Data Scientist in Risk and Fraud analytics

- Develop and deploy machine learning models to detect, predict, and prevent fraudulent transactions and behavior patterns.(use fraud detection tools)
- Design and monitor KPIs to evaluate model performance and improve fraud detection systems over time.
- Understanding of supervised and unsupervised fraud detection techniques, including anomaly detection, behavioral modeling, and network analysis.
- identify patterns and trends from data.
- deploying machine learning models, statistical methods, and data-driven strategies to detect risky behaviors and prevent fraudulent activities across our products and services.
- Conduct deep-dive investigations into fraud cases, creating detailed reports and actionable insights to detect risky behavior and prevent fraudulent activities across various systems and services.
- Stay current with emerging fraud techniques, industry best practices, and data science tools

Experience working with large datasets and cloud platforms (e.g., AWS, GCP, Azure).

1. step: represents a unit of time where 1 step equals 1 hour
2. type: type of online transaction
3. amount: the amount of the transaction
4. nameOrig: customer starting the transaction
5. oldbalanceOrg: balance before the transaction
6. newbalanceOrig: balance after the transaction
7. nameDest: recipient of the transaction
8. oldbalanceDest: initial balance of recipient before the transaction
9. newbalanceDest: the new balance of recipient after the transaction
10. isFraud: fraud transaction binary classififcation problem.Huge imbalance dataset

In [2]:
```
import sklearn
print(sklearn.__version__)  # should show 1.3.2
```

```
1.3.2
```

In [3]:
```
# !pip install scikit-learn==1.3.2
```

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
```

```
warnings.filterwarnings("ignore")
sns.set(style="whitegrid")
```

pip install numpy pip install pandas pip install matplotlib pip install seaborn

pip install scikit-learn==1.3.2 pip install xgboost pip install imbalanced-learn

import pandas as pd from sklearn.model_selection import train_test_split from sklearn.compose import ColumnTransformer from sklearn.preprocessing import StandardScaler, OneHotEncoder from sklearn.metrics import classification_report from imblearn.pipeline import Pipeline from imblearn.over_sampling import SMOTE from sklearn.linear_model import LogisticRegression from sklearn.tree import DecisionTreeClassifier from sklearn.ensemble import RandomForestClassifier from xgboost import XGBClassifier

STEP 1: Exploratory Data Analysis (EDA) Discover patterns, detect anomalies, and understand features

In [5]:
```
df = pd.read_csv('AIML_Dataset.csv')
df.head()
```

Out[5]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameD
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1979787
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701

Step 1: Data Analysis

- statistical summary
- Outlier detection
- Pattern matchig -Correlation matrics
- Daue /Time handling

Statistical summary using

- df.describe()
- df.info()
- df.isnull().sum()

use info( ) to learn abot data types

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype  
---  ------          -----  
 0   step            int64  
 1   type            object 
 2   amount          float64
 3   nameOrig        object 
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object 
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64  
 10  isFlaggedFraud  int64  
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

check the columns to find the fraud feature

In [7]:
```
df.columns
```

Out[7]:
```
Index(['step', 'type', 'amount', 'nameOrig', 'oldbalanceOrg', 'newbalanceOrig',
       'nameDest', 'oldbalanceDest', 'newbalanceDest', 'isFraud',
       'isFlaggedFraud'],
      dtype='object')
```

count the no of fraud and non fraud transactions

In [8]:
```
# df.isFraud.count()
df['isFraud'].value_counts()
```

Out[8]:
```
isFraud
0    6354407
1       8213
Name: count, dtype: int64
```

In [9]:
```
# df.isFraud.count() in terms of percentage

