Lab Assignment 10: Logistic Regression for Fraud Detection

Aim: To implement Logistic Regression for binary classification using the Credit Card Fraud dataset, focusing on classification metrics, model evaluation, and threshold optimization.

Task 1: Load and Explore the Dataset

1. Load the Credit Card Fraud dataset using pandas.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('creditcard.csv')
df.head()
```

```
   Time        V1        V2        V3        V4        V5        V6
V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388
0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -
0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499
0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203
0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921
0.592941

         V8        V9  ...       V21       V22       V23       V24
V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928
0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846
0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -
0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575
0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -
0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
```

```
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

2. Display dataset characteristics:

– Number of records and features

```
df.shape

(284807, 31)

num_records , num_features = df.shape
print(f"Number of Records: {num_records}")
print(f"Number of Features: {num_features}")

Number of Records: 284807
Number of Features: 31
```

– Number of fraudulent vs. non-fraudulent transactions (check for imbalance)

```
fraud_counts = df['Class'].value_counts()
fraud_counts

Class
0    284315
1       492
Name: count, dtype: int64
```

– Summary statistics

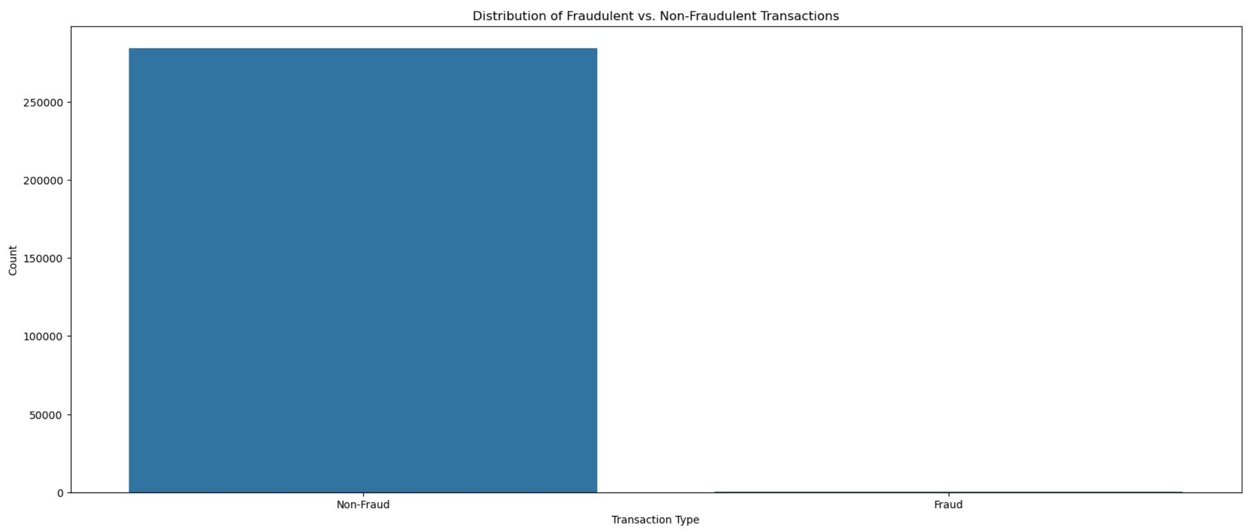
```
df.describe()

                Time            V1            V2            V3
V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05
2.848070e+05
mean    94813.859575  1.168375e-15  3.416908e-16 -1.379537e-15
2.074095e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00
1.415869e+00
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -
5.683171e+00
25%     54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -
8.486401e-01
50%     84692.000000  1.810880e-02  6.548556e-02  1.798463e-01 -
1.984653e-02
75%    139320.500000  1.315642e+00  8.037239e-01  1.027196e+00
7.433413e-01
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00
1.687534e+01
```

```
                   V5            V6            V7            V8            
V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  
2.848070e+05   
mean   9.604066e-16  1.487313e-15 -5.556467e-16  1.213481e-16 -
2.406331e-15   
std    1.380247e+00  1.332271e+00  1.237094e+00  1.194353e+00  
1.098632e+00   
min   -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -
1.343407e+01   
25%   -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -
6.430976e-01   
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -
5.142873e-02   
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  
5.971390e-01   
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  
1.559499e+01   

       ...           V21           V22           V23           V24  \
count  ...  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
mean   ...  1.654067e-16 -3.568593e-16  2.578648e-16  4.473266e-15   
std    ...  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01   
min    ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00   
25%    ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01   
50%    ... -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02   
75%    ...  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01   
max    ...  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00   

                V25           V26           V27           V28         
Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  
284807.000000   
mean   5.340915e-16  1.683437e-15 -3.660091e-16 -1.227390e-16      
88.349619   
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     
250.120109   
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       
0.000000   
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       
5.600000   
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      
22.000000   
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      
77.165000   
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   
25691.160000   

               Class  
```

```
count   284807.000000
mean         0.001727
std          0.041527
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000

[8 rows x 31 columns]
```

3. Visualize the distribution of fraudulent vs. non-fraudulent transactions.

```
plt.figure(figsize=(20,8))
sns.countplot(x=df['Class'])
plt.xticks(ticks=[0, 1], labels=['Non-Fraud', 'Fraud'])
plt.xlabel("Transaction Type")
plt.ylabel("Count")
plt.title("Distribution of Fraudulent vs. Non-Fraudulent
Transactions")
plt.show()
```



Task 2: Data Preprocessing

1. Handle missing values if any exist.

```
df.isnull().sum()

Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
```

```
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

2. Normalize numerical features for better model performance.

