

```
In [1]: import pandas as pd # Pandas for data reading and manipulation

# Importing Fraud Dataset
path = '/Users/quentinjonneaux/Desktop/ Experiment/Coursera/financial_tra

df=pd.read_csv(path)

# Display dataset info
df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 12 columns):

#	Column	Non-Null Count	Dtype
0	transaction_id	20000 non-null	int64
1	timestamp	20000 non-null	object
2	amount	20000 non-null	float64
3	currency	20000 non-null	object
4	merchant_name	20000 non-null	object
5	merchant_category	20000 non-null	object
6	card_type	20000 non-null	object
7	location_city	20000 non-null	object
8	location_country	20000 non-null	object
9	latitude	20000 non-null	float64
10	longitude	20000 non-null	float64
11	is_fraud	20000 non-null	int64

dtypes: float64(3), int64(2), object(7)
memory usage: 1.8+ MB

```
In [2]: # Feature Engineering

# Defining features and targets
features = df.drop('is_fraud',axis=1)
target = df['is_fraud']

# Transaction times
# Converting to series to datetime object
features['timestamp'] = pd.to_datetime(features['timestamp'])

# Creating variable for year as integer
features['trans_date_year'] = features['timestamp'].dt.strftime('%Y')
features['trans_date_year'] = features['trans_date_year'].astype(int)

# Creating variable for month as integer
features['trans_date_month'] = features['timestamp'].dt.strftime('%m')
features['trans_date_month'] = features['trans_date_month'].astype(int)

# Creating variable for day as integer
features['trans_date_day'] = features['timestamp'].dt.strftime('%d')
features['trans_date_day'] = features['trans_date_day'].astype(int)

# Creating variable for hour as integer
features['trans_date_hour'] = features['timestamp'].dt.strftime('%H')
features['trans_date_hour'] = features['trans_date_hour'].astype(int)

# Creating variable for minute as integer
features['trans_date_minute'] = features['timestamp'].dt.strftime('%M')
features['trans_date_minute'] = features['trans_date_minute'].astype(int)

# Creating variable for second as integer
features['trans_date_second'] = features['timestamp'].dt.strftime('%S')
features['trans_date_second'] = features['trans_date_second'].astype(int)

# Dropping timestamp variable
features=features.drop('timestamp',axis=1)

# Replace
#get all categorical columns
cat_columns = features.select_dtypes(['object']).columns

#convert all categorical columns to numeric
features[cat_columns] = features[cat_columns].apply(lambda x: pd.factoriz

# dropping Trans_num (only used for tracking)
features=features.drop('transaction_id',axis=1)

print('preprocessing done')

preprocessing done
```

```
In [3]: from sklearn import neighbors # Scikit Learn neighbors for creating a KNN

# Create a KNN instance with 4 neighbours
clf = neighbors.KNeighborsClassifier(n_neighbors=4, metric='minkowski')
```

```
In [4]: from sklearn import metrics # Scikit Learn metrics for computing confusio
from sklearn import model_selection # Scikit Learn model_selection to app
import matplotlib.pyplot as plt # matplotlib.pyplot to display plots

