002710e+01	-1.656723e
25%	3.241685e+05	1.800429e+14	9.650000e+00	2.623700e+04	3.462050e+01	-9.679800e
50%	6.483370e+05	3.521417e+15	4.752000e+01	4.817400e+04	3.935430e+01	-8.747690e
75%	9.725055e+05	4.642255e+15	8.314000e+01	7.204200e+04	4.194040e+01	-8.015800e
max	1.296674e+06	4.992346e+18	2.894890e+04	9.978300e+04	6.669330e+01	-6.795030e

```
df_test.describe()
```

	Unnamed: 0	cc_num	amt	zip	lat	long	city_pop	unix_time	merch_lat	
count	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1.296675e+06	1
mean	6.483370e+05	4.171920e+17	7.035104e+01	4.880067e+04	3.853762e+01	-9.022634e+01	8.882444e+04	1.349244e+09	3.853734e+01	-9
std	3.743180e+05	1.308806e+18	1.603160e+02	2.689322e+04	5.075808e+00	1.375908e+01	3.019564e+05	1.284128e+07	5.109788e+00	1
min	0.000000e+00	6.041621e+10	1.000000e+00	1.257000e+03	2.002710e+01	-1.656723e+02	2.300000e+01	1.325376e+09	1.902779e+01	-1
25%	3.241685e+05	1.800429e+14	9.650000e+00	2.623700e+04	3.462050e+01	-9.679800e+01	7.430000e+02	1.338751e+09	3.473357e+01	-9
50%	6.483370e+05	3.521417e+15	4.752000e+01	4.817400e+04	3.935430e+01	-8.747690e+01	2.456000e+03	1.349250e+09	3.936568e+01	-8
75%	9.725055e+05	4.642255e+15	8.314000e+01	7.204200e+04	4.194040e+01	-8.015800e+01	2.032800e+04	1.359385e+09	4.195716e+01	-8
max	1.296674e+06	4.992346e+18	2.894890e+04	9.978300e+04	6.669330e+01	-6.795030e+01	2.906700e+06	1.371817e+09	6.751027e+01	-6

```
df_train["is_fraud"].value_counts()
```

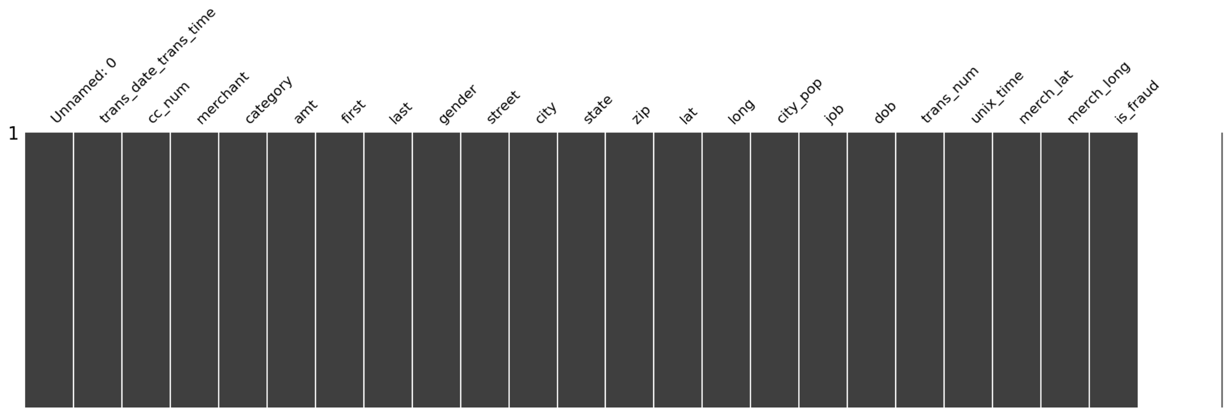
```
is_fraud
0    1289169
1       7506
Name: count, dtype: int64
```

```
df_test["is_fraud"].value_counts()
```

```
is_fraud
0    1289169
1       7506
Name: count, dtype: int64
```

```
msno.matrix(df_train)
```

