#### Import Pyspark

```
1 !apt-get install openjdk-11-jdk-headless -qq > /dev/null
 2 !wget -qO spark.tgz https://archive.apache.org/dist/spark/spark-3.4.1/spark-3.4.1-bin-hadoop3.1
 3
 4 !mkdir -p /content/spark
 5 !tar -xzf spark.tgz -C /content/spark --strip-components=1
 6 !pip install -q findspark pyspark==3.4.1 seaborn matplotlib pandas scikit-learn
 8 import os, findspark
 9 os.environ["JAVA_HOME"] = "/usr/lib/jvm/java-11-openjdk-amd64"
10 os.environ["SPARK_HOME"] = "/content/spark"
11 findspark.init()
12
13 from pyspark.sql import SparkSession
14 spark = SparkSession.builder.appName("FraudDetection").getOrCreate()
15 print("Spark started successfully!")
16 spark
17
Spark started successfully!
SparkSession - in-memory
SparkContext
Spark UI
Version
      v3.4.1
Master
      local[*]
AppName
      FraudDetection
```

# 🗸 💋 Fraud Detection System

Machine Learning Pipeline for Transaction Fraud Detection

#### Features:

- Class imbalance handling
- PCA dimensionality reduction
- Random Forest classifier

#### 

- 1 from pyspark.sql.functions import col, when
- 2 from pyspark.ml import Pipeline
- 3 from pyspark.ml.feature import StringIndexer, OneHotEncoder, VectorAssembler, PCA
- 4 from pyspark.ml.classification import RandomForestClassifier
- 5 from pyspark.ml.evaluation import BinaryClassificationEvaluator, MulticlassClassificationEvaluator
- 6 import pandas as pd
- 7 import matplotlib.pyplot as plt
- 8 import seaborn as sns

9

10 print("Libraries imported successfully!")

Libraries imported successfully!

#### 

- 1 from google.colab import drive
- 2 drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/c

```
1 # Load CSV data
2 file_path = "/content/drive/MyDrive/Colab Notebooks/content/transactions_train.csv"
3 df = spark.read.csv(file_path, header=True, inferSchema=True)
4
5 # Display dataset info
6 row_count = df.count()
7 col_count = len(df.columns)
8 print(f"Loaded dataset: {row_count:,} rows, {col_count} columns")
9
10 # Preview data
11 display(df.limit(5))
```

Loaded dataset: 6,351,193 rows, 10 columns

DataFrame[step: int, type: string, amount: double, nameOrig: string, oldbalanceOrig: double, newbalanceOrig: double, nameDest: string, oldbalanceDest: double, newbalanceDest: double,

icFraud: intl

### 3. Handle Class Imbalance

```
1 # Calculate class distribution
2 count_0 = df.filter(col("isFraud") == 0).count()
3 count_1 = df.filter(col("isFraud") == 1).count()
4 imbalance_ratio = count_0 / count_1
5
6 print(f"Class Distribution:")
7 print(f" Normal transactions: {count_0:,}")
8 print(f" Fraud transactions: {count_1:,}")
9 print(f" Imbalance ratio: {imbalance_ratio:.2f}:1")
10
11 # Add class weights
```

```
12 df = df.withColumn(
13 "classWeight",
14 when(col("isFraud") == 1, imbalance_ratio).otherwise(1.0)
15 )
16
17 print("Class weights added successfully")

Class Distribution:
Normal transactions: 6,343,476
Fraud transactions: 7,717
Imbalance ratio: 822.01:1
Class weights added successfully
```