df['isFraud'].value_counts(normalize=True)
# this indiccates class imbalance in data set (with 99 % non faud and 1% fraud d
```

Out[9]:
```
isFraud
0    0.998709
1    0.001291
Name: proportion, dtype: float64
```

The above results show that the data set is highly imbalance with 99.87% non fraud data (class 0) and 1.2% fraudulent data (class 1). this affects the accuracy in the predicted model . So we need to balance the data set

In [10]:
```
df['isFlaggedFraud'].value_counts()
```

Out[10]:
```
isFlaggedFraud
0    6362604
1         16
Name: count, dtype: int64
```

Check for NA vales

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

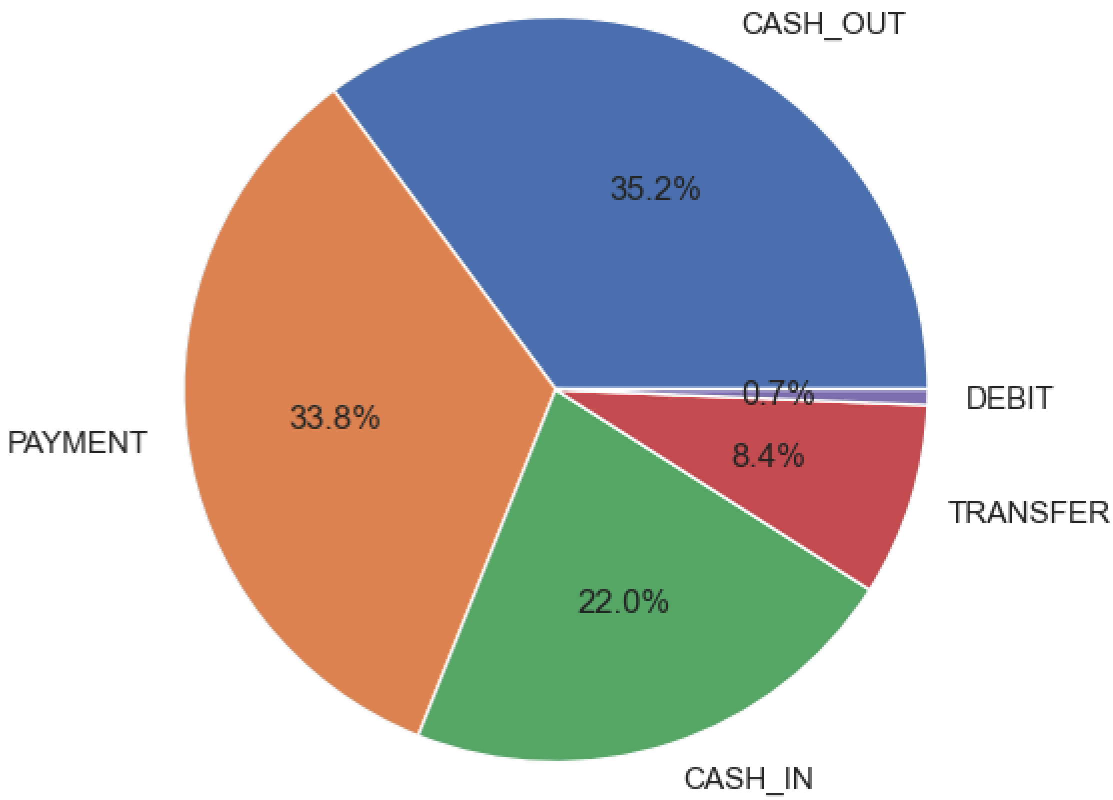
In [12]:
```
# df shape
df.shape
```

Out[12]:
```
(6362620, 11)
```

In [13]:
```
# df fraud %
round((df['isFraud'].value_counts()[1] / df.shape[0]) * 100,2)
```

Out[13]:
```
0.13
```

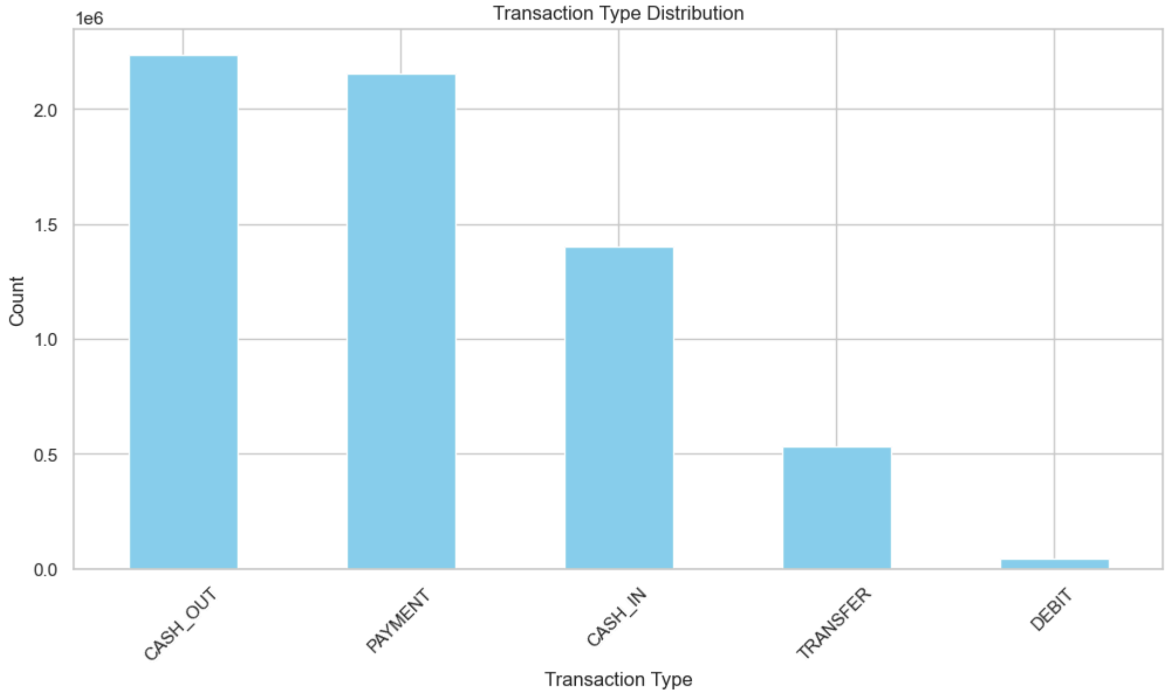
In [14]:
```
# in the feature 'type', gives the type of transaction made. So let us make a pi
plt.figure(figsize=(6,8))
plt.pie(df['type'].value_counts(),
       labels=df['type'].value_counts().index,
       autopct='%1.1f%%');
```



bar chart of each transaction type

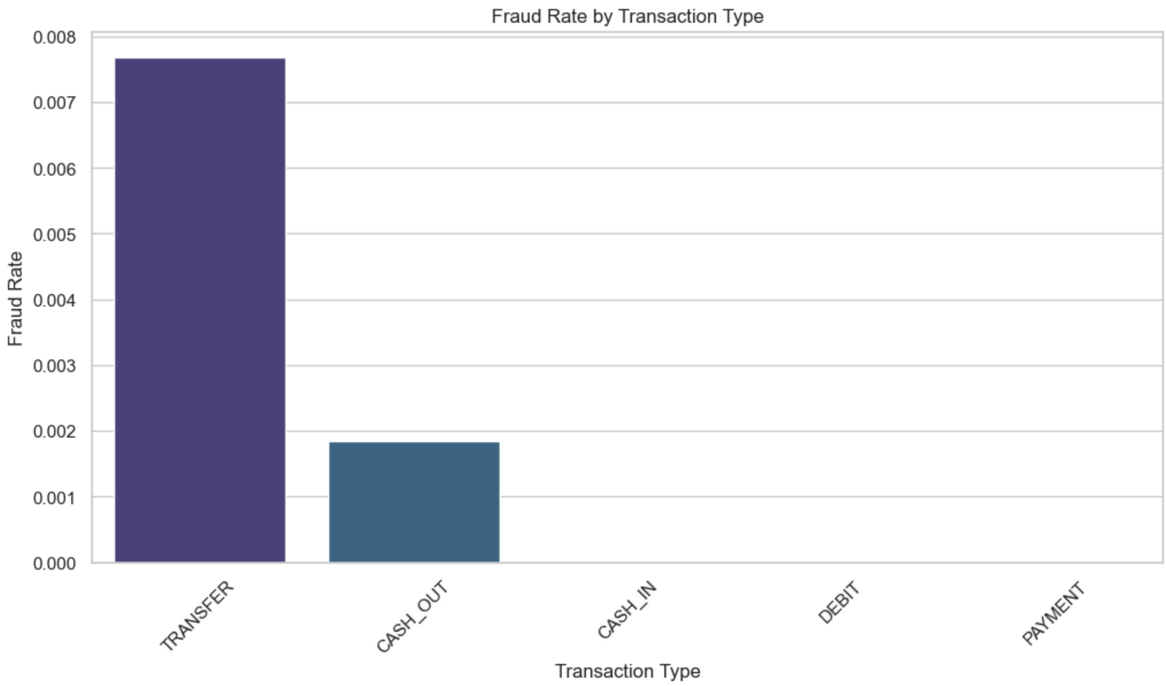
In [15]:
```
df['type'].value_counts().plot(kind='bar', figsize=(12, 6), color='skyblue')
plt.title('Transaction Type Distribution')
plt.xlabel('Transaction Type')
plt.ylabel('Count')
plt.xticks(rotation=45)
```

Out[15]:
```
(array([0, 1, 2, 3, 4]),
 [Text(0, 0, 'CASH_OUT'),
  Text(1, 0, 'PAYMENT'),
  Text(2, 0, 'CASH_IN'),
  Text(3, 0, 'TRANSFER'),
  Text(4, 0, 'DEBIT')])
```



group fraud rate by each transaction type

In [16]:
```
fraud_rate_by_type = df.groupby('type')['isFraud'].mean().reset_index()
fraud_rate_by_type = fraud_rate_by_type.sort_values(by='isFraud', ascending=Fals
plt.figure(figsize=(12, 6))
sns.barplot(x='type', y='isFraud', data=fraud_rate_by_type, palette='viridis')
plt.title('Fraud Rate by Transaction Type')
plt.xlabel('Transaction Type')
plt.ylabel('Fraud Rate')
plt.xticks(rotation=45)
plt.show()
```



In [17]:
```
fraud_rate_by_type
```

Out[17]:

	type	isFraud
4	TRANSFER	0.007688
1	CASH_OUT	0.001840
0	CASH_IN	0.000000
2	DEBIT	0.000000
3	PAYMENT	0.000000

In [18]:

```
# statistcs
df['amount'].describe().astype(int)
```

Out[18]:

