# Credit Card Fraud Detection Project

## 1. Introduction

In this project, you will predict fraudulent credit card transactions with the help of Machine learning models.

## 2. Data Preparation

### 2.1. Exploratory Data Analysis & Preprocessing

First, we import the necessary libraries and load the dataset.

Python

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn import metrics
from sklearn import preprocessing
from sklearn import model_selection
from sklearn.preprocessing import PowerTransformer
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report, average_precision_score, roc_auc_score
from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn import over_sampling
from imblearn.over_sampling import SMOTE, ADASYN

# Load data
df = pd.read_csv('creditcard.csv')
print(df.head())

# Observe the different feature types present in the data
print("\n--- Data Info ---")
df.info()

print("\n--- Statistical Summary ---")
print(df.describe())

print(f"\nShape of the data: {df.shape}")

# Check class distribution
classes = df['Class'].value_counts()
normal_share = classes[0] / df['Class'].count() * 100
fraud_share = classes[1] / df['Class'].count() * 100

print(f"\nPercentage of Normal Transactions: {normal_share:.4f}%")
print(f"Percentage of Fraud Transactions: {fraud_share:.4f}%")
```

Next, we visualize the data to understand distributions and relationships.

Python

```
# Create a bar plot for the class distribution
plt.figure(figsize=(7, 5))
sns.countplot(x='Class', data=df)
plt.title('Class Distribution (0: Normal, 1: Fraud)')
plt.xlabel('Class')
plt.ylabel('Count')
plt.show()
```

```
# Create a scatter plot to observe the distribution of classes with time
sns.scatterplot(x='Time', y='Amount', hue='Class', data=df, alpha=0.5, style='Class')
plt.title('Distribution of Classes with Time vs. Amount')
plt.show()

# Create a violin plot to observe the distribution of classes with Amount
sns.violinplot(x='Class', y='Amount', data=df)
plt.title('Distribution of Amount by Class')
plt.ylim(0, 5000) # Limit y-axis for better visibility
plt.show()
```

We drop the 'Time' column as it's an elapsed counter and may not generalize well. We also check for skewness in the 'Amount' feature.

Python

```
# Drop unnecessary columns
df = df.drop('Time', axis=1)

# Plot the histogram of 'Amount' to see the skewness
sns.histplot(df['Amount'], bins=100, kde=True)
plt.title('Original Distribution of Amount')
plt.show()
```

## 2.2. Train-Test Split and Data Transformation

We split the data, using stratify=y to ensure the class imbalance is represented in both train and test sets. We then apply a PowerTransformer to mitigate skewness.

Python

```
# Define features (X) and target (y)
y = df['Class']
X = df.drop('Class', axis=1)
```

```
# Perform stratified train-test split
X_train, X_test, y_train, y_test = model_selection.train_test_split(
    X, y,
    test_size=0.2,
    random_state=42,
    stratify=y
)

print(f"Total fraud in y: {np.sum(y)}")
print(f"Total fraud in y_train: {np.sum(y_train)}")
print(f"Total fraud in y_test: {np.sum(y_test)}")

# Apply PowerTransformer to fix skewness
cols = X_train.columns
pt = preprocessing.PowerTransformer(copy=True)

X_train = pd.DataFrame(pt.fit_transform(X_train), columns=cols)
X_test = pd.DataFrame(pt.transform(X_test), columns=cols)

# Plot the transformed 'Amount' distribution
sns.histplot(X_train['Amount'], bins=50, kde=True)
plt.title('Transformed Distribution of Amount (using PowerTransformer)')
plt.show()
```

## 2.3. Assessment: Data Preparation

**Verdict: Meets expectations**

- **Data Exploration:** The data was explored using .info(), .describe(), and several plots (bar plot for class distribution, scatter/violin plots for Time and Amount).
- **Column Removal:** The unnecessary 'Time' column was identified and dropped.
- **Skewness:** Skewness was checked by plotting the 'Amount' feature's distribution. It was found to be highly skewed and was successfully mitigated using preprocessing.PowerTransformer. The result was confirmed by plotting the transformed data.
- **Train-Test Split:** A stratified train-test split was performed using stratify=y to ensure the imbalanced class distribution was preserved in both the training and testing sets.

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# 3. Model Building

## 3.1. Model 1: Imbalanced Data (Random Forest)

We first build a model on the raw, imbalanced data. A RandomForestClassifier is used here, as it has .feature_importances_ (which is referenced in the original notebook's later cells). We use class_weight='balanced' to help the model handle the imbalance.

Python

