

INTRODUCTION

PROBLEM DEFINITION

**DEEP LEARING** 

**REAL-TIME MONITORING** 

IMPLANCED DATA HANDLING

**DISCRIPTIVE ANALYSIST** 

**ANOMALY DETECTION** 

**PREDICTIVE ANALYSIST** 

**NETWORK ANALYSIS** 

TIME SERIES ANALYSIS

CONCLUSION

# CREDIT CARD FRAUD DEDECTION

### INTRODUCTION

Machine learning algorithms play a crucial role identifying fraudulent transactions by analyzing patterns and anomalies in credit card data.

Commonly used machine learning algorithms for credit card fraud detection include logistic regression, decision trees, random for ests, and neural networks.



The problem is to develop a machine learning-based system for real-time credit card fraud detection.

The goal is to create a solution that can accurately identify fraudulent transactions while minimizing false positives.

This project involves data preprocessing, feature engineering, model selection, training, and evaluation to create a robust fraud detection systems



## What the Credit Card Fraud Dedection?

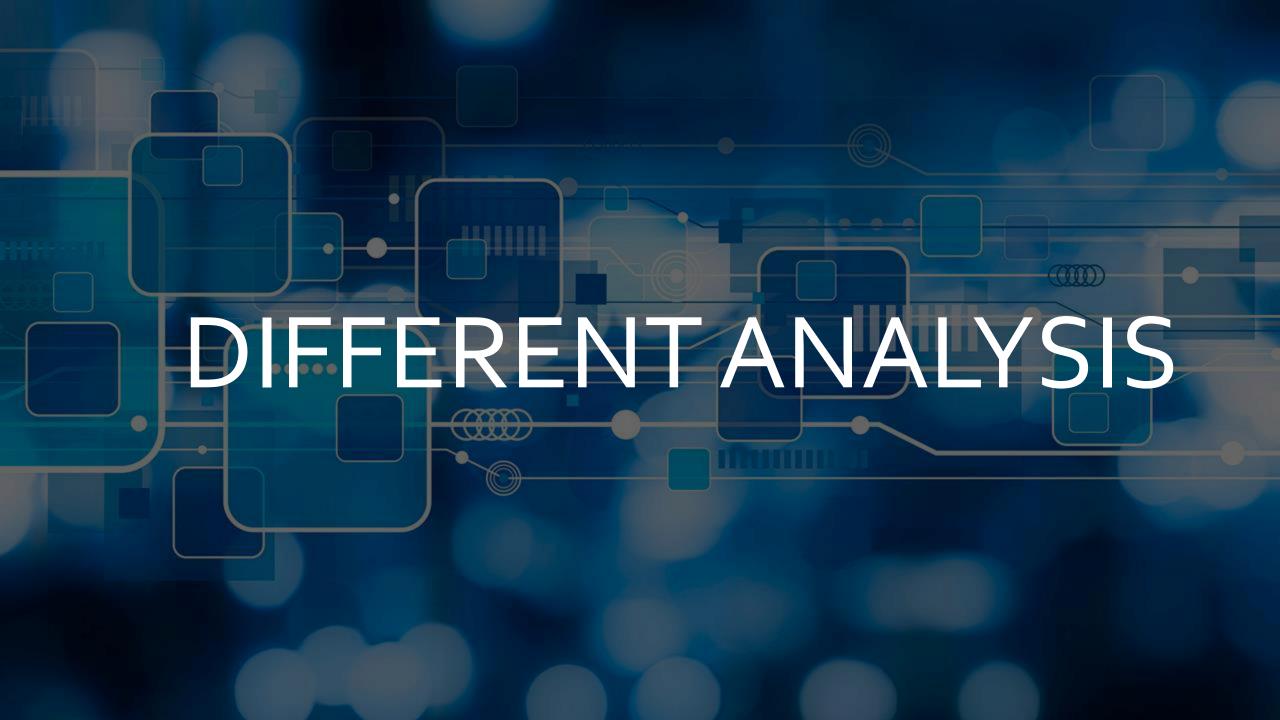
- Credit card fraud is the act of using another person's credit card to make purchases or request cash advances without the cardholder's knowledge or consent.
- These criminals may obtain the card itself through physical theft, though increasingly fraudsters are leveraging digital means to steal the credit card number and accompanying personal information to make illicit transactions