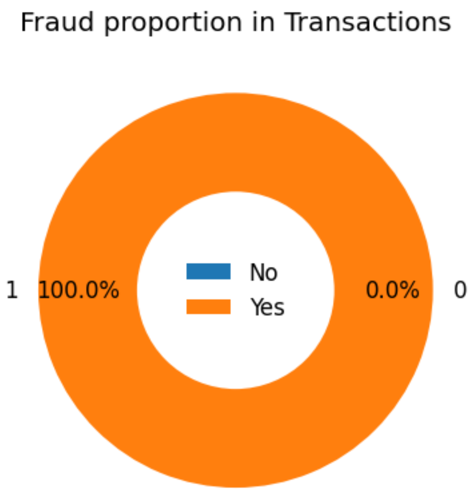
```
<Axes: >
```



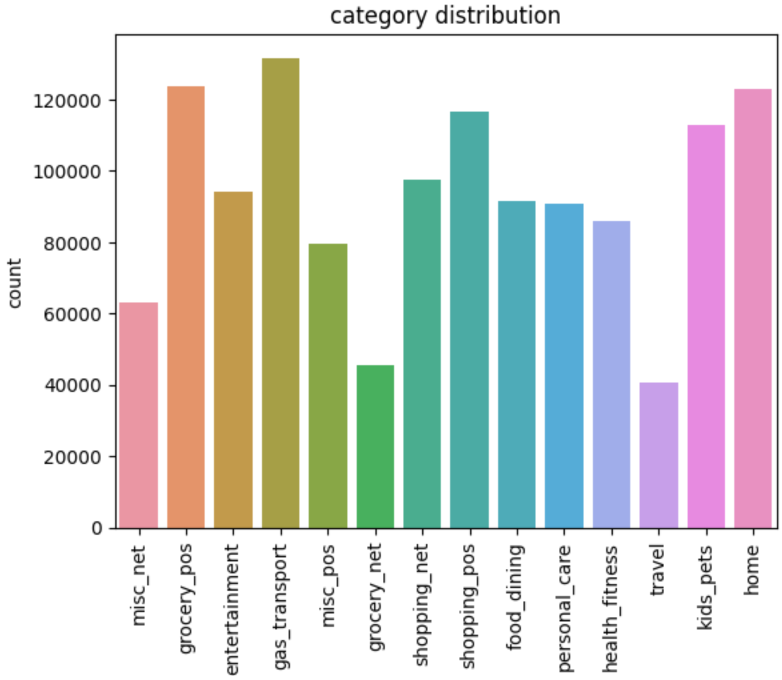

```
df_train["amt"].describe()
```

```
count    1.296675e+06
mean     7.035104e+01
std      1.603160e+02
min      1.000000e+00
25%      9.650000e+00
50%      4.752000e+01
75%      8.314000e+01
max      2.894890e+04
Name: amt, dtype: float64
```

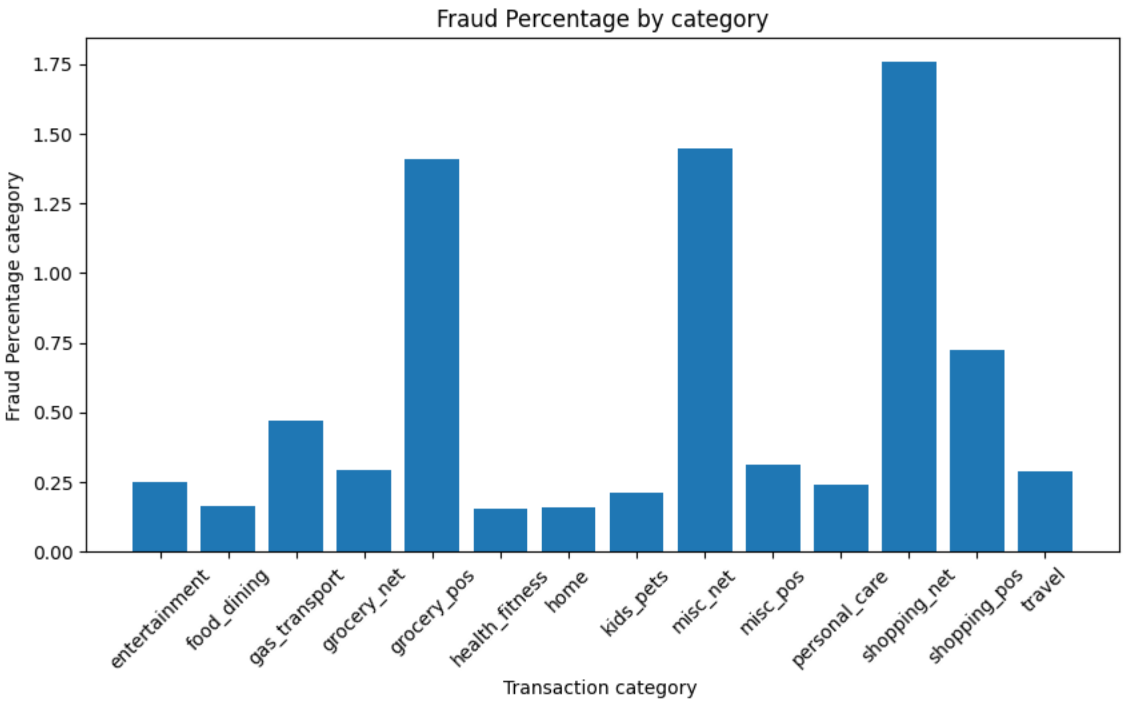
```
donut = df_train["is_fraud"].value_counts().reset_index()

labels = ["No", "Yes"]
explode = (0, 0)

fig, ax = plt.subplots(dpi=120, figsize=(8, 4))
plt.pie(donut["is_fraud"],
        labels=donut["is_fraud"],
        autopct="%1.1f%%",
        pctdistance=0.8,
        explode=explode)

centre_circle = plt.Circle((0.0, 0.0), 0.5, fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title("Fraud proportion in Transactions")
plt.legend(labels, loc="center", frameon=False)
plt.show();
```