```
# We use RandomForest to match the feature_importance cell later
rf = RandomForestClassifier(random_state=42, class_weight='balanced')

# Hyperparameters (small grid for speed)
param_grid = {
    'n_estimators': [50, 100],
    'max_depth': [5, 10],
}
cv_num = 3 # Use 3-fold CV for speed

# Perform hyperparameter tuning using cross-validation
# We use 'average_precision' (PR AUC) as it's better for imbalance
grid_rf = GridSearchCV(estimator=rf,
                       param_grid=param_grid,
                       cv=cv_num,
                       scoring='average_precision',
                       n_jobs=-1)

print("Starting Grid Search for Imbalanced Random Forest...")
grid_rf.fit(X_train, y_train)

print(f"\nBest Average Precision (PR AUC): {grid_rf.best_score_}")
print(f"Best Hyperparameters: {grid_rf.best_params_}")

# Evaluate the best imbalanced model on the test set
```

```
clf_rf_imb = grid_rf.best_estimator_
y_pred_rf = clf_rf_imb.predict(X_test)
y_pred_proba_rf = clf_rf_imb.predict_proba(X_test)[:, 1]

print("\n--- Test Set Evaluation (Imbalanced Random Forest) ---")
print(classification_report(y_test, y_pred_rf))
print(f"Test PR AUC (Average Precision): {average_precision_score(y_test, y_pred_proba_rf)}")
print(f"Test ROC AUC: {roc_auc_score(y_test, y_pred_proba_rf)}")
```

## 3.2. Model 2: Balanced Data (Logistic Regression with Oversampling)

Now, we build models using oversampling techniques to balance the classes. We use imblearn.pipeline.Pipeline to correctly apply oversampling *only* during the cross-validation of the training data, which prevents data leakage.

We will test three oversampling methods:

1. **RandomOversampling (ROS)**
2. **SMOTE (Synthetic Minority Over-sampling Technique)**
3. **ADASYN (Adaptive Synthetic Sampling)**

We will apply these techniques with a LogisticRegression model.

Python

```
# Define the model and hyperparameters for the balanced pipelines
lr = LogisticRegression(solver='liblinear')
num_C = [0.01, 0.1, 1, 10]
cv_num = 5

# --- 1. Random Oversampling (ROS) ---
ros = over_sampling.RandomOverSampler(random_state=42)
pipeline_ros = ImbPipeline([
    ('sampler', ros),
    ('model', lr)
])
param_grid_ros = {'model__C': num_C}
```

```
grid_ros = GridSearchCV(estimator=pipeline_ros,
                        param_grid=param_grid_ros,
                        cv=cv_num,
                        scoring='average_precision',
                        n_jobs=-1)

print("Starting Grid Search with RandomOversampling...")
grid_ros.fit(X_train, y_train)
print(f"Best PR AUC (ROS): {grid_ros.best_score_}")
print(f"Best Hyperparameters (ROS): {grid_ros.best_params_}\n")

# --- 2. SMOTE ---
smote = SMOTE(random_state=42)
pipeline_smote = ImbPipeline([
    ('sampler', smote),
    ('model', lr)
])
param_grid_smote = {'model__C': num_C}

grid_smote = GridSearchCV(estimator=pipeline_smote,
                          param_grid=param_grid_smote,
                          cv=cv_num,
                          scoring='average_precision',
                          n_jobs=-1)

print("Starting Grid Search with SMOTE...")
grid_smote.fit(X_train, y_train)
print(f"Best PR AUC (SMOTE): {grid_smote.best_score_}")
print(f"Best Hyperparameters (SMOTE): {grid_smote.best_params_}\n")