### Types of credit card fraud

Credit card fraud falls into two basic categories:

1) Card present fraud

2) Card-not-present fraud



## Deep Learning for Fraud Detection

- Explore advanced neural network architectures like convolutional neural
- networks (CNNs) and recurrent neural networks (RNNs) for more
- •sophisticated feature extraction and time series analysis.
- You can use deep learning models, such as a neural network,
- •to capture complex patterns in the data.

#### PROGRAM

```
from tensorflow.keras.models import Sequential from tensorflow.keras.layers import Dense model = Sequential([

Dense(128, input_dim=X_train.shape[1], activation='relu'),

Dense(64, activation='relu'),

Dense(1, activation='sigmoid') ])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics['accuracy']) model.fit(X_train, y_train, epochs=10, batch_size=32)
```

## Real-time Monitoring

To detect fraud in realtime, you can set up an automated system that continuously monitors incoming transactions and applies your trained model to identify anomalies.

#### program

```
from skmultiflow.classification
import HoeffdingTree
from skmultiflow.data import FileStream
# Define a stream data source (replace
'data_stream.arff' with your data source)
stream = FileStream('data_stream.arff',
n_targets=2)
# Create an online learning model (Hoeffding
Tree)
model = HoeffdingTree()
```

Credit card fraud datasets are often imbalanced, with a majority of non-fraudulent transactions. You may need to use techniques

Like oversampling, under sampling, or Synthetic Minority Oversampling Technique (SMOTE) to handle this imbalance

# IMPLANCED DATA HANDLNG

**PROGRAM** 

from imblearn.over\_sampling import SMOTE sm = SMOTE(sampling\_strategy=0.5) X\_resampled, y\_resampled = sm.fit\_resample(X\_train, y\_train) # Train the model with the resampled data model.fit(X\_resampled, y\_resampled)

## Descriptive Analytics

Data Exploration:

Initial analysis to understand

data characteristics.

Data Visualization:

Using charts to spot trends and patterns.

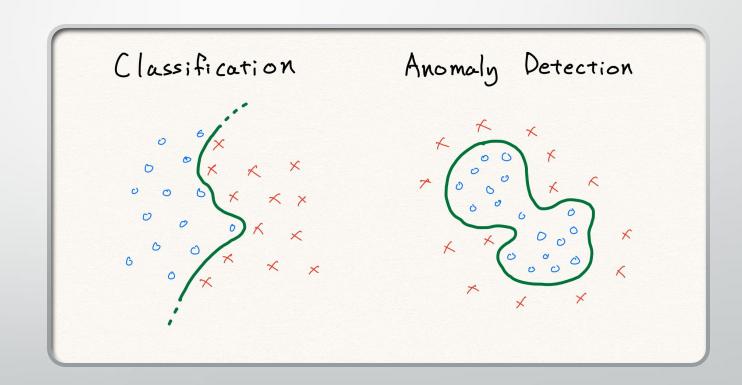
#### PROGRAM

```
# Data Exploration
legitimate_transactions.describe()
fraudulent_transactions.describe()
# Data Visualization import matplotlib.pyplot as plt
plt.scatter(legitimate_transactions['amount'],
legitimate_transactions['hour'],
label='Legitimate', color='green')
plt.scatter(fraudulent_transactions['amount'],
fraudulent_transactions['hour'], label='Fraudulent',
color='red') plt.legend() plt.show()
```

## **Anomaly Detection**

Identifying outliers in data using Isolation Forest.

Set a contamination parameter for the expected proportion of outliers.



Program

```
from sklearn.ensemble
import IsolationForest
clf =
IsolationForest(contamination=0.05)
clf.fit(X)
  # X is your transaction data
predictions = clf.predict(X)
```

### **Predictive Analytics**

Using logistic regression to predict fraud.