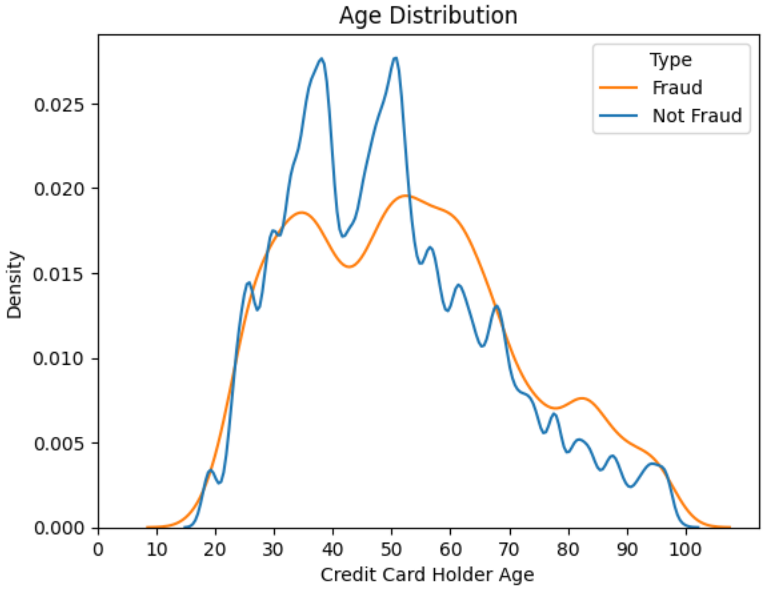

```
sns.countplot(x="category",data=df_train)
plt.title("category distribution")
plt.xticks(rotation=90)
plt.show()
```