```
count     6362620
mean       179861
std        603858
min             0
25%         13389
50%         74871
75%        208721
max      92445516
Name: amount, dtype: int32
```

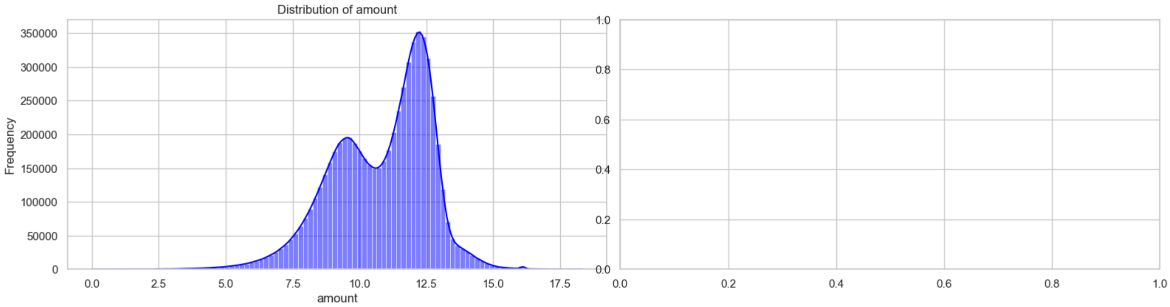
Ploting the numerical features (amount,oldbalanceOrg, newbalanceOrig, oldbalanceDest, newbalanceDest) for distribution check using histplot

In [19]:

```
# Numerical features of interest
numerical_cols = ['amount', 'oldbalanceOrg', 'newbalanceOrig', 'oldbalanceDest',

# Plot distribution for each feature
plt.figure(figsize=(16, 12))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(3, 2, i)
    # sns.histplot(np.log1p(df['amount']), bins=100, kde=True, color='green')
    # sns.histplot(df[col], bins=100, kde=True)
    sns.histplot(np.log1p(df[col]), bins=100, kde=True, color='blue')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.tight_layout()

plt.show()
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
Cell In[19], line 10
      7 plt.subplot(3, 2, i)
      8 # sns.histplot(np.log1p(df['amount']), bins=100, kde=True, color='green')
      9 # sns.histplot(df[col], bins=100, kde=True)
---> 10 sns.histplot(np.log1p(df[col]), bins=100, kde=True, color='blue')
     11 plt.title(f'Distribution of {col}')
     12 plt.xlabel(col)

File ~\anaconda3\envs\env_fraud\lib\site-packages\seaborn\distributions.py:1379,
in histplot(data, x, y, hue, weights, stat, bins, binwidth, binrange, discrete, c
umulative, common_bins, common_norm, multiple, element, fill, shrink, kde, kde_kw
s, line_kws, thresh, pthresh, pmax, cbar, cbar_ax, cbar_kws, palette, hue_order,
hue_norm, color, log_scale, legend, ax, **kwargs)
   1358 def histplot(
   1359     data=None, *,
   1360     # Vector variables
   (...)
   1376     **kwargs,
   1377 ):
-> 1379     p = _DistributionPlotter(
   1380         data=data,
   1381         variables=dict(x=x, y=y, hue=hue, weights=weights),
   1382     )
   1384     p.map_hue(palette=palette, order=hue_order, norm=hue_norm)
   1386     if ax is None:

File ~\anaconda3\envs\env_fraud\lib\site-packages\seaborn\distributions.py:110, i
n _DistributionPlotter.__init__(self, data, variables)
    104 def __init__(
    105     self,
    106     data=None,
    107     variables={},
    108 ):
--> 110     super().__init__(data=data, variables=variables)

File ~\anaconda3\envs\env_fraud\lib\site-packages\seaborn\_base.py:634, in Vector
Plotter.__init__(self, data, variables)
    629 # var_ordered is relevant only for categorical axis variables, and may
    630 # be better handled by an internal axis information object that tracks
    631 # such information and is set up by the scale_* methods. The analogous
    632 # information for numeric axes would be information about log scales.
    633 self._var_ordered = {"x": False, "y": False}  # alt., used DefaultDict
--> 634 self.assign_variables(data, variables)
    636 # TODO Lots of tests assume that these are called to initialize the
    637 # mappings to default values on class initialization. I'd prefer to
    638 # move away from that and only have a mapping when explicitly called.
    639 for var in ["hue", "size", "style"]:

File ~\anaconda3\envs\env_fraud\lib\site-packages\seaborn\_base.py:673, in Vector
Plotter.assign_variables(self, data, variables)
    671 if x is None and y is None:
    672     self.input_format = "wide"
--> 673     frame, names = self._assign_variables_wideform(data, **variables)
    674 else:
    675     # When dealing with long-form input, use the newer PlotData
    676     # object (internal but introduced for the objects interface)
    677     # to centralize / standardize data consumption logic.
    678     self.input_format = "long"
```

```
File ~\anaconda3\envs\env_fraud\lib\site-packages\seaborn\_base.py:733, in VectorPlotter._assign_variables_wideform(self, data, **kwargs)
    731 else:
    732     values = np.atleast_1d(np.asarray(data, dtype=object))
--> 733 flat = not any(
    734     isinstance(v, Iterable) and not isinstance(v, (str, bytes))
    735     for v in values
    736 )
    738 if empty:
    739 
    740     # Make an object with the structure of plot_data, but empty
    741     plot_data = pd.DataFrame()

File ~\anaconda3\envs\env_fraud\lib\site-packages\seaborn\_base.py:733, in <genexpr>(.0)
    731 else:
    732     values = np.atleast_1d(np.asarray(data, dtype=object))
--> 733 flat = not any(
    734     isinstance(v, Iterable) and not isinstance(v, (str, bytes))
    735     for v in values
    736 )
    738 if empty:
    739 
    740     # Make an object with the structure of plot_data, but empty
    741     plot_data = pd.DataFrame()

KeyboardInterrupt:
```



In [ ]:
```python
sns.histplot(df['amount'], bins=100, kde=True, color='green')
plt.title('Distribution of Transaction Amounts')
plt.xlabel('Amount')
plt.ylabel('Frequency')
plt.show()
```

Draw the same histogram plot in log scale

In [ ]:
```python
sns.histplot(np.log1p(df['amount']), bins=100, kde=True, color='green')
plt.title('Distribution of Transaction Amounts (Log Scale)')
plt.xlabel('Log(Amount + 1)')
plt.ylabel('Frequency')
plt.show()
```

correlation plot that gives the corelation between multiple features including target (use heatmap)

Since there are no missing values in any of the features, and only the numerical features are meaningful for a correlation matrix, we can proceed by excluding the categorical and string columns (type, nameOrig, nameDest) and plotting the correlation matrix for the remaining numerical ones.

In [ ]:
```
# Drop non-numeric columns for correlation
df_numeric = df.drop(columns=['type', 'nameOrig', 'nameDest'])

# Compute correlation matrix
corr_matrix = df_numeric.corr()

# Plot heatmap (correlation can take values between -1 and 1)
# 1 - highly positive corre; -1 - highly neg corr; 0- no correlation
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', square=True)
plt.title("Correlation Matrix (Numerical Features Only)")
plt.show()
```

Relationship between fraud and amount using box plot

In [ ]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='isFraud', y='amount', data=df, showfliers=False)
plt.title('Transaction Amounts by Fraud Status')
plt.xlabel('Is Fraud')
plt.ylabel('Transaction Amount')
plt.xticks([0, 1], ['Non-Fraud', 'Fraud'])
plt.show()
```