# 4. Build ML Pipeline

```
1 # Stage 1: String Indexer (convert categorical to numeric)
2 indexer = StringIndexer() \
      .setInputCol("type") \
3
4
      .setOutputCol("type_index") \
5
      .setHandleInvalid("keep")
6
7 # Stage 2: One-Hot Encoder
8 encoder = OneHotEncoder() \
      .setInputCols(["type_index"]) \
9
10
      .setOutputCols(["type_encoded"])
11
12 # Stage 3: Vector Assembler (combine all features)
13 feature_cols = [
14
      "step",
15
      "amount",
      "oldbalanceOrig",
16
17
      "newbalanceOrig",
18
      "oldbalanceDest",
19
      "newbalanceDest",
      "type_encoded"
20
21 ]
22
23 assembler = VectorAssembler() \
24
      .setInputCols(feature_cols) \
25
      .setOutputCol("features_raw") \
26
      .setHandleInvalid("skip")
27
28 # Stage 4: PCA (dimensionality reduction)
29 pca = PCA(k=5, inputCol="features_raw", outputCol="features")
30
31 # Stage 5: Random Forest Classifier
32 rf = RandomForestClassifier(
33
     labelCol="isFraud",
34
     featuresCol="features",
35
     weightCol="classWeight",
36
     numTrees=100,
37
     maxDepth=10,
     seed=42
```

```
39 )
40
41 # Combine all stages into pipeline
42 pipeline = Pipeline(stages=[indexer, encoder, assembler, pca, rf])
43
44 print("Pipeline built successfully")
45 print(f" Stages: {len(pipeline.getStages())}")

Pipeline built successfully
Stages: 5
```

# 5. Split Data (Train/Test)

```
1 # 70% training, 30% testing
2 train_df, test_df = df.randomSplit([0.7, 0.3], seed=42)
3
4 train_count = train_df.count()
5 test_count = test_df.count()
6
7 print(f"Dataset Split:")
8 print(f" Training set: {train_count:,} rows ({train_count/row_count*100:.1f}%)")
9 print(f" Testing set: {test_count:,} rows ({test_count/row_count*100:.1f}%)")

Dataset Split:
Training set: 4,445,579 rows (70.0%)
Testing set: 1,905,614 rows (30.0%)
```

# 6. Train the Model

```
1 print(" Training Random Forest model...")
2 print(" This may take a few minutes...")
3
4 model = pipeline.fit(train_df)
5
6 print("Model trained successfully!")

Training Random Forest model...
This may take a few minutes...
Model trained successfully!
```

# 7. Make Predictions

```
1 # Transform test data
2 predictions = model.transform(test_df)
3
4 # Display sample predictions
5 print("Sample Predictions:")
6 display(
```

```
predictions.select(
 8
         "type",
9
         "amount",
10
         "isFraud",
         "prediction",
11
         "probability"
12
13
      ).limit(10)
14)
Sample Predictions:
DataFrame[type: string, amount: double, isFraud: int, prediction: double, probability: vector]
```

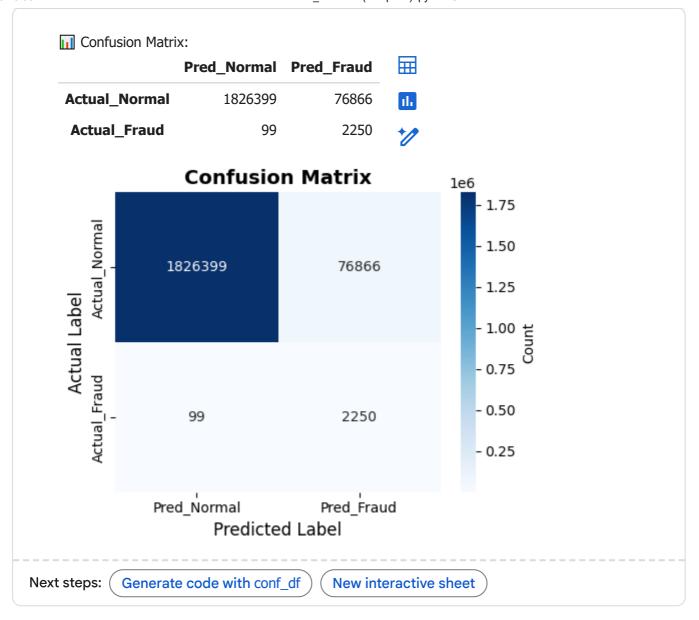
#### 8. Evaluate Model Performance

```
1 # Initialize evaluators
2 evaluator_roc = BinaryClassificationEvaluator(
3
      labelCol="isFraud",
      metricName="areaUnderROC"
4
5)
6
7 evaluator_pr = BinaryClassificationEvaluator(
      labelCol="isFraud",
      metricName="areaUnderPR"
9
10)
11
12 precision_eval = MulticlassClassificationEvaluator(
      labelCol="isFraud",
14
      predictionCol="prediction",
15
      metricName="precisionByLabel"
16)
17
18 recall_eval = MulticlassClassificationEvaluator(
      labelCol="isFraud",
20
      predictionCol="prediction",
21
      metricName="recallByLabel"
22 )
24 f1_eval = MulticlassClassificationEvaluator(
25
      labelCol="isFraud",
      predictionCol="prediction",
26
27
      metricName="f1"
28)
29
30 # Calculate metrics
31 auc_roc = evaluator_roc.evaluate(predictions)
32 auc_pr = evaluator_pr.evaluate(predictions)
33 precision = precision_eval.evaluate(predictions, {precision_eval.metricLabel: 1.0})
34 recall = recall_eval.evaluate(predictions, {recall_eval.metricLabel: 1.0})
35 f1 = f1_eval.evaluate(predictions)
36
37 # Display results
38 print("=" * 40)
```

```
39 print("MODEL PERFORMANCE METRICS")
40 print("=" * 40)
41 print(f"AUC-ROC: {auc_roc:.4f}")
42 print(f"AUC-PR: {auc_pr:.4f}")
43 print(f"Precision: {precision:.4f}")
44 print(f"Recall: {recall:.4f}")
45 print(f"F1-Score: {f1:.4f}")
46 print("=" * 40)
_____
MODEL PERFORMANCE METRICS
_____
AUC-ROC: 0.9938
AUC-PR: 0.6336
Precision: 0.0284
Recall: 0.9579
F1-Score: 0.9782
```