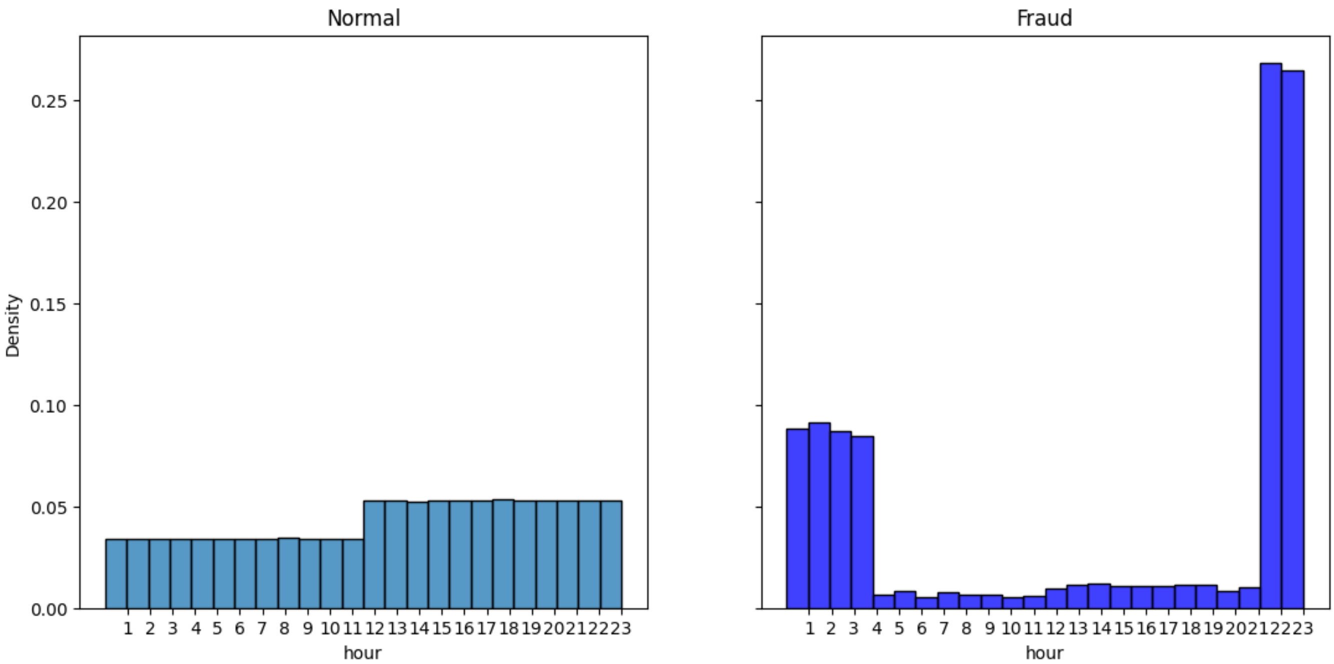

```
plt.figure(figsize=(10,5))
# Group by "TransactionType" and calculate the mean of "isFraud"
fraud_percentage_by_category = df_train.groupby('category')['is_fraud'].mean() * 100
# Create a bar plot
plt.bar(fraud_percentage_by_category.index, fraud_percentage_by_category.values)
# Adding labels and title
plt.xlabel('Transaction category ')
plt.ylabel('Fraud Percentage category')
plt.title('Fraud Percentage by category')

# Rotate x labels for better readability
plt.xticks(rotation=45)

plt.show()
```