In [ ]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(x='isFraud', y='amount', data=df[df['amount'] < 50000], showfliers=F
plt.title('Transaction Amounts by Fraud Status (Amount < 50k)')
plt.xlabel('Is Fraud')
plt.ylabel('Transaction Amount')
plt.xticks([0, 1], ['Non-Fraud', 'Fraud'])
plt.show()
```

The box plot comparing transaction amounts by fraud status shows that fraudulent transactions generally involve higher amounts than non-fraudulent ones. The median transaction amount for fraud cases is significantly greater, and the interquartile range is wider, indicating more variability. This suggests that fraudsters tend to target larger transactions. Additionally, after filtering for amounts less than 50,000, the difference remains noticeable, confirming that even among smaller transactions, frauds are associated with higher amounts compared to non-fraudulent transactions.

Balance change and anamolies

In [ ]:
```
df.columns
```

In [ ]:
```
df['balance_diffOrg'] = df['oldbalanceOrg'] - df['newbalanceOrig']
df[['oldbalanceOrg', 'newbalanceOrig', 'balance_diffOrg']].head()
```

balance diffrence of the destination

```
In [ ]: df['balance_diffDest'] = df['oldbalanceDest'] - df['newbalanceDest']
        df[['oldbalanceDest', 'newbalanceDest', 'balance_diffDest']].head()
```

```
In [ ]: # Count negative values for balance_diffOrg and balance_diffDest
        num_negative_balance_diffOrg = (df['balance_diffOrg'] < 0).sum()
        num_negative_balance_diffDest = (df['balance_diffDest'] < 0).sum()

        print(f"Negative balance_diffOrg: {num_negative_balance_diffOrg}")
        print(f"Negative balance_diffDest: {num_negative_balance_diffDest}")
```

```
In [ ]: fraud_per_step = df[df['isFraud'] == 1].groupby('step')['isFraud'].count()
        plt.figure(figsize=(14, 6))
        fraud_per_step.plot()
        plt.title('Number of Fraudulent Transactions per Step')
        plt.xlabel('Step')
        plt.ylabel('Fraud Count')
        plt.grid(True)
        plt.show()
```

drop the coloumn 'step' from the original df

```
In [ ]: # df.drop(columns=['step'], inplace=True)
```

Step 2: Data Preprocessing/ Data Preparation:

- Time series
- Missing value imputation
- Normalization
- Imbalanced Data Processing
- Sampling
- Testing / Validation split
- Filtering
- Feature selection
- Date/time Algebra

```
In [ ]: # lets identify the customers who are top senders and top receivers
        topsenders = df['nameOrig'].value_counts().head(10)
        topsenders
```

```
In [ ]: topreceivers = df['nameDest'].value_counts().head(10)
        topreceivers
```

```
In [ ]: # Fraud making customers
        fraud_users = df[df['isFraud']==1]['nameOrig'].value_counts().head(10)
        fraud_users
```

```
In [ ]: # it si already observed that fraud rate is high mainly duirng 'transfer ' and '
        fraud_types = df[df['type'].isin(['TRANSFER','CASH_OUT'])]
        fraud_types
```

```
In [ ]: fraud_types['type'].value_counts()
```

In [ ]:
```
sns.countplot(data=fraud_types,x= 'type', hue='isFraud')
plt.title('Fraud distribution during TRANSFER and CASH_OUT')
plt.show()
# orange portion is not visible in graph
```

In [ ]:
```
# let us find the names and other details of customers(senders) whose balance we
# create a df using three filters
zero_after_trans = df[
    (df['oldbalanceOrg']> 0) &
    (df['newbalanceOrig'] ==0) &
    (df['type'].isin(['TRANSFER','CASH_OUT']))
]
zero_after_trans.head()
```

In [ ]:
```
len(zero_after_trans)
# indicates the no of fraudulent trans
```

In [ ]:
```
# Calculate percentage distribution
fraud_distribution = df['isFraud'].value_counts(normalize=True) * 100
labels = ['Non-Fraud', 'Fraud']
colors = ['skyblue', 'salmon']

# Plot pie chart
plt.figure(figsize=(4, 6))
plt.pie(fraud_distribution, labels=labels, colors=colors, autopct='%1.2f%%', sta
plt.title('Fraud vs Non-Fraud Transactions')
plt.axis('equal')  # Equal aspect ratio ensures the pie chart is circular
plt.show()
```

The above results show that the data set is highly imbalance with 99.87% non fraud data (class 0) and 1.2% fraudulent data (class 1). this affects the accuracy in the predicted model . So we need to balance the data set

In [ ]:
```
# feature selection and preparation to handle class imbalance
```

In [40]:
```
# ! pip install scikit-learn
```

In [20]:
```
# !pip install xgboost
```

Step 3: Model Training for binary classification (fraud and non fraud) prediction

- XGBoost
- Random forest
- K means
- SVM
- Logistic Regression

In [38]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Logistic Regression
from sklearn.linear_model import LogisticRegression

# Support Vector Machine
from sklearn.svm import SVC
```

```
# Random Forest
from sklearn.ensemble import RandomForestClassifier

# K-Means Clustering
from sklearn.cluster import KMeans

# XGBoost Classifier
from xgboost import XGBClassifier

from sklearn.metrics import classification_report, confusion_matrix
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
```

In [22]:
```
# let us remove teh unnecessary columns while creating the model to predict frau
df_model = df.drop(['nameOrig','nameDest','isFlaggedFraud'],axis=1)
df_model.head()
```

Out[22]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbala
0	1	PAYMENT	9839.64	170136.0	160296.36	0.0	
1	1	PAYMENT	1864.28	21249.0	19384.72	0.0	
2	1	TRANSFER	181.00	181.0	0.00	0.0	
3	1	CASH_OUT	181.00	181.0	0.00	21182.0	
4	1	PAYMENT	11668.14	41554.0	29885.86	0.0	

In [23]:
```
y = df_model['isFraud']
X = df_model.drop(['isFraud'], axis = 1)
```

In [24]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.3, stratify
```

Using Column transformer pipeline

1. Apply different preprocessing steps to different feature types (e.g., numerical vs categorical),
2. Combine them using ColumnTransformer,
3. Chain it into a full Pipeline with a classifier or regressor.

In [25]:
```
# Defining the columns as separating the muerical and categorical data
categorical_features = ['type']
numerical_features = ['amount','oldbalanceOrg','newbalanceOrig','oldbalanceDest'
```

In [26]:
```
# Define Preprocessing for Each Column Type
# 1. drop='first':
# Purpose: To avoid multicollinearity (especially for linear models like Logisti
# Drops the first category from each categorical feature.If a categorical featur
# it encodes only B and C. A is inferred when both are 0.
# 2. handle_unknown='ignore':
# Purpose: To safely handle unseen categories in test data that weren’t present
```

```
# If your training data contains categories ['A', 'B'] but test data contains 'C
# Best Practice — Combine Both:
# But drop='first' is not recommended for folowing Tree-based Models:
# Decision trees (like Random Forest, XGBoost) do not suffer from multicollinear
numerical_transformer = StandardScaler()
categorical_transformer = OneHotEncoder(drop='first', handle_unknown='ignore')
```

In [27]:
```
# Combine with ColumnTransformer
# preprocessing using column transformer
preprocessor = ColumnTransformer(
    transformers = [
        ('num', numerical_transformer, numerical_features),
        ('cat',categorical_transformer, categorical_features)
    ],
    remainder = 'drop'   # optional: drop other columns not listed
)
```

In [28]:
```
# !pip install scikit-learn==1.3.2
```

In [29]:
```
import sklearn
print(sklearn.__version__)  # should show 1.3.2
```