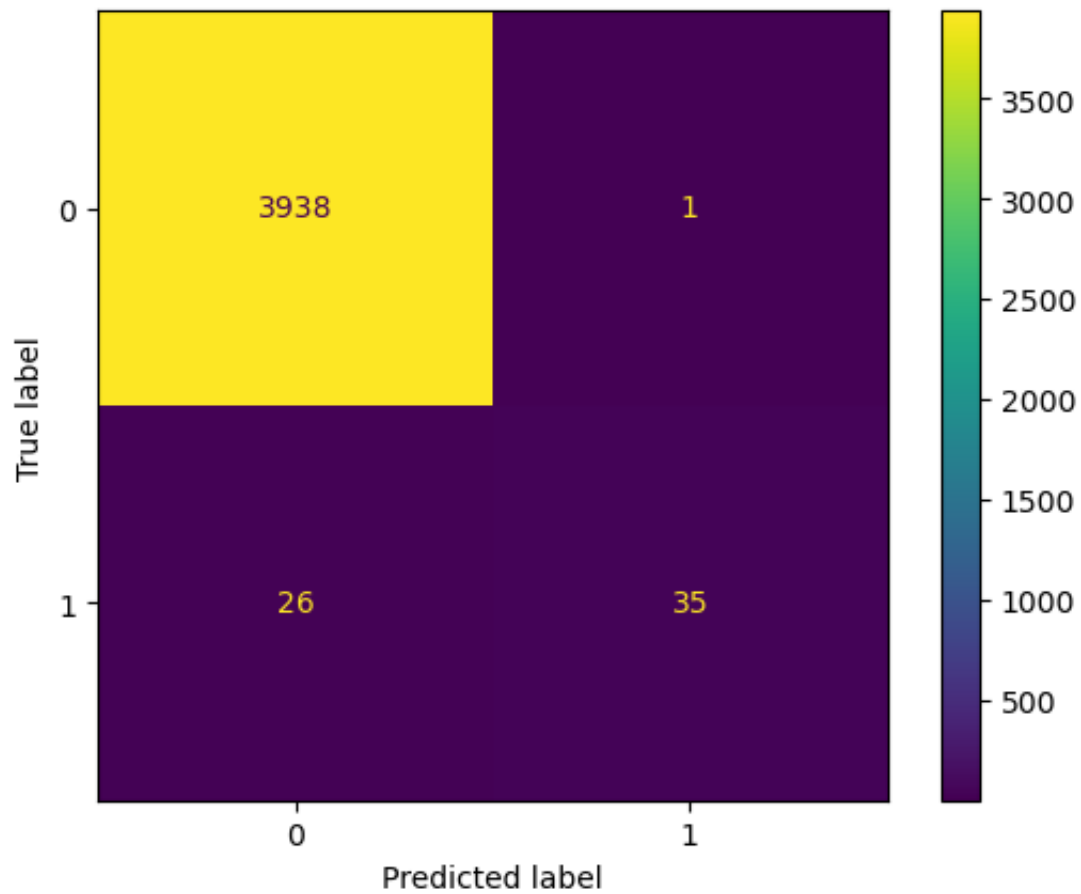
# Split set into training set (80% of data) and test set (20% of data) wi
test_features, train_features, test_labels, train_labels = model_selectio

clf.fit(train_features, train_labels)
print('training done')
preds = clf.predict(test_features)
print('predictions done')
confusion_matrix = metrics.confusion_matrix(test_labels, preds)
print('Confusion matrix: ',confusion_matrix)
accuracy = metrics.accuracy_score(test_labels, preds)
print('Accuracy score: ',accuracy)

disp = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix,
                                       display_labels=clf.classes_)

disp.plot()
plt.show()

training done
predictions done
Confusion matrix: [[3938    1]
 [   26   35]]
Accuracy score: 0.99325
```



```
In [5]: from sklearn import linear_model # Scikit Learn linear model for creating  
# Create a Perceptron instance  
clf = linear_model.Perceptron()
```

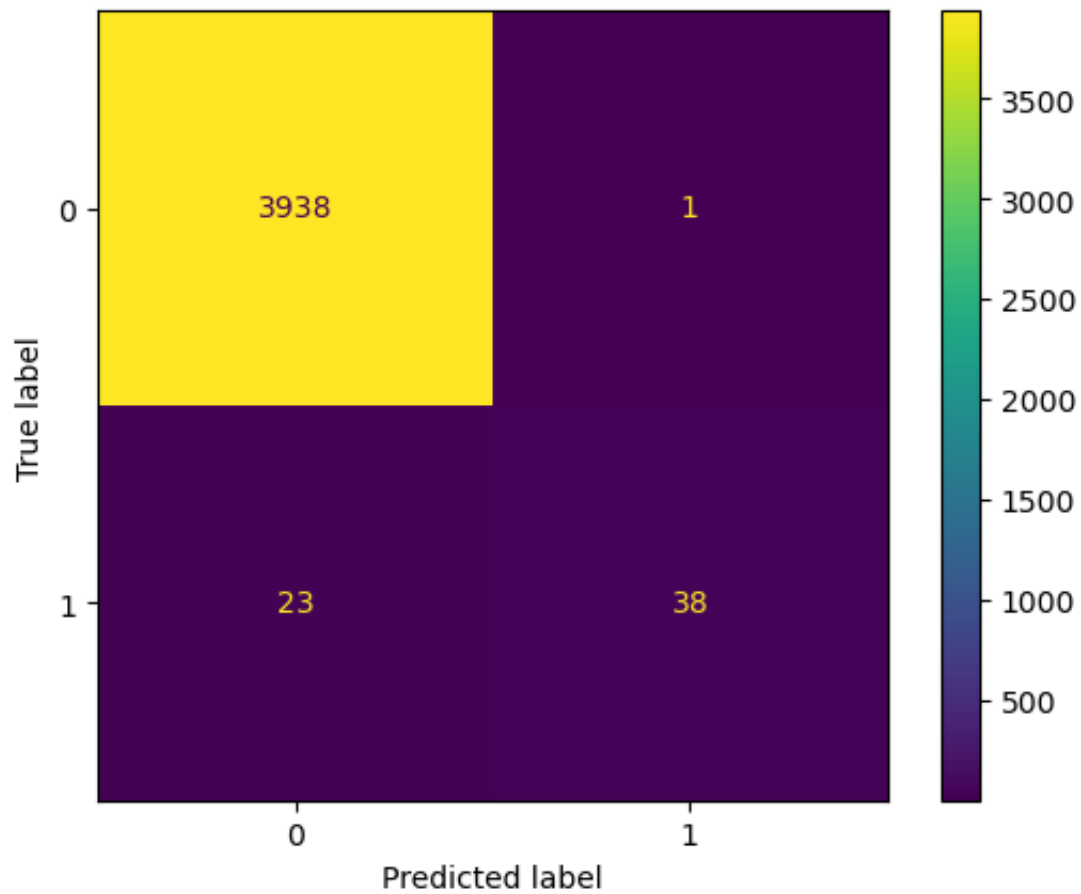
```
In [6]: from sklearn import metrics # Scikit Learn metrics for computing confusio
from sklearn import model_selection # Scikit Learn model_selection to app
import matplotlib.pyplot as plt # matplotlib.pyplot to display plots