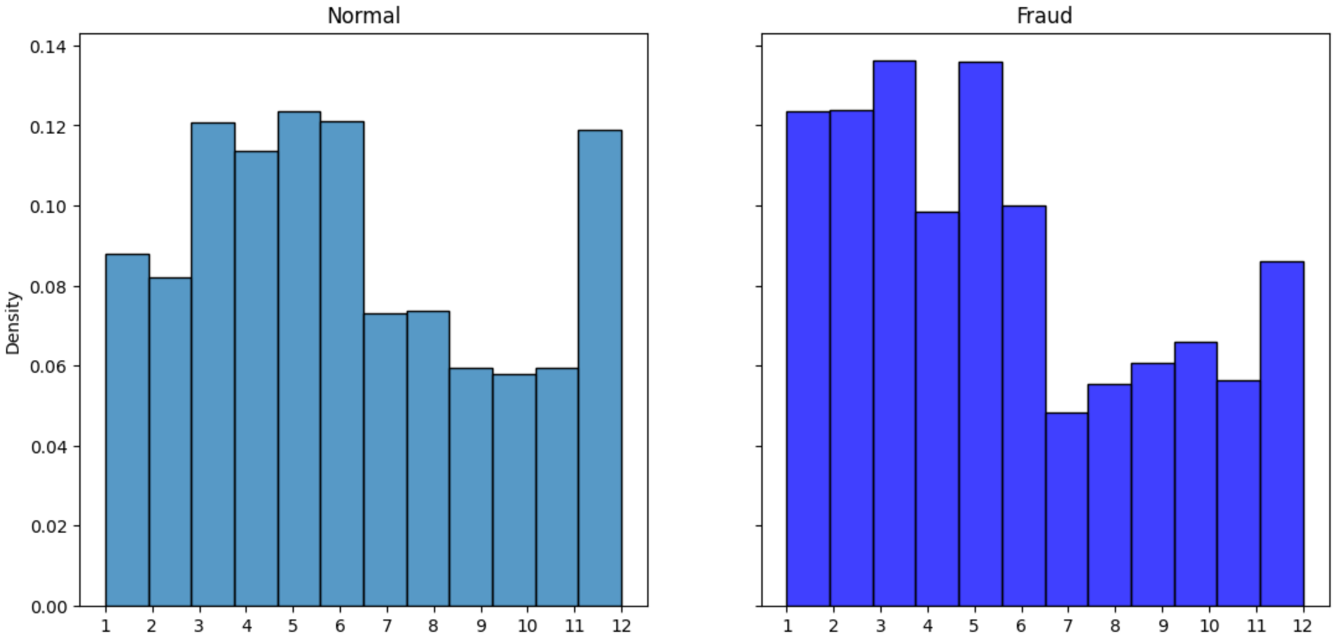

```
df_train['age'] = dt.date.today().year-pd.to_datetime(df_train['dob']).dt.year
ax = sns.kdeplot(x='age', data=df_train, hue='is_fraud', common_norm=False)
ax.set_xlabel('Credit Card Holder Age')
ax.set_ylabel('Density')
plt.xticks(np.arange(0, 110, 10))
plt.title('Age Distribution')
plt.legend(title='Type', labels=['Fraud', 'Not Fraud']);
```




```
df_train['hour'] = pd.to_datetime(df_train['trans_date_trans_time']).dt.hour
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(13, 6), sharey=True)
ax1 = sns.histplot(x='hour', data=df_train[df_train["is_fraud"] == 0],
                   stat="density", bins=24, ax=ax1)
ax2 = sns.histplot(x='hour', data=df_train[df_train["is_fraud"] == 1],
                   stat="density", bins=24, ax=ax2, color="blue")
ax1.set_title("Normal")
ax2.set_title("Fraud")
ax1.set_xticks(np.arange(1, 24))
ax2.set_xticks(np.arange(1, 24));
```




```
df_train['month'] = pd.to_datetime(df_train['trans_date_trans_time']).dt.month
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(13, 6), sharey=True)
ax1 = sns.histplot(x='month', data=df_train[df_train["is_fraud"] == 0],
                   stat="density", bins=12, ax=ax1)
ax2 = sns.histplot(x='month', data=df_train[df_train["is_fraud"] == 1],
                   stat="density", bins=12, ax=ax2, color="blue")
ax1.set_title("Normal")
ax2.set_title("Fraud")
ax1.set_xticks(np.arange(1, 13))
ax2.set_xticks(np.arange(1, 13));
```



Feature engineering

```
df_train.drop(columns=["merchant", "first", "last", "street","unix_time", "trans_num","month","age","hour"], inplace=True)
df_test.drop(columns=["merchant", "first", "last", "street","unix_time", "trans_num"], inplace=True)
print(df_train.shape)
print(df_test.shape)
```

```
(1296675, 17)
(1296675, 17)
```

```
#training data
x_train=df_train.drop("is_fraud",axis=1)
y_train=df_train["is_fraud"]
```

```
#testing data
x_test=df_test.drop("is_fraud",axis=1)
y_test=df_test["is_fraud"]
x_train.info()
print(x_train.shape)
print(x_test.shape)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 16 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   Unnamed: 0             1296675 non-null  int64
 1   trans_date_trans_time  1296675 non-null  object
 2   cc_num                 1296675 non-null  int64
 3   category               1296675 non-null  object
 4   amt                    1296675 non-null  float64
 5   gender                 1296675 non-null  object
 6   city                   1296675 non-null  object
 7   state                  1296675 non-null  object
 8   zip                    1296675 non-null  int64
 9   lat                    1296675 non-null  float64
 10  long                   1296675 non-null  float64
 11  city_pop               1296675 non-null  int64
 12  job                    1296675 non-null  object
 13  dob                    1296675 non-null  object
 14  merch_lat              1296675 non-null  float64
 15  merch_long             1296675 non-null  float64
dtypes: float64(5), int64(4), object(7)
memory usage: 158.3+ MB
(1296675, 16)
(1296675, 16)
```

pipeline creation

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler,OneHotEncoder

#numerical features
num_feats=x_train.drop(["trans_date_trans_time","category","gender","city","state","job","dob"],axis=1)
num_feats_pipe=Pipeline([
    ("scalar",MinMaxScaler())
    ])
num_feats_preprocessed=num_feats_pipe.fit_transform(num_feats)