```
1.3.2
```

In [30]:
```
from imblearn.pipeline import Pipeline  # NOT sklearn.pipeline
from imblearn.over_sampling import SMOTE
```

pipeline = Pipeline([('prep',preprocessor), ('clf',LogisticRegression(class_weight='balanced', max_iter=1000)

])

- When to Use SMOTE? (Synthetic Minority Over-sampling Technique) is a powerful way to generate synthetic examples of the minority class (fraud). Apply SMOTE only to the training data, after preprocessing but before model training. This avoids: Data leakage (synthesizing frauds using knowledge of the test set),Overfitting to synthetic data in test metrics.
- Where to Apply SMOTE in Your Pipeline
- Don't apply SMOTE inside Pipeline if it includes train_test_split. Instead, apply SMOTE after splitting data and before fitting model.

In [31]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import classification_report
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

pipeline = Pipeline([
    ('prep',preprocessor),
```

```
    ('clf',LogisticRegression(class_weight='balanced', max_iter=1000))
])
```

Model training using pipeline - use the 'fit' command

In [32]:
```
pipeline.fit(X_train,y_train)
```

Out[32]:
```
Pipeline
prep: ColumnTransformer
num                cat
StandardScaler     OneHotEncoder
LogisticRegression
```

In [35]:
```
# make predictions
y_pred= pipeline.predict(X_test)
```

In [36]:
```
# compare y_pred with y_test using classification report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      0.95      0.97   1906322
           1       0.02      0.94      0.04      2464

    accuracy                           0.95   1908786
   macro avg       0.51      0.94      0.51   1908786
weighted avg       1.00      0.95      0.97   1908786
```

In [37]:
```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\joe antony\anaconda3\lib\site-
packages (3.0.3)
Requirement already satisfied: numpy in c:\users\joe antony\anaconda3\lib\site-pa
ckages (from xgboost) (2.1.3)
Requirement already satisfied: scipy in c:\users\joe antony\anaconda3\lib\site-pa
ckages (from xgboost) (1.15.3)
```

In [39]:
```
# Models dictionary (10 min to run)
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss', ver
  }

# Train each model inside a pipeline
results = {}
for name, model in models.items():
    pipe = Pipeline([
        ('prep', preprocessor),
        ('clf', model)
    ])
    pipe.fit(X_train, y_train)
    y_pred = pipe.predict(X_test)
```

```
    report = classification_report(y_test, y_pred, output_dict=True, zero_divisi
    results[name] = {
        'Precision': report['1']['precision'],
        'Recall': report['1']['recall'],
        'F1-Score': report['1']['f1-score'],
        'Accuracy': report['accuracy']
    }

# View results
results_df = pd.DataFrame(results).T
print(results_df)
```

```
                     Precision    Recall  F1-Score  Accuracy
Logistic Regression   0.907354  0.385552  0.541156  0.999156
Decision Tree         0.891591  0.877841  0.884663  0.999705
XGBoost               0.936458  0.729708  0.820255  0.999587
```

In [40]:
```
confusion_matrix(y_test,y_pred)
```

Out[40]:
```
array([[1906200,     122],
       [    666,    1798]], dtype=int64)
```

In [41]:
```
# accuracy of testing data
pipeline.score(X_test,y_test)
```

Out[41]:
```
0.9471360330597564
```

For better precision and accuracy of class imbalance data use

1. SMOTE (a kind of oversampling the minority class) or
2. undersampling method

In [42]:
```
# undersampling method as follows
non_fraud_data = df[df['isFraud']==0]
fraud_data = df[df['isFraud']==1]
```

In [43]:
```
non_fraud_data.shape
```

Out[43]:
```
(6354407, 11)
```

In [44]:
```
fraud_data.shape
```

Out[44]:
```
(8213, 11)
```

In [45]:
```
# resample  or undersample the 'non fraud' data to match the 'fraud data size'
resampled_nonfraud_data = non_fraud_data.sample(n=8213)
resampled_nonfraud_data.shape
```

Out[45]:
```
(8213, 11)
```

In [46]:
```
# concatenate resampled non_fraud with fraud dat which has sample size of 8123 =
undersampled_data = pd.concat([resampled_nonfraud_data,fraud_data], ignore_index
undersampled_data.shape
```

Out[46]:
```
(16426, 11)
```

In [47]:
```
# check fraud and non fraud distribution
undersampled_data['isFraud'].value_counts()
```

Out[47]:
```
isFraud
0    8213
1    8213
Name: count, dtype: int64
```

In [48]:
```
# split X and y
X_us = undersampled_data.drop('isFraud', axis = 1)
y_us= undersampled_data['isFraud']
```

In [49]:
```
X_train_us, X_test_us, y_train_us, y_test_us = train_test_split(X_us, y_us, test
```

In [50]:
```
# Models dictionary already defined
# models = {
#     "Logistic Regression": LogisticRegression(max_iter=1000),
#     "Decision Tree": DecisionTreeClassifier(random_state=42),
#     "Random Forest": RandomForestClassifier(random_state=42),
#     "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss', v
#   }

# # Train each model inside a pipeline
# results = {}
# for name, model in models.items():
#     pipe = Pipeline([
#         ('prep', preprocessor),
#         ('clf', model)
#     ])

pipe.fit(X_train_us, y_train_us)
y_pred_us = pipe.predict(X_test_us)
report_us = classification_report(y_test_us, y_pred_us, output_dict=True, zero_d
results[name] = {
    'Precision': report['1']['precision'],
    'Recall': report['1']['recall'],
    'F1-Score': report['1']['f1-score'],
    'Accuracy': report['accuracy']
}

# View results
us_results_df = pd.DataFrame(results).T
print(us_results_df)
```

```
                     Precision    Recall  F1-Score  Accuracy
Logistic Regression   0.907354  0.385552  0.541156  0.999156
Decision Tree         0.891591  0.877841  0.884663  0.999705
XGBoost               0.936458  0.729708  0.820255  0.999587
```

using SMOTE (oversampling maethod)

In [51]:
```
from imblearn.over_sampling import SMOTE
```

Drop or encode non-numeric features first

Preprocess with StandardScaler and OneHotEncoder via ColumnTransformer

Apply SMOTE to preprocessed numeric data

In [52]:
```
from imblearn.pipeline import Pipeline
# # resampling done using the command 'SMOTE'
# preprocessor = ColumnTransformer([
#     ('num', StandardScaler(), numerical_features),
#     ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
# ])

pipe = Pipeline([
    ('prep', preprocessor),          # preprocessing includes string column name
    ('smote', SMOTE(random_state=42)),  # oversampling works on numeric output o
    ('clf', LogisticRegression(max_iter=1000))
])

# Split before applying SMOTE (which is now in pipeline)
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, random_sta

# Train
pipe.fit(X_train, y_train)

# Predict
y_pred = pipe.predict(X_test)
```

1. Classification Report

In [53]:
```
report = classification_report(y_test, y_pred, output_dict=True, zero_division=0
results[name] = {
    'Precision': report['1']['precision'],
    'Recall': report['1']['recall'],
    'F1-Score': report['1']['f1-score'],
    'Accuracy': report['accuracy']
}

# View results
smote_results_df = pd.DataFrame(results).T
print(smote_results_df)
```

```
                     Precision    Recall  F1-Score  Accuracy
Logistic Regression   0.907354  0.385552  0.541156  0.999156
Decision Tree         0.891591  0.877841  0.884663  0.999705
XGBoost               0.022425  0.950804  0.043817  0.946441
```

In [54]:
```
# oversampling here should be based on the minority class 'fraud =1' and undersa
```

Step 4: Model Evaluation

- ROC table
- error rate
- Confusion matrics -R squared
- MSE
- Cross validation

In [55]:
```
y_proba = pipe.predict_proba(X_test)[:, 1]  # For ROC AUC
y_proba
```