# Split set into training set (80% of data) and test set (20% of data) wi
test_features, train_features, test_labels, train_labels = model_selectio

clf.fit(train_features, train_labels)
print('training done')
preds = clf.predict(test_features)
print('predictions done')
confusion_matrix = metrics.confusion_matrix(test_labels, preds)
print('Confusion matrix: ',confusion_matrix)
accuracy = metrics.accuracy_score(test_labels, preds)
print('Accuracy score: ',accuracy)

disp = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix,
                                       display_labels=clf.classes_)
disp.plot()
plt.show()

training done
predictions done
Confusion matrix:  [[3938    1]
 [  23   38]]
Accuracy score:  0.994
```



```
In [7]: from sklearn import tree # Scikit Learn tree for creating a decision tree  
# Create a Decision Tree Instance  
clf = tree.DecisionTreeClassifier()
```

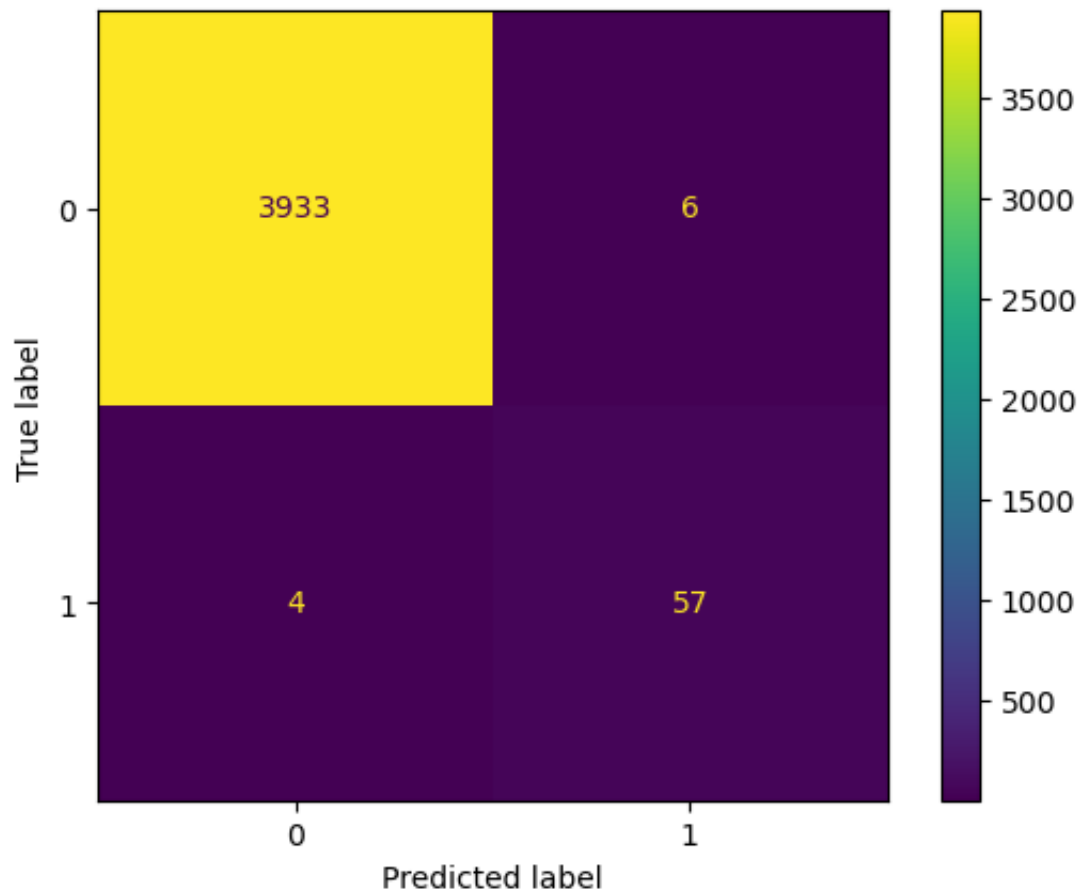
```
In [8]: from sklearn import metrics # Scikit Learn metrics for computing confusio
from sklearn import model_selection # Scikit Learn model_selection to app
import matplotlib.pyplot as plt # matplotlib.pyplot to display plots