Split data into training and test sets for model evaluation.

### Program:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score,
confusion_matrix X_train,
X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
model = LogisticRegression() model.fit(X_train, y_train)
predictions = model.predict(X_test)
accuracy = accuracy_score(y_test, predictions)
cm = confusion_matrix(y_test, predictions)
```

## Rule-Based System

Define rules to classify transactions as legitimate or fraudulent.

Rules may be based on transaction amount, location, or other factors.

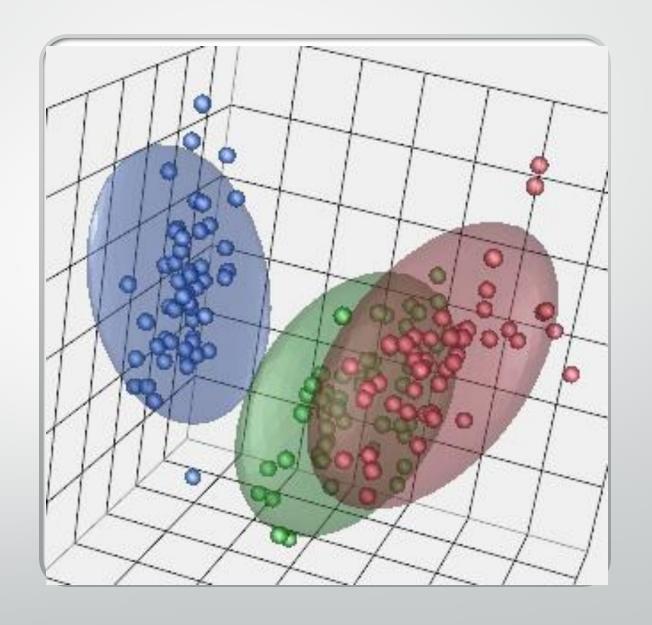
#### Program:

```
def rule_based_fraud_detection(transaction):
  if transaction['amount'] > 1000 and
  transaction['location'] not in trusted_locations:
    return "Fraudulent" else:
    return "Legitimate" result =
    rule_based_fraud_detection(transaction_data)
```

# Unsupervised Learning (K-Means Clustering)

Grouping transactions into clusters.

Requires specifying the number of clusters.



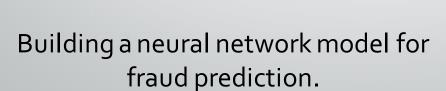
#### PROGRAM

from sklearn.cluster import KMeans kmeans = KMeans(n\_clusters=2)

kmeans.fit(X) labels = kmeans.labels\_

#### Deep Learning (Using TensorFlow and Keras)







Training the model using labeled data and an appropriate loss function.

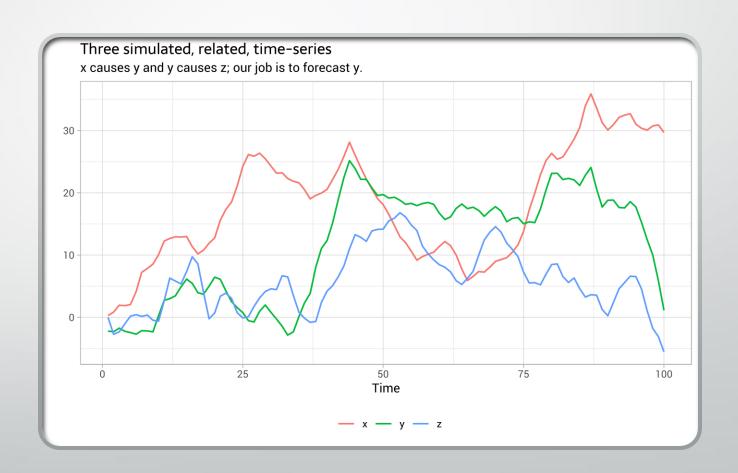
#### **Network Analysis:**

Examining transaction networks and relationships to identify

patterns of fraud, especially in cases of organized fraud rings.

### Time Series Analysis

Studying transaction time series data to detect anomalies and seasonality in fraud patterns.



## THANKYOU