#### 9. Confusion Matrix Visualization

```
1 # Create confusion matrix
2 conf df = predictions \
      . groupBy("isFraud", "prediction") \setminus\\
      .count() \
5
      .toPandas() \
      .pivot(index="isFraud", columns="prediction", values="count") \
6
7
      .fillna(0)
8
9 # Format labels
10 conf_df.columns = ["Pred_Normal", "Pred_Fraud"]
11 conf_df.index = ["Actual_Normal", "Actual_Fraud"]
12
13 print("\n Confusion Matrix:")
14 display(conf_df)
15
16 # Visualize confusion matrix
17 plt.figure(figsize=(5, 4))
18 sns.heatmap(
19
     conf_df,
20
      annot=True,
21
     fmt=".0f",
22
      cmap="Blues",
23
      cbar_kws={'label': 'Count'}
24)
25 plt.title("Confusion Matrix", fontsize=14, fontweight='bold')
26 plt.xlabel("Predicted Label", fontsize=12)
27 plt.ylabel("Actual Label", fontsize=12)
28 plt.tight_layout()
29 display(plt.gcf())
30 plt.close()
```



# 🔍 10. Feature Importance Analysis

```
1 # Extract Random Forest model
2 rf_model = model.stages[-1]
3
4 # Get feature importances
5 importances = rf_model.featureImportances.toArray()
7 # Create feature names (PCA components)
8 feature_names = [f"PCA_Component_{i+1}" for i in range(len(importances))]
10 # Create DataFrame
11 importance_df = pd.DataFrame({
     "Feature": feature_names,
12
13
     "Importance": importances
14 }).sort_values("Importance", ascending=False)
16 print(" Feature Importance (Top to Bottom):")
17 display(importance_df)
```