# Split set into training set (80% of data) and test set (20% of data) wi
test_features, train_features, test_labels, train_labels = model_selectio

clf.fit(train_features, train_labels)
print('training done')
preds = clf.predict(test_features)
print('predictions done')
confusion_matrix = metrics.confusion_matrix(test_labels, preds)
print('Confusion matrix: ',confusion_matrix)
accuracy = metrics.accuracy_score(test_labels, preds)
print('Accuracy score: ',accuracy)

disp = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix,
                                       display_labels=clf.classes_)
disp.plot()
plt.show()

training done
predictions done
Confusion matrix:  [[3933    6]
 [   4   57]]
Accuracy score:  0.9975
```



```
In [9]: from sklearn import svm # Scikit Learn svm for creating a support vector  
  
# Create a SVM instance with a gamme parameter of 1e-6  
clf = svm.SVC(gamma=float(1e-6))
```



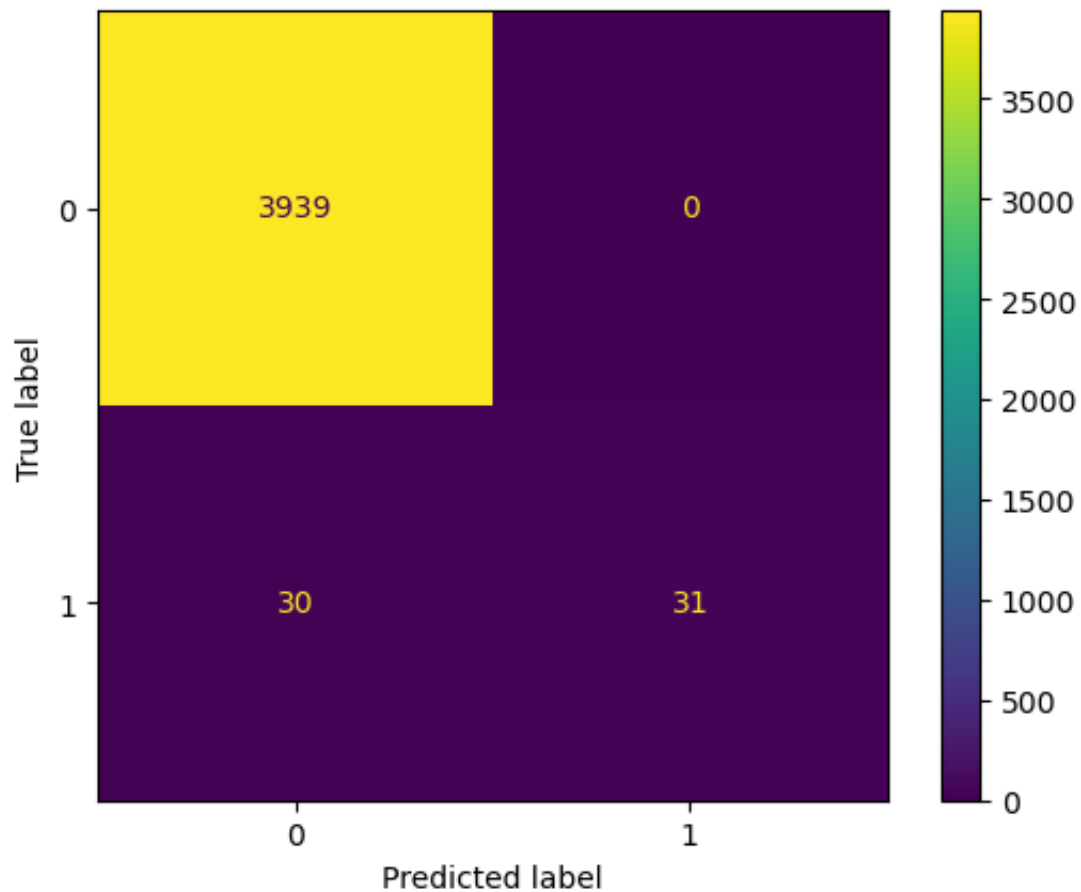
```
In [10]: from sklearn import metrics # Scikit Learn metrics for computing confusio
from sklearn import model_selection # Scikit Learn model_selection to app
import matplotlib.pyplot as plt # matplotlib.pyplot to display plots