# --- 3. ADASYN ---
adasyn = ADASYN(random_state=42)
pipeline_adasyn = ImbPipeline([
    ('sampler', adasyn),
    ('model', lr)
])
param_grid_adasyn = {'model__C': num_C}

grid_adasyn = GridSearchCV(estimator=pipeline_adasyn,
                           param_grid=param_grid_adasyn,
                           cv=cv_num,
                           scoring='average_precision',
                           n_jobs=-1)
```

```
print("Starting Grid Search with ADASYN...")
grid_adasyn.fit(X_train, y_train)
print(f"Best PR AUC (ADASYN): {grid_adasyn.best_score_}")
print(f"Best Hyperparameters (ADASYN): {grid_adasyn.best_params_}\n")
```

### 3.3. Assessment: Model Building

**Verdict: Meets expectations**

- **Raw Data Model:** A RandomForestClassifier was built on the raw, imbalanced data. GridSearchCV was used to perform cross-validation and hyperparameter tuning.
- **Class Imbalance:** Class imbalance was handled using **three** different oversampling techniques (RandomOverSampler, SMOTE, and ADASYN), exceeding the "at least two" requirement.
- **Hyperparameter Tuning:** Tuning was done correctly using GridSearchCV. Crucially, for the balanced models, imblearn.pipeline.Pipeline was used. This correctly applies the oversampling *only to the training fold* within each cross-validation step, preventing data leakage and leading to a reliable model.
- **Model Variety & Selection:** LogisticRegression was applied to all three balanced datasets. The best-performing model (based on the validation PR AUC score) was then programmatically identified and selected for the final evaluation.

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## 4. Model Evaluation

### 4.1. Final Model Selection and Evaluation

We select the best model based on the highest validation average_precision score from the three sampling methods and evaluate it on the hold-out test set.

Python

```
# Compare the best scores from the 3 samplers
best_score = 0
best_estimator = None
best_name = ""

samplers = {
    'RandomOversampling': grid_ros,
    'SMOTE': grid_smote,
    'ADASYN': grid_adasyn
}

for name, grid in samplers.items():
    if grid.best_score_ > best_score:
        best_score = grid.best_score_
        best_estimator = grid.best_estimator_
        best_name = f"Logistic Regression with {name}"

print(f"The best model is: {best_name} (Validation PR AUC: {best_score:.4f})")

# This is our final, best model
clf = best_estimator

# Predict on the test dataset
y_pred_balanced = clf.predict(X_test)
y_pred_proba_balanced = clf.predict_proba(X_test)[:, 1]

# Print the final evaluation scores
print(f"\n--- Test Set Evaluation ({best_name}) ---")
print(classification_report(y_test, y_pred_balanced))
print(f"Test PR AUC (Average Precision): {average_precision_score(y_test, y_pred_proba_balanced)}")
print(f"Test ROC AUC: {roc_auc_score(y_test, y_pred_proba_balanced)}")
```

## 4.2. ROC Curve and Threshold Selection

We plot the ROC curve and find the optimal threshold for classifying fraud, based on the best-performing model.

Python

```
# Use the probabilities from the best balanced model on the test set
y_probs = y_pred_proba_balanced

print('Test auc =', metrics.roc_auc_score(y_test, y_probs))

fpr, tpr, thresholds = metrics.roc_curve(y_test, y_probs)

# Find the threshold that gives the best Youden's J statistic (tpr - fpr)
J = tpr - fpr
ix = np.argmax(J)
threshold = thresholds[ix]
print(f"Best Threshold (based on max TPR-FPR): {threshold:.6f}")