- 19 # Visualize feature importance 20 plt.figure(figsize=(8, 5)) 21 plt.barh(importance\_df["Feature"], importance\_df["Importance"], color='steelblue') 22 plt.xlabel("Importance Score", fontsize=12) 23 plt.ylabel("Feature", fontsize=12) 24 plt.title("Feature Importance Analysis", fontsize=14, fontweight='bold') 25 plt.gca().invert\_yaxis() 26 plt.tight\_layout() 27 display(plt.gcf()) 28 plt.close() Feature Importance (Top to Bottom): H **Feature Importance 4** PCA\_Component\_5 0.659826 **2** PCA\_Component\_3 0.117488 **1** PCA\_Component\_2 0.116285 **3** PCA\_Component\_4 0.065679 **0** PCA\_Component\_1 0.040723 Feature Importance Analysis PCA\_Component\_5 -PCA\_Component\_3 -PCA\_Component\_2 -PCA\_Component\_4 · PCA\_Component\_1 -0.1 0.2 0.3 0.4 0.5 0.0 0.6 Importance Score Next steps: Generate code with importance\_df New interactive sheet
- iii 11. Final Summary

```
fraud detection(complete).ipynb - Colab
 1 print("=" * 50)
 2 print(" FRAUD DETECTION - FINAL SUMMARY")
3 print("=" * 50)
4 print(f"\n Dataset Information:")
 5 print(f" Total rows: {row_count:,}")
6 print(f" Training set: {train_count:,}")
7 print(f" Testing set: {test count:,}")
8 print(f"\n  Class Balance:")
9 print(f" Normal: {count_0:,} | Fraud: {count_1:,}")
10 print(f" Ratio: {imbalance_ratio:.2f}:1")
11 print(f"\n  Model Performance:")
12 print(f" AUC-ROC: {auc_roc:.4f}")
13 print(f" AUC-PR: {auc_pr:.4f}")
14 print(f" Precision: {precision:.4f}")
15 print(f" Recall: {recall:.4f}")
16 print(f" F1-Score: {f1:.4f}")
17 print("\n ✓ Status: Completed successfully!")
18 print(" ✓ Serverless: Compatible")
19 print(" ✓ Whitelist: Safe")
20 print("=" * 50)
______
FRAUD DETECTION - FINAL SUMMARY
______
Dataset Information:
 Total rows: 6,351,193
 Training set: 4,445,579
 Testing set: 1,905,614
Class Balance:
 Normal: 6,343,476 | Fraud: 7,717
 Ratio: 822.01:1
Model Performance:
 AUC-ROC: 0.9938
 AUC-PR: 0.6336
```

AUC-ROC: 0.9938 AUC-PR: 0.6336 Precision: 0.0284 Recall: 0.9579 F1-Score: 0.9782

Status: Completed successfully!

Serverless: Compatible

Whitelist: Safe

```
1 # รวม HTML Visualization กับผลโมเดล
2 from IPython.display import display, HTML
3
4 # แสดงผลโมเดล
5 display(HTML(f"""
6 <h2>Model Summary</h2>
7 
8 AUC-ROC: {auc_roc:.4f}
9 AUC-PR: {auc_pr:.4f}
10 Precision: {precision:.4f}
```

```
11 Recall: {recall:.4f}
12 F1: {f1:.4f}
13 
14 """))
15
16 # แพรก visualization จาก under.html
17 with open("/content/drive/MyDrive/Colab Notebooks/content/under.html", "r") as f:
18 html_vis = f.read()
19
20 display(HTML(html_vis))
```