# Split set into training set (80% of data) and test set (20% of data) wi
test_features, train_features, test_labels, train_labels = model_selectio

clf.fit(train_features, train_labels)
print('training done')
preds = clf.predict(test_features)
print('predictions done')
confusion_matrix = metrics.confusion_matrix(test_labels, preds)
print('Confusion matrix: ',confusion_matrix)
accuracy = metrics.accuracy_score(test_labels, preds)
print('Accuracy score: ',accuracy)

disp = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix,
                                       display_labels=clf.classes_)
disp.plot()
plt.show()

training done
predictions done
Confusion matrix:  [[3939    0]
 [   30   31]]
Accuracy score:  0.9925
```



In [11]: *# Best Classifier is Decision Tree*

```
clf = tree.DecisionTreeClassifier()  
clf.fit(features, target)
```

Out[11]: ▾ DecisionTreeClassifier

DecisionTreeClassifier()

In [12]: *# Importing Test Fraud Dataset*

```
path = '/Users/quentinjonjeaux/Desktop/ Experiment/Coursera/Test.csv'
```

```
test_df=pd.read_csv(path)
```

Display dataset info

```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50 entries, 0 to 49
Data columns (total 11 columns):
#   Column                Non-Null Count  Dtype
---  -
0   transaction_id         50 non-null    object
1   timestamp              50 non-null    object
2   amount                 50 non-null    float64
3   currency               50 non-null    object
4   merchant_name          50 non-null    object
5   merchant_category      50 non-null    object
6   card_type              50 non-null    object
7   location_city          50 non-null    object
8   location_country       50 non-null    object
9   latitude               50 non-null    float64
10  longitude              50 non-null    float64
dtypes: float64(3), object(8)
memory usage: 4.4+ KB
```

```
In [13]: def predict_fraud(test_df):
        """
        A fraud detection ML model.
        """

        processed_df = test_df
        # Feature Engineering

        # Transaction times
        # Converting to series to datetime object
        processed_df['timestamp'] = pd.to_datetime(processed_df['timestamp'])

        # Creating variable for year as integer
        processed_df['trans_date_year'] = processed_df['timestamp'].dt.strftime('%Y')
        processed_df['trans_date_year'] = processed_df['trans_date_year'].astype(int)

        # Creating variable for month as integer
        processed_df['trans_date_month'] = processed_df['timestamp'].dt.strftime('%m')
        processed_df['trans_date_month'] = processed_df['trans_date_month'].astype(int)

        # Creating variable for day as integer
        processed_df['trans_date_day'] = processed_df['timestamp'].dt.strftime('%d')
        processed_df['trans_date_day'] = processed_df['trans_date_day'].astype(int)

        # Creating variable for hour as integer
        processed_df['trans_date_hour'] = processed_df['timestamp'].dt.strftime('%H')
        processed_df['trans_date_hour'] = processed_df['trans_date_hour'].astype(int)

        # Creating variable for minute as integer
        processed_df['trans_date_minute'] = processed_df['timestamp'].dt.strftime('%M')
        processed_df['trans_date_minute'] = processed_df['trans_date_minute'].astype(int)

        # Creating variable for second as integer
        processed_df['trans_date_second'] = processed_df['timestamp'].dt.strftime('%S')
        processed_df['trans_date_second'] = processed_df['trans_date_second'].astype(int)