Out[55]:
```
array([6.31915364e-03, 1.54832605e-10, 8.37503648e-01, ...,
       2.35078975e-10, 5.80115361e-13, 1.50260511e-10])
```

2. Confusion Matrix

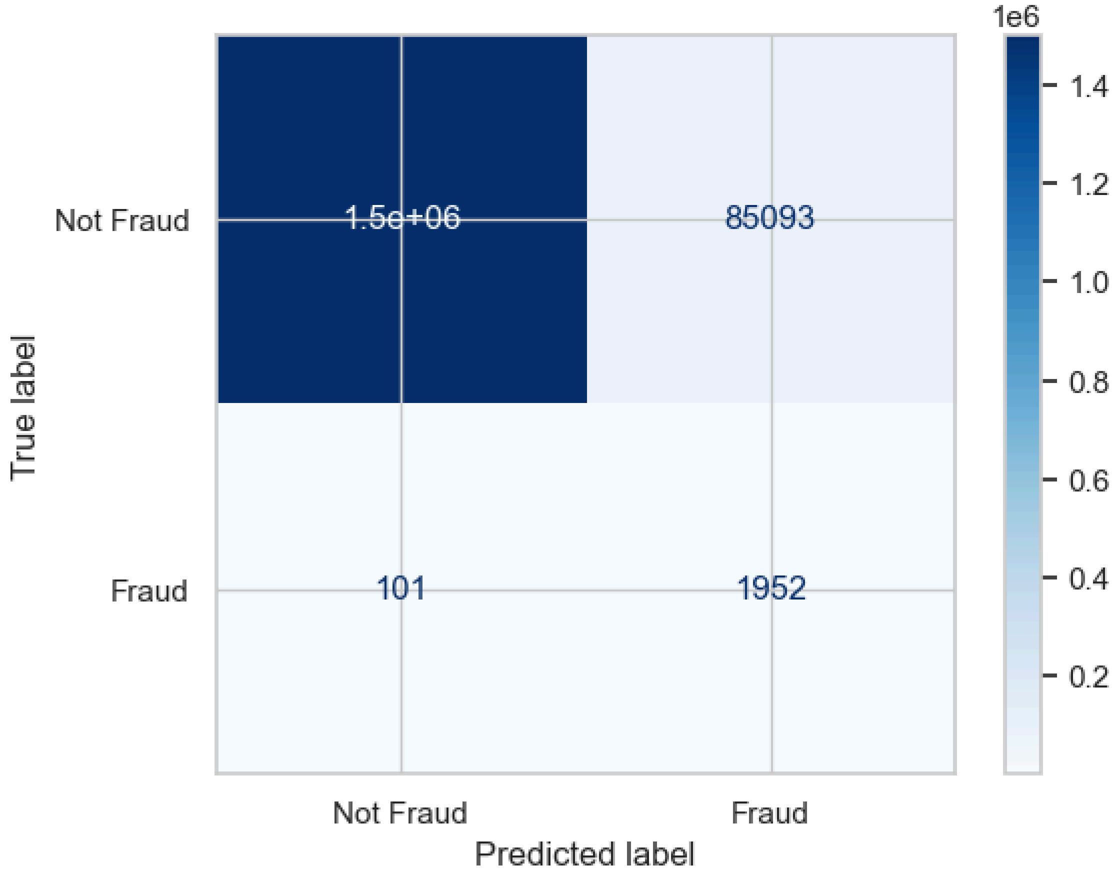
True Positives (fraud correctly caught)

False Positives (false alarms)

False Negatives (missed fraud)

In [56]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Not Fraud',
disp.plot(cmap='Blues')
```

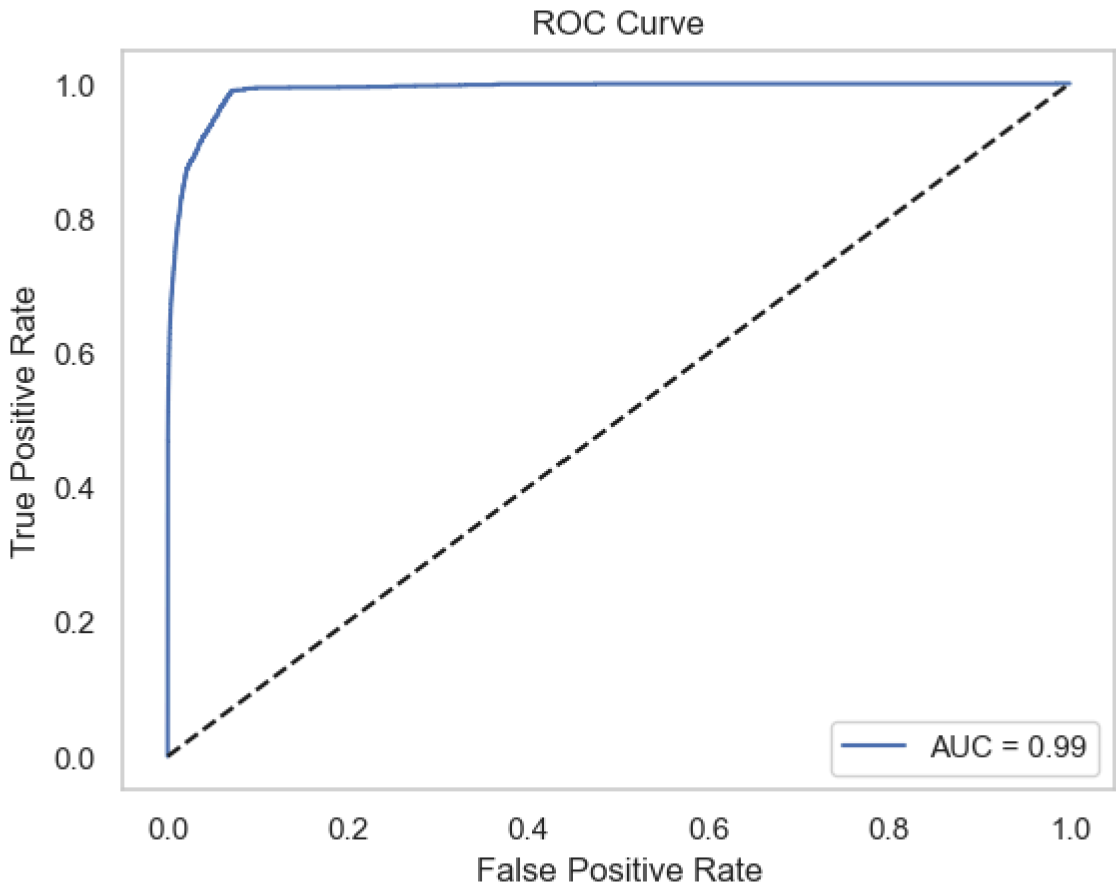
Out[56]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x27173d1fbb0
>
```



3. ROC Curve + AUC Table for imbalanced problems — tells how well the model ranks fraud vs non-fraud.

In [57]:
```
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

fpr, tpr, thresholds = roc_curve(y_test, y_proba)
roc_auc = roc_auc_score(y_test, y_proba)

plt.figure()
plt.plot(fpr, tpr, label=f"AUC = {roc_auc:.2f}")
plt.plot([0, 1], [0, 1], 'k--')
```

```
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid()
plt.show()
```



k fold Cross-Validation

In [58]:
```
# If you want to validate your model’s average performance across multiple folds
```

In [59]:
```
from sklearn.model_selection import cross_val_score

cv_scores = cross_val_score(pipe, X, y, cv=5, scoring='f1')  # or 'roc_auc', 'ac
print("5-Fold CV F1-Score:", cv_scores)
print("Mean F1:", cv_scores.mean())
```

```
5-Fold CV F1-Score: [0.03733953 0.04352933 0.04552985 0.04840122 0.04872521]
Mean F1: 0.04470502854152025
```

FRAUD AND RISK ANALYSIS

- fraud analysis (detecting fraudulent patterns)
- risk analysis (understanding behaviors that increase fraud risk).