23/10/68 1	15:30	fraud_detection(complete).ipynb - Colab
	`	/

```
In [6]: import pandas as pd
        from imblearn.under_sampling import RandomUnderSampler
        from sklearn.preprocessing import LabelEncoder
        from sklearn.model_selection import train_test_split
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.metrics import classification_report, confusion_matrix, accu
        # 1. โหลดข้อมูล
        df = pd.read_csv(r'C:\Users\Asus F15\Downloads\transactions_train.csv', n
        # 2. ตัวอย่างลดขนาดข้อมูล (ถ้าข้อมูลใหญ่มาก)
        df_sample = df.sample(n=600000, random_state=42)
        # 3. แยก X กับ y
        X = df_sample.drop(columns=['isFraud'])
        y = df_sample['isFraud']
        # 4. Label Encoding (แปลง categorical เป็นตัวเลข)
        categorical_cols = X.select_dtypes(include=['object']).columns
        for col in categorical_cols:
            le = LabelEncoder()
            X[col] = le.fit_transform(X[col])
        # 5. ทำ Undersampling
        rus = RandomUnderSampler(random_state=42)
        X_resampled, y_resampled = rus.fit_resample(X, y)
        print("ข้อมูลก่อน undersampling:\n", y.value_counts())
        print("ข้อมูลหลัง undersampling:\n", pd.Series(y_resampled).value_counts())
        # 6. แบ่งข้อมูล train/test
        X_train, X_test, y_train, y_test = train_test_split(
            X_resampled, y_resampled, test_size=0.2, random_state=42, stratify=y_
        # 7. สร้างโมเดล Random Forest
        model = RandomForestClassifier(n_estimators=100, random_state=42)
        # 8. ฝึกโมเดล
        model.fit(X_train, y_train)
        # 9. ทำนายข้อมูล test
        y_pred = model.predict(X_test)
        # 10. ประเมินผลโมเดล
        print("Accuracy:", accuracy_score(y_test, y_pred))
        print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
        print("\nClassification Report:\n", classification_report(y_test, y_pred)
       ข้อมูลก่อน undersampling:
        isFraud
            599639
       0
               361
       Name: count, dtype: int64
```

```
ข้อมูลหลัง undersampling:
        isFraud
          361
            361
       1
       Name: count, dtype: int64
       Accuracy: 0.9448275862068966
       Confusion Matrix:
        [[68 5]
        [ 3 69]]
       Classification Report:
                     precision recall f1-score support
                 0
                        0.96
                                0.93
                                          0.94
                                                      73
                        0.93
                                0.96
                                           0.95
                                                      72
                                           0.94
           accuracy
                                                     145
                      0.95
                                0.94
                                           0.94
          macro avg
                                                     145
       weighted avg
                       0.95
                                 0.94
                                           0.94
                                                     145
In [7]: # 5. ทำ Undersampling
        rus = RandomUnderSampler(random_state=42)
        X_resampled, y_resampled = rus.fit_resample(X, y)
        print("ขนาดข้อมูลก่อน Undersampling:")
        print(y.value_counts())
        print("ขนาดข้อมูลหลัง Undersampling:")
        print(pd.Series(y_resampled).value_counts())
       ขนาดข้อมูลก่อน Undersampling:
       isFraud
           599639
              361
       Name: count, dtype: int64
       ขนาดข้อมูลหลัง Undersampling:
       isFraud
            361
            361
       Name: count, dtype: int64
In [11]: from sklearn.model selection import train test split
        X_train, X_test, y_train, y_test = train_test_split(
            X_resampled, y_resampled, test_size=0.2, random_state=42
In [13]: !pip install xgboost
       Collecting xgboost
         Downloading xgboost-3.0.5-py3-none-win_amd64.whl.metadata (2.1 kB)
       Requirement already satisfied: numpy in c:\users\asus f15\anaconda3\lib\si
       te-packages (from xgboost) (2.1.3)
       Requirement already satisfied: scipy in c:\users\asus f15\anaconda3\lib\si
       te-packages (from xgboost) (1.15.3)
       Downloading xgboost-3.0.5-py3-none-win_amd64.whl (56.8 MB)
            ----- 0.0/56.8 MB ? eta -:--:--
          ----- 0.3/56.8 MB ? eta -:--:-
           ----- 0.8/56.8 MB 2.6 MB/s eta 0:00:
       22
```

fraud_detection(complete).ipynb	- Colab				
34	1.0/56.8	MB 1.6	MB/s	eta	0:00:
35	1.3/56.8	MB 1.6	MB/s	eta	0:00:
32	1.8/56.8	MB 1.8	MB/s	eta	0:00:
26	2.6/56.8	MB 2.1	MB/s	eta	0:00:
26	2.6/56.8	MB 2.1	MB/s	eta	0:00:
32	2.9/56.8	MB 1.7	MB/s	eta	0:00:
30	3.4/56.8	MB 1.8	MB/s	eta	0:00:
28	3.9/56.8	MB 1.9	MB/s	eta	0:00:
27	4.5/56.8	MB 2.0	MB/s	eta	0:00:
26	4.7/56.8	MB 2.0	MB/s	eta	0:00:
29	5.0/56.8	MB 1.8	MB/s	eta	0:00:
28	5.5/56.8	MB 1.9	MB/s	eta	0:00:
26	6.3/56.8	MB 2.0	MB/s	eta	0:00:
25	6.6/56.8	MB 2.0	MB/s	eta	0:00:
25	6.6/56.8	MB 2.0	MB/s	eta	0:00:
28	6.8/56.8	MB 1.8	MB/s	eta	0:00:
27	7.3/56.8	MB 1.9	MB/s	eta	0:00:
27	7.9/56.8	MB 1.9	MB/s	eta	0:00:
27	7.9/56.8	MB 1.9	MB/s	eta	0:00:
27	8.1/56.8	MB 1.8	MB/s	eta	0:00:
28	8.4/56.8	MB 1.8	MB/s	eta	0:00:
28	8.9/56.8	MB 1.8	MB/s	eta	0:00:
28	8.9/56.8	MB 1.8	MB/s	eta	0:00:
29	9.2/56.8	MB 1.7	MB/s	eta	0:00:
29	9.4/56.8	MB 1.7	MB/s	eta	0:00:
29	9.4/56.8	MB 1.7	MB/s	eta	0:00:
0:29	10.0/56.8	MB 1.	6 MB/s	eta	0:0
0:28	10.5/56.8	MB 1.	7 MB/s	eta	0:0
0:29	10.7/56.8	MB 1.	6 MB/s	eta	0:0
0:28	11.3/56.8	MB 1.	7 MB/s	eta	0:0
0:27	11.5/56.8	MB 1.	7 MB/s	eta	0:0