        # Dropping timestamp variable
        processed_df = processed_df.drop('timestamp', axis=1)
```

```

# Replace
#get all categorical columns
cat_columns = processed_df.select_dtypes(['object']).columns

#convert all categorical columns to numeric
processed_df[cat_columns] = processed_df[cat_columns].apply(lambda x:

# dropping Trans_num (only used for tracking)
processed_df=processed_df.drop('transaction_id',axis=1)

print('preprocessing done')
# Predict Fraud

preds = clf.predict(processed_df)
test_df['flagged']=preds
#processed_df['flagged']=preds
#col=test_df['transaction_id']
#processed_df.insert(0, 'transaction_id', col)
return test_df

```

```

In [14]: def compliance_workflow(test_df):
        """
        The compliance workflow that checks each transaction.
        """
        processed_df = predict_fraud(test_df)
        flagged_transactions = processed_df[processed_df['flagged']==1]
        print(flagged_transactions)
        return flagged_transactions

```

```

In [15]: import datetime

def generate_report(flagged_transactions):
    """
    Generates a report of flagged transactions.
    """
    print("--- Fraud Detection Report ---")
    print(f"Report generated on: {datetime.datetime.now().strftime('%Y-%m')}")
    print(f"\nTotal flagged transactions: {len(flagged_transactions)}")
    print("-----")

    if len(flagged_transactions) == 0:
        print("\nNo suspicious transactions detected.")
    else:
        print("\nFlagged Transactions:\n")
        for index, row in flagged_transactions.iterrows():
            print(f"Transaction ID: {row['transaction_id']}")
            print(f"Timestamp: {row['timestamp']}")
            print(f"Amount: {row['amount']} {row['currency']}")
            print(f"Merchant: {row['merchant_name']}")
            print(f>Action Taken: Flagged for review")
            print("-----")

```