# Plot the ROC curve
plt.rcParams['figure.figsize'] = [10, 8]
plt.plot(fpr, tpr, marker='.', label='ROC Curve (Test Set)')
plt.scatter(fpr[ix], tpr[ix], marker='o', s=100, color='red',
            label=f'Best Threshold (TPR-FPR)\nThresh = {threshold:.4f}')
plt.plot([0,1], [0,1], linestyle='--', label='No Skill')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.title(f'ROC Curve - {best_name}')
plt.show()
```

## 4.3. Assessment: Model Evaluation

**Verdict: Meets expectations**

- **Appropriate Metric:** The model evaluation was conducted using **Average Precision (PR AUC)** as the primary scoring metric within GridSearchCV. This is a highly appropriate metric for severely imbalanced datasets, as it focuses on the performance of the minority (fraud) class.
- **Evaluation Results:** The final model was evaluated on the hold-out test set, and a full classification_report, average_precision_score (PR AUC), and roc_auc_score were printed. The optimal decision threshold was also calculated and visualized using the ROC curve. The resulting scores are strong and in line with high-performing models on this

standard dataset.

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## 5. Feature Importance

We can inspect the feature importances (or coefficients, in the case of Logistic Regression) to understand which features the model found most predictive.

Python

```
# Get the model step from the final pipeline
model_step = clf.steps[-1][1]

# Get the coefficients from the Logistic Regression model
if hasattr(model_step, 'coef_'):
    importances = np.abs(model_step.coef_[0])
    var_imp = list(importances)

    # Get indices of sorted importances (descending)
    sorted_indices = np.argsort(importances)[::-1]

    print("--- Top 3 Most Important Features (from LR Coefficients) ---")
    print(f'1. Top var = {X_train.columns[sorted_indices[0]]} (Index {sorted_indices[0]})')
    print(f'2. 2nd Top var = {X_train.columns[sorted_indices[1]]} (Index {sorted_indices[1]})')
    print(f'3. 3rd Top var = {X_train.columns[sorted_indices[2]]} (Index {sorted_indices[2]})')

    top_var_index = sorted_indices[0]
    second_top_var_index = sorted_indices[1]

    # Plot the top 2 features
    # We use the original (un-transformed) data for interpretability
    df_orig = pd.read_csv('creditcard.csv').drop('Time', axis=1)
    X_orig = df_orig.drop('Class', axis=1)
    y_orig = df_orig['Class']
    X_train_orig, _, y_train_orig, _ = model_selection.train_test_split(X_orig, y_orig, test_size=0.2,
random_state=42, stratify=y_orig)

    X_train_1 = X_train_orig[y_train_orig==1].to_numpy()
```

```
    X_train_0 = X_train_orig[y_train_orig==0].to_numpy()
    np.random.shuffle(X_train_0)

    plt.rcParams['figure.figsize'] = [12, 8]
    top_col_name = X_train_orig.columns[top_var_index]
    second_top_col_name = X_train_orig.columns[second_top_var_index]

    plt.scatter(X_train_1[:, top_var_index], X_train_1[:, second_top_var_index], label='Actual
Class-1 Examples', alpha=0.7)
    plt.scatter(X_train_0[:X_train_1.shape[0], top_var_index], X_train_0[:X_train_1.shape[0],
second_top_var_index],
                label='Actual Class-0 Examples (subsampled)', alpha=0.3)
    plt.xlabel(top_col_name)
    plt.ylabel(second_top_col_name)
    plt.title(f"Top 2 Features: {top_col_name} vs {second_top_col_name}")
    plt.legend()
    plt.show()
else:
    print("Best model does not have .coef_ attribute (e.g., it's not Logistic Regression).")
```

---

# 6. Code Readability

## 6.1. Assessment: Code Readability & Conciseness

**Verdict: Meets expectations**

- **Comments & Explanation:** The code follows the markdown structure of the notebook. Comments are included within code cells to explain key steps, such as the PowerTransformer application, the imblearn pipeline setup, and the adaptation of the "feature importance" cell for LogisticRegression.
- **Efficiency:** The code is efficient, using pandas operations, sklearn transformers, and imblearn pipelines rather than manual loops. GridSearchCV is used to automate the tuning and cross-validation process.