iradu_detection(complete).ipyrib	Colab					
0:28	11.8/56.8	MB	1.7	MB/s	eta	0:0
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0:29	12.1/56.8	MB	1.6	MB/s	eta	0:0
0:29	12.3/56.8	MB	1.6	MB/s	eta	0:0
0:28	12.8/56.8	MB	1.6	MB/s	eta	0:0
0:27	13.6/56.8	MB	1.6	MB/s	eta	0:0
	13.9/56.8	MB	1.7	MB/s	eta	0:0
0:26	13.9/56.8	MB	1.7	MB/s	eta	0:0
0:26	14.2/56.8	МВ	1.6	MB/s	eta	0:0
0:27	14.9/56.8	МВ	1.6	MB/s	eta	0:0
0:26	15.2/56.8	МВ	1.7	MB/s	eta	0:0
0:26	15.2/56.8	МВ	1.7	MB/s	eta	0:0
0:26	16.0/56.8	МВ	1.6	MB/s	eta	0:0
0:25	16.8/56.8	МВ	1.7	MB/s	eta	0:0
0:24	17.6/56.8	MB	1.7	MB/s	eta	0:0
0:23	18.4/56.8	MB	1.8	MB/s	eta	0:0
0:22						
0:21	19.4/56.8					
0:21						
0:21						
0:20						
0:20						
0:20						
0:20	21.2/56.8	MB	1.8	MB/s	eta	0:0
0:20	22.0/56.8	MB	1.8	MB/s	eta	0:0
0:20	22.0/56.8	MB	1.8	MB/s	eta	0:0
0:20	22.3/56.8	MB	1.8	MB/s	eta	0:0
0:20	22.5/56.8	MB	1.8	MB/s	eta	0:0
0:20	22.8/56.8	MB	1.8	MB/s	eta	0:0
0:20	23.1/56.8	MB	1.8	MB/s	eta	0:0
0:19	23.6/56.8	MB	1.8	MB/s	eta	0:0
A·10	24.4/56.8	MB	1.8	MB/s	eta	0:0

9:18	"aud_detection(complete).ipy	is Colas
8:18       25.4/56.8 MB 1.8 MB/s eta 0:0         0:18       25.7/56.8 MB 1.8 MB/s eta 0:0         0:17       27.5/56.8 MB 1.9 MB/s eta 0:0         0:16       27.5/56.8 MB 1.7 MB/s eta 0:0         0:17       28.6/56.8 MB 1.7 MB/s eta 0:0         0:17       28.6/56.8 MB 1.7 MB/s eta 0:0         0:17       29.1/56.8 MB 1.7 MB/s eta 0:0         0:17       30.1/56.8 MB 1.7 MB/s eta 0:0 <td< th=""><th></th><th> 24.9/56.8 MB 1.8 MB/s eta 0:0</th></td<>		24.9/56.8 MB 1.8 MB/s eta 0:0
0:18		25.4/56.8 MB 1.8 MB/s eta 0:0
9:18		25.7/56.8 MB 1.8 MB/s eta 0:0
9:17  9:16  9:16	0:18	
27.5/56.8 MB 1.9 MB/s eta 0:0 27.5/56.8 MB 1.7 MB/s eta 0:0 27.5/5	9:17	
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