```
In [16]: # --- Execute the Workflow ---
flagged = compliance_workflow(test_df)
print(flagged)
```

preprocessing done

	transaction_id	timestamp	amount	currency	merchant_name
\					
0	txn_1	2025-11-01 10:25:00	150.75	USD	Gadget World
2	txn_3	2025-11-01 10:32:00	800.00	GBP	FlyAway
3	txn_4	2025-11-01 10:35:00	250.20	USD	Tech Central
6	txn_7	2025-11-01 10:50:00	500.00	USD	Holiday Planners
8	txn_9	2025-11-01 11:00:00	300.50	USD	ElectroGoods
10	txn_11	2025-11-01 11:10:00	600.00	EUR	Global Tours
14	txn_15	2025-11-01 11:30:00	900.25	USD	FlyAway
18	txn_19	2025-11-01 11:50:00	450.70	EUR	Holiday Planners
20	txn_21	2025-11-01 12:00:00	320.80	USD	ElectroGoods
25	txn_26	2025-11-01 12:25:00	950.00	USD	FlyAway
29	txn_30	2025-11-01 12:45:00	480.00	EUR	Holiday Planners
31	txn_32	2025-11-01 12:55:00	340.00	USD	ElectroGoods
36	txn_37	2025-11-01 13:20:00	980.50	USD	FlyAway
38	txn_39	2025-11-01 13:30:00	250.75	GBP	Tech Central
40	txn_41	2025-11-01 13:40:00	500.00	EUR	Holiday Planners
42	txn_43	2025-11-01 13:50:00	360.40	USD	ElectroGoods
47	txn_48	2025-11-01 14:15:00	1050.00	USD	FlyAway
49	txn_50	2025-11-01 14:25:00	270.00	GBP	Tech Central

	merchant_category	card_type	location_city	location_country	latitude
\					
0	electronics	Visa	New York	USA	40.7128
2	travel	Amex	Manchester	UK	53.4808
3	electronics	Visa	Los Angeles	USA	34.0522
6	travel	Amex	New York	USA	40.7128
8	electronics	Visa	Los Angeles	USA	34.0522
10	travel	Mastercard	Berlin	Germany	52.5200
14	travel	Visa	Los Angeles	USA	34.0522
18	travel	Mastercard	Munich	Germany	48.1351
20	electronics	Amex	Los Angeles	USA	34.0522
25	travel	Visa	Los Angeles	USA	34.0522
29	travel	Amex	Munich	Germany	48.1351
31	electronics	Visa	Los Angeles	USA	34.0522
36	travel	Mastercard	Los Angeles	USA	34.0522
38	electronics	Amex	Manchester	UK	53.4808
40	travel	Visa	Munich	Germany	48.1351
42	electronics	Mastercard	Los Angeles	USA	34.0522
47	travel	Amex	Los Angeles	USA	34.0522
49	electronics	Visa	London	UK	51.5074

	longitude	trans_date_year	trans_date_month	trans_date_day	\
0	-74.0060	2025	11	1	
2	-2.2426	2025	11	1	
3	-118.2437	2025	11	1	
6	-74.0060	2025	11	1	
8	-118.2437	2025	11	1	
10	13.4050	2025	11	1	
14	-118.2437	2025	11	1	
18	11.5820	2025	11	1	

20	-118.2437	2025	11	1
25	-118.2437	2025	11	1
29	11.5820	2025	11	1
31	-118.2437	2025	11	1
36	-118.2437	2025	11	1
38	-2.2426	2025	11	1
40	11.5820	2025	11	1
42	-118.2437	2025	11	1
47	-118.2437	2025	11	1
49	-0.1278	2025	11	1

	trans_date_hour	trans_date_minute	trans_date_second	flagged
0	10	25	0	1
2	10	32	0	1
3	10	35	0	1
6	10	50	0	1
8	11	0	0	1
10	11	10	0	1
14	11	30	0	1
18	11	50	0	1
20	12	0	0	1
25	12	25	0	1
29	12	45	0	1
31	12	55	0	1
36	13	20	0	1
38	13	30	0	1
40	13	40	0	1
42	13	50	0	1
47	14	15	0	1
49	14	25	0	1

	transaction_id	timestamp	amount	currency	merchant_name
\					
0	txn_1	2025-11-01 10:25:00	150.75	USD	Gadget World
2	txn_3	2025-11-01 10:32:00	800.00	GBP	FlyAway
3	txn_4	2025-11-01 10:35:00	250.20	USD	Tech Central
6	txn_7	2025-11-01 10:50:00	500.00	USD	Holiday Planners
8	txn_9	2025-11-01 11:00:00	300.50	USD	ElectroGoods
10	txn_11	2025-11-01 11:10:00	600.00	EUR	Global Tours
14	txn_15	2025-11-01 11:30:00	900.25	USD	FlyAway
18	txn_19	2025-11-01 11:50:00	450.70	EUR	Holiday Planners
20	txn_21	2025-11-01 12:00:00	320.80	USD	ElectroGoods
25	txn_26	2025-11-01 12:25:00	950.00	USD	FlyAway
29	txn_30	2025-11-01 12:45:00	480.00	EUR	Holiday Planners
31	txn_32	2025-11-01 12:55:00	340.00	USD	ElectroGoods
36	txn_37	2025-11-01 13:20:00	980.50	USD	FlyAway
38	txn_39	2025-11-01 13:30:00	250.75	GBP	Tech Central
40	txn_41	2025-11-01 13:40:00	500.00	EUR	Holiday Planners
42	txn_43	2025-11-01 13:50:00	360.40	USD	ElectroGoods
47	txn_48	2025-11-01 14:15:00	1050.00	USD	FlyAway
49	txn_50	2025-11-01 14:25:00	270.00	GBP	Tech Central

	merchant_category	card_type	location_city	location_country	latitude
\					
0	electronics	Visa	New York	USA	40.7128
2	travel	Amex	Manchester	UK	53.4808
3	electronics	Visa	Los Angeles	USA	34.0522
6	travel	Amex	New York	USA	40.7128

8	electronics	Visa	Los Angeles	USA	34.0522
10	travel	Mastercard	Berlin	Germany	52.5200
14	travel	Visa	Los Angeles	USA	34.0522
18	travel	Mastercard	Munich	Germany	48.1351
20	electronics	Amex	Los Angeles	USA	34.0522
25	travel	Visa	Los Angeles	USA	34.0522
29	travel	Amex	Munich	Germany	48.1351
31	electronics	Visa	Los Angeles	USA	34.0522
36	travel	Mastercard	Los Angeles	USA	34.0522
38	electronics	Amex	Manchester	UK	53.4808
40	travel	Visa	Munich	Germany	48.1351
42	electronics	Mastercard	Los Angeles	USA	34.0522
47	travel	Amex	Los Angeles	USA	34.0522
49	electronics	Visa	London	UK	51.5074

	longitude	trans_date_year	trans_date_month	trans_date_day	\
0	-74.0060	2025	11	1	
2	-2.2426	2025	11	1	
3	-118.2437	2025	11	1	
6	-74.0060	2025	11	1	
8	-118.2437	2025	11	1	
10	13.4050	2025	11	1	
14	-118.2437	2025	11	1	
18	11.5820	2025	11	1	
20	-118.2437	2025	11	1	
25	-118.2437	2025	11	1	
29	11.5820	2025	11	1	
31	-118.2437	2025	11	1	
36	-118.2437	2025	11	1	
38	-2.2426	2025	11	1	
40	11.5820	2025	11	1	
42	-118.2437	2025	11	1	
47	-118.2437	2025	11	1	
49	-0.1278	2025	11	1	

	trans_date_hour	trans_date_minute	trans_date_second	flagged
0	10	25	0	1
2	10	32	0	1
3	10	35	0	1
6	10	50	0	1
8	11	0	0	1
10	11	10	0	1
14	11	30	0	1
18	11	50	0	1
20	12	0	0	1
25	12	25	0	1
29	12	45	0	1
31	12	55	0	1
36	13	20	0	1
38	13	30	0	1
40	13	40	0	1
42	13	50	0	1
47	14	15	0	1
49	14	25	0	1