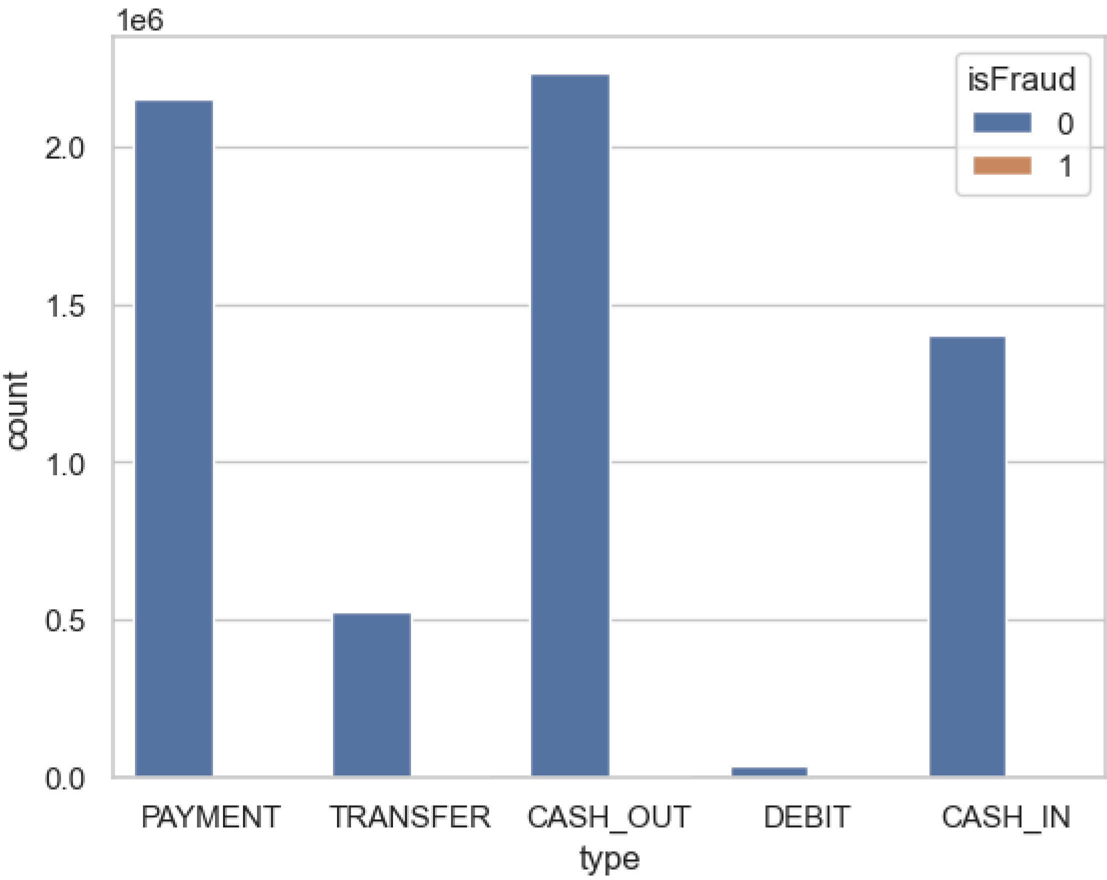
1. FRAUD ANALYSIS Goal: Detect and understand fraud patterns

- What types of transactions are most likely to be fraud?
- Are there specific time windows or amounts that show higher fraud?

- Which accounts or destinations are repeatedly involved in fraud?

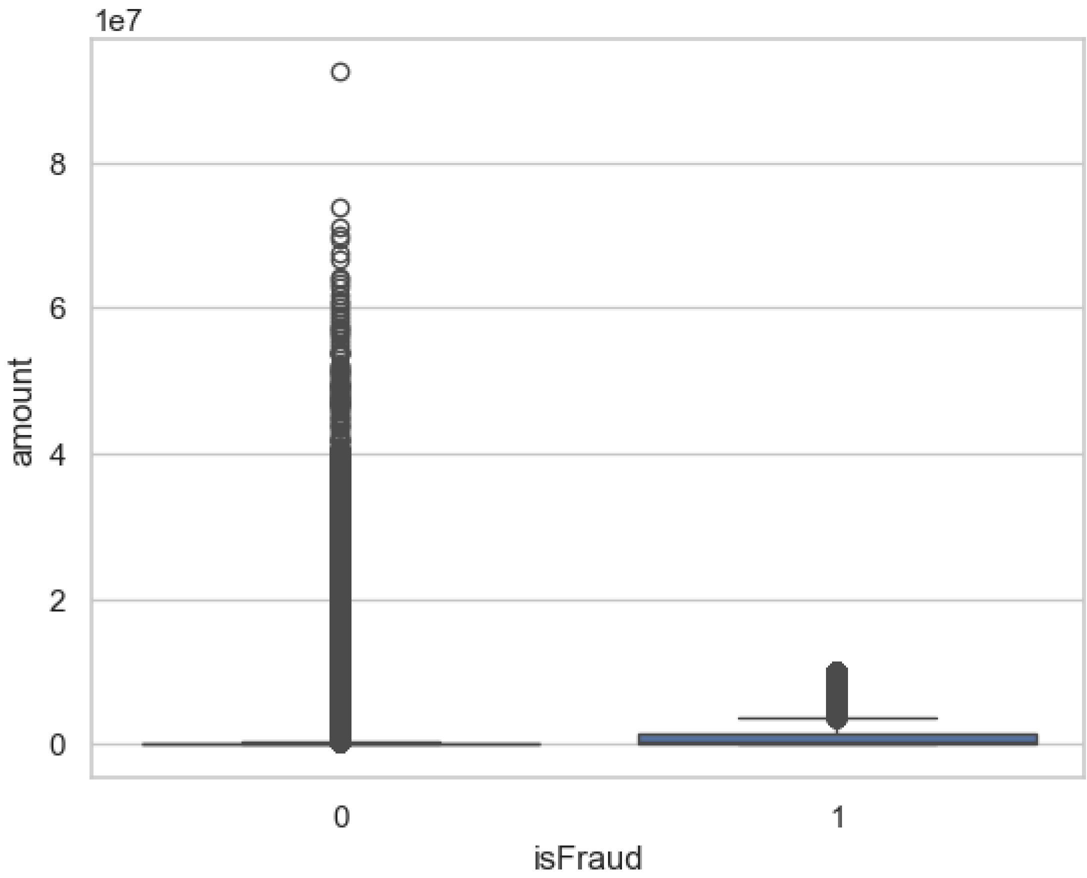
In [60]:
```python
# Shows which types (TRANSFER, CASH_OUT) are most fraud-prone
import seaborn as sns
sns.countplot(data=df, x='type', hue='isFraud')
```