#catagorical features
cat_feats=x_train[["trans_date_trans_time","category","gender","city","state","job","dob"]]
cat_feats_pipe=Pipeline([
    ("encoder",OneHotEncoder())
    ])
cat_feats_preprocessed=cat_feats_pipe.fit_transform(cat_feats)
print(num_feats)
```

```
         Unnamed: 0               cc_num     amt    zip      lat      long  \
0                 0     2703186189652095    4.97  28654  36.0788  -81.1781
1                 1         630423337322  107.23  99160  48.8878 -118.2105
2                 2       38859492057661  220.11  83252  42.1808 -112.2620
3                 3     3534093764340240   45.00  59632  46.2306 -112.1138
4                 4      375534208663984   41.96  24433  38.4207  -79.4629
...             ...                  ...     ...    ...      ...       ...
1296670     1296670       30263540414123   15.56  84735  37.7175 -112.4777
1296671     1296671     6011149206456997   51.70  21790  39.2667  -77.5101
1296672     1296672     3514865930894695  105.93  88325  32.9396 -105.8189
1296673     1296673     2720012583106919   74.90  57756  43.3526 -102.5411
1296674     1296674  4292902571056973207    4.30  59871  45.8433 -113.8748

         city_pop  merch_lat  merch_long
0            3495  36.011293  -82.048315
1             149  49.159047 -118.186462
2            4154  43.150704 -112.154481
3            1939  47.034331 -112.561071
4              99  38.674999  -78.632459
...           ...        ...         ...
1296670       258  36.841266 -111.690765
1296671       100  38.906881  -78.246528
1296672       899  33.619513 -105.130529
1296673      1126  42.788940 -103.241160
1296674       218  46.565983 -114.186110

[1296675 rows x 9 columns]
```

final pipeline

```
from sklearn.compose import ColumnTransformer
num_list=list(num_feats)
cat_list=list(cat_feats)

final_pipeline=ColumnTransformer([
    ("num",num_feats_pipe,num_list),
    ("cat",cat_feats_pipe,cat_list)])
X_train_preprocessed=final_pipeline.fit_transform(x_train)
print(df_train)
X_train_preprocessed

X_test_preprocessed = final_pipeline.fit_transform(x_test)
X_test_preprocessed
```

```
         Unnamed: 0 trans_date_trans_time               cc_num       category  \
0                 0   2019-01-01 00:00:18     2703186189652095       misc_net
1                 1   2019-01-01 00:00:44         630423337322    grocery_pos
2                 2   2019-01-01 00:00:51       38859492057661  entertainment
3                 3   2019-01-01 00:01:16     3534093764340240  gas_transport
4                 4   2019-01-01 00:03:06      375534208663984       misc_pos
...             ...                   ...                  ...            ...
1296670     1296670   2020-06-21 12:12:08       30263540414123  entertainment
1296671     1296671   2020-06-21 12:12:19     6011149206456997    food_dining
1296672     1296672   2020-06-21 12:12:32     3514865930894695    food_dining
1296673     1296673   2020-06-21 12:13:36     2720012583106919    food_dining
1296674     1296674   2020-06-21 12:13:37  4292902571056973207    food_dining

            amt gender                     city state    zip      lat  \
0          4.97      F           Moravian Falls    NC  28654  36.0788
1        107.23      F                   Orient    WA  99160  48.8878
2        220.11      M               Malad City    ID  83252  42.1808
3         45.00      M                  Boulder    MT  59632  46.2306
4         41.96      M                 Doe Hill    VA  24433  38.4207
...         ...    ...                      ...   ...    ...      ...
1296670   15.56      M                    Hatch    UT  84735  37.7175
```