```
In [17]: # --- Generate the Report ---
generate_report(flagged)

--- Fraud Detection Report ---
Report generated on: 2025-11-30 21:49:08

Total flagged transactions: 18
-----

Flagged Transactions:

Transaction ID: txn_1
Timestamp: 2025-11-01 10:25:00
Amount: 150.75 USD
Merchant: Gadget World
Action Taken: Flagged for review
-----
Transaction ID: txn_3
Timestamp: 2025-11-01 10:32:00
Amount: 800.0 GBP
Merchant: FlyAway
Action Taken: Flagged for review
-----
Transaction ID: txn_4
Timestamp: 2025-11-01 10:35:00
Amount: 250.2 USD
Merchant: Tech Central
Action Taken: Flagged for review
-----
Transaction ID: txn_7
Timestamp: 2025-11-01 10:50:00
Amount: 500.0 USD
Merchant: Holiday Planners
Action Taken: Flagged for review
-----
Transaction ID: txn_9
Timestamp: 2025-11-01 11:00:00
Amount: 300.5 USD
Merchant: ElectroGoods
Action Taken: Flagged for review
-----
Transaction ID: txn_11
Timestamp: 2025-11-01 11:10:00
Amount: 600.0 EUR
Merchant: Global Tours
Action Taken: Flagged for review
-----
Transaction ID: txn_15
Timestamp: 2025-11-01 11:30:00
Amount: 900.25 USD
Merchant: FlyAway
Action Taken: Flagged for review
-----
Transaction ID: txn_19
Timestamp: 2025-11-01 11:50:00
Amount: 450.7 EUR
```



```
Merchant: Holiday Planners
Action Taken: Flagged for review
-----
Transaction ID: txn_21
Timestamp: 2025-11-01 12:00:00
Amount: 320.8 USD
Merchant: ElectroGoods
Action Taken: Flagged for review
-----
Transaction ID: txn_26
Timestamp: 2025-11-01 12:25:00
Amount: 950.0 USD
Merchant: FlyAway
Action Taken: Flagged for review
-----
Transaction ID: txn_30
Timestamp: 2025-11-01 12:45:00
Amount: 480.0 EUR
Merchant: Holiday Planners
Action Taken: Flagged for review
-----
Transaction ID: txn_32
Timestamp: 2025-11-01 12:55:00
Amount: 340.0 USD
Merchant: ElectroGoods
Action Taken: Flagged for review
-----
Transaction ID: txn_37
Timestamp: 2025-11-01 13:20:00
Amount: 980.5 USD
Merchant: FlyAway
Action Taken: Flagged for review
-----
Transaction ID: txn_39
Timestamp: 2025-11-01 13:30:00
Amount: 250.75 GBP
Merchant: Tech Central
Action Taken: Flagged for review
-----
Transaction ID: txn_41
Timestamp: 2025-11-01 13:40:00
Amount: 500.0 EUR
Merchant: Holiday Planners
Action Taken: Flagged for review
-----
Transaction ID: txn_43
Timestamp: 2025-11-01 13:50:00
Amount: 360.4 USD
Merchant: ElectroGoods
Action Taken: Flagged for review
-----
Transaction ID: txn_48
Timestamp: 2025-11-01 14:15:00
Amount: 1050.0 USD
Merchant: FlyAway
Action Taken: Flagged for review
-----
```

```
Transaction ID: txn_50
Timestamp: 2025-11-01 14:25:00
Amount: 270.0 GBP
Merchant: Tech Central
Action Taken: Flagged for review
-----
```