Out[60]: <Axes: xlabel='type', ylabel='count'>



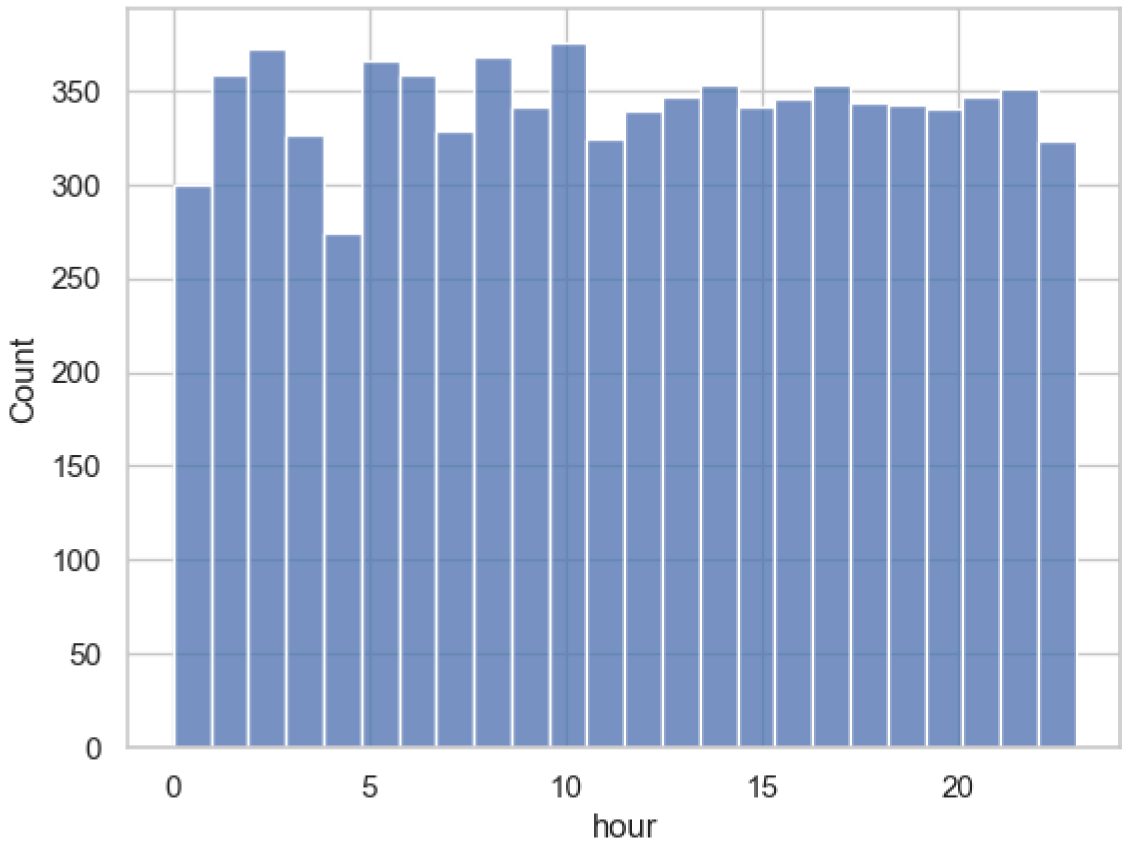
In [61]:
```python
# Amount Distribution for Fraud vs. Non-Fraud
# Are frauds happening at high or specific amounts? (< $50000)
sns.boxplot(data=df, x='isFraud', y='amount')
```

Out[61]: <Axes: xlabel='isFraud', ylabel='amount'>



In [62]:
```
# Hourly Trend of Fraud
# Identify time-of-day with higher fraud activity.
df['hour'] = df['step'] % 24
sns.histplot(data=df[df['isFraud']==1], x='hour', bins=24)
```

Out[62]: <Axes: xlabel='hour', ylabel='Count'>



In [63]:
```
# Frequent Fraudulent Accounts
# Flag accounts with repeated frauds.
df[df['isFraud']==1]['nameOrig'].value_counts().head()
```

Out[63]:
```
nameOrig
C1305486145    1
C755286039     1
C973279667     1
C258213312     1
C1640703547    1
Name: count, dtype: int64
```

In [64]:
```
# Origin-Destination Behavior
# let us find the names and other details of customers(senders) whose balance we
# create a df using three filters
zero_after_trans = df[
    (df['oldbalanceOrg']> 0) &
    (df['newbalanceOrig'] ==0) &
    (df['type'].isin(['TRANSFER','CASH_OUT']))
]
zero_after_trans.head()
```

Out[64]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	name
2	1	TRANSFER	181.00	C1305486145	181.0	0.0	C55326
3	1	CASH_OUT	181.00	C840083671	181.0	0.0	C3899
15	1	CASH_OUT	229133.94	C905080434	15325.0	0.0	C47640
19	1	TRANSFER	215310.30	C1670993182	705.0	0.0	C110043
24	1	TRANSFER	311685.89	C1984094095	10835.0	0.0	C93258

2. RISK ANALYSIS Goal: Identify accounts or transaction profiles at high risk of future fraud

a. Flag Suspicious Transactions Even If Not Labeled Fraud:

TRANSFER or CASH_OUT with:

- zero original balance (oldbalanceOrg == 0)
- large amount transferred
- no change in destination balance

In [65]:
```
risky = df[
    (df['type'].isin(['TRANSFER', 'CASH_OUT'])) &
    (df['oldbalanceOrg'] == 0) &
    (df['amount'] > 10000) &
    (df['newbalanceDest'] == df['oldbalanceDest'])
]
```

b.Create a Risk Score Per Account

- Use heuristics or a model to score:

- Sort by risk score to monitor accounts

In [66]:
```
df['riskScore'] = (
    (df['amount'] > 10000).astype(int) +
    (df['oldbalanceOrg'] == 0).astype(int) +
    (df['type'].isin(['TRANSFER', 'CASH_OUT'])).astype(int)
)
df['riskScore']
```

Out[66]:
```
0          0
1          0
2          1
3          1
4          1
          ..
6362615    2
6362616    2
6362617    2
6362618    2
6362619    2
Name: riskScore, Length: 6362620, dtype: int32
```

c.Unsupervised Anomaly Detection:

- Use Isolation Forest or Autoencoders to catch unknown fraud:
- anomaly = -1 are suspicious

In [67]:
```
from sklearn.ensemble import IsolationForest
iso = IsolationForest(contamination=0.01, random_state=42)
df['anomaly'] = iso.fit_predict(df[numerical_features])
df['anomaly']
```

Out[67]:
```
0          1
1          1
2          1
3          1
4          1
          ..
6362615    1
6362616    1
6362617    1
6362618    1
6362619    1
Name: anomaly, Length: 6362620, dtype: int32
```

export the trained models for use in your Streamlit app:

In [68]:
```
# Logistic Regression Training with Export
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
import joblib

pipe_logreg = Pipeline([
    ('prep', preprocessor),
    ('clf', LogisticRegression(max_iter=1000))
])

pipe_logreg.fit(X_train, y_train)
```

```python
joblib.dump(pipe_logreg, 'fraud_model_logreg.pkl')  # Save model

# Decision Tree Training with Export
from sklearn.tree import DecisionTreeClassifier

pipe_tree = Pipeline([
    ('prep', preprocessor),
    ('clf', DecisionTreeClassifier(random_state=42))
])

pipe_tree.fit(X_train, y_train)
joblib.dump(pipe_tree, 'fraud_model_tree.pkl')  # Save model
```

Out[68]: ['fraud_model_tree.pkl']

In [69]:

```python
model = joblib.load("fraud_model_logreg.pkl")  # or fraud_model_tree.pkl
```

Step 5 Deployment