```
1296671   51.70      M                Tuscarora    MD  21790  39.2667
1296672  105.93      M  High Rolls Mountain Park    NM  88325  32.9396
1296673   74.90      M                Manderson    SD  57756  43.3526
1296674    4.30      M                     Sula    MT  59871  45.8433

             long  city_pop                          job         dob  \
0        -81.1781      3495        Psychologist, counselling  1988-03-09
1       -118.2105       149  Special educational needs teacher  1978-06-21
2       -112.2620      4154      Nature conservation officer  1962-01-19
3       -112.1138      1939                  Patent attorney  1967-01-12
4        -79.4629        99     Dance movement psychotherapist  1986-03-28
...           ...       ...                              ...         ...
1296670 -112.4777       258                     Geoscientist  1961-11-24
1296671  -77.5101       100  Production assistant, television  1979-12-11
1296672 -105.8189       899                  Naval architect  1967-08-30
1296673 -102.5411      1126            Volunteer coordinator  1980-08-18
1296674 -113.8748       218          Therapist, horticultural  1995-08-16

         merch_lat  merch_long  is_fraud
0        36.011293  -82.048315         0
1        49.159047 -118.186462         0
2        43.150704 -112.154481         0
3        47.034331 -112.561071         0
4        38.674999  -78.632459         0
...            ...         ...       ...
1296670  36.841266 -111.690765         0
1296671  38.906881  -78.246528         0
1296672  33.619513 -105.130529         0
1296673  42.788940 -103.241160         0
1296674  46.565983 -114.186110         0

[1296675 rows x 17 columns]
<1296675x1277223 sparse matrix of type '<class 'numpy.float64'>'
	with 20737890 stored elements in Compressed Sparse Row format>
```

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier

# Create a Random Forest classifier
rf_model = RandomForestClassifier(n_estimators=50, random_state=21)

# Train the model on your training data
rf_model.fit(X_train_preprocessed,y_train)

# Make predictions on your testing data
y_test_pred_rf = rf_model.predict(X_test_preprocessed)
```

```
# Make predictions on your training data
y_train_pred_rf = rf_model.predict(X_train_preprocessed)
y_train_pred_rf
y_test_pred_rf
```

```
array([0, 0, 0, ..., 0, 0, 0])
```

F1 score of train and test

```
from sklearn.metrics import f1_score
f1 = f1_score(y_train,y_train_pred_rf)
print("F1 Score of train data:", f1)

f2 = f1_score(y_test,y_test_pred_rf)
print("F1 Score of test data:", f2)
```

```
F1 Score of train data: 0.9980644730694788
F1 Score of test data: 0.9980644730694788
```

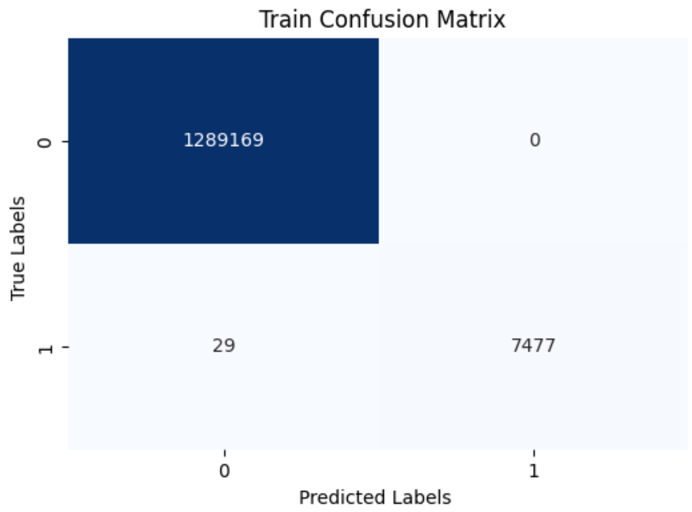
```
from sklearn.metrics import classification_report
report = classification_report(y_test, y_test_pred_rf)
print(report)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1289169
           1       1.00      1.00      1.00      7506

    accuracy                           1.00   1296675
   macro avg       1.00      1.00      1.00   1296675
```

```
weighted avg       1.00      1.00      1.00   1296675
```

Train Confusion Matrix

```
from sklearn.metrics import confusion_matrix

# Compute the confusion matrix
cm = confusion_matrix(y_train, y_train_pred_rf)

# Create a heatmap to visualize the confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.xlabel("Predicted Labels ")
plt.ylabel("True Labels ")
plt.title(" Train Confusion Matrix")
plt.show()
```



Test Confusion Matrix

```
from sklearn.metrics import confusion_matrix

# Compute the confusion matrix
cm = confusion_matrix(y_test, y_test_pred_rf)

# Create a heatmap to visualize the confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.xlabel("Predicted Labels ")
plt.ylabel("True Labels ")
plt.title(" Test Confusion Matrix")
plt.show()
```