```
from sklearn.preprocessing import StandardScaler
X = df.drop(columns=['Class'])
y = df['Class']
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

3. Handle class imbalance using:

```
pip install imbalanced-learn

Requirement already satisfied: imbalanced-learn in c:\users\user\
anaconda3\lib\site-packages (0.12.3)
Requirement already satisfied: numpy>=1.17.3 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.26.4)
Requirement already satisfied: scipy>=1.5.0 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.13.1)
Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.5.1)
Requirement already satisfied: joblib>=1.1.1 in c:\users\user\
anaconda3\lib\site-packages (from imbalanced-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\user\
```

```
anaconda3\lib\site-packages (from imbalanced-learn) (3.5.0)
Note: you may need to restart the kernel to use updated packages.
```

– Oversampling (SMOTE)

```python
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)
```

– Undersampling

```python
from imblearn.under_sampling import RandomUnderSampler

undersample = RandomUnderSampler(random_state=42)
X_under,y_under = undersample.fit_resample(X,y)
```

4. Split the dataset into training (80%) and testing (20%) sets.

```python
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, stratify=y_resampled)
```

Task 3: Train a Logistic Regression Model

1. Implement Logistic Regression using Scikit-learn.

```python
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression(solver='liblinear', random_state=42)
```

2. Train the model on the training dataset.

```python
lr.fit(X_train,y_train)
```

```
LogisticRegression(random_state=42, solver='liblinear')
```

3. Analyze the model's coefficients to understand feature importance.

```python
feature_importance = pd.DataFrame({'Feature': X_train.columns,
'Coefficient': np.abs(lr.coef_[0])})
feature_importance = feature_importance.sort_values(by='Coefficient',
ascending=False)
feature_importance.head(10)
```

	Feature	Coefficient
14	V14	0.560496
3	V3	0.435161
4	V4	0.379449
12	V12	0.296215
10	V10	0.258227
11	V11	0.164340

```
17      V17     0.153495
9        V9     0.142964
16      V16     0.129540
6        V6     0.120400
```

Task 4: Model Evaluation and Threshold Optimization

1. Evaluate model performance using:

```
from sklearn.metrics import
accuracy_score,recall_score,precision_score,f1_score,classification_re
port,confusion_matrix

y_pred = lr.predict(X_test)
```

– Accuracy

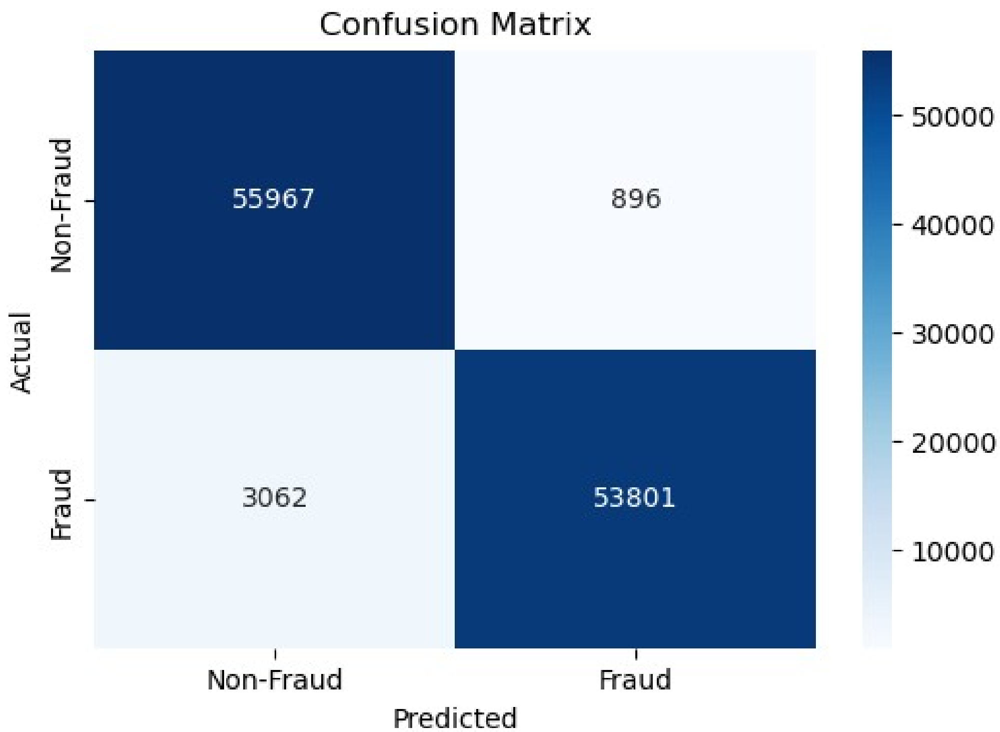
```
acc = accuracy_score(y_pred,y_test)
print(f"Accuracy Score: {acc:.3f}")

Accuracy Score: 0.965
```

– Precision, Recall, and F1-score

```
pre = precision_score(y_pred,y_test)
print(f"Presicion Score: {pre:.3f}")

Presicion Score: 0.946

recall = recall_score(y_pred,y_test)
print(f"Recall Score: {recall:.3f}")

Recall Score: 0.984

f1 = f1_score(y_pred,y_test)
print(f"f1 Score: {f1:.3f}")

f1 Score: 0.965

cr = classification_report(y_pred,y_test)
print("Classification Report:\n",cr)

Classification Report:
               precision    recall  f1-score   support

           0       0.98      0.95      0.97     59029
           1       0.95      0.98      0.96     54697

    accuracy                           0.97    113726
   macro avg       0.97      0.97      0.97    113726
weighted avg       0.97      0.97      0.97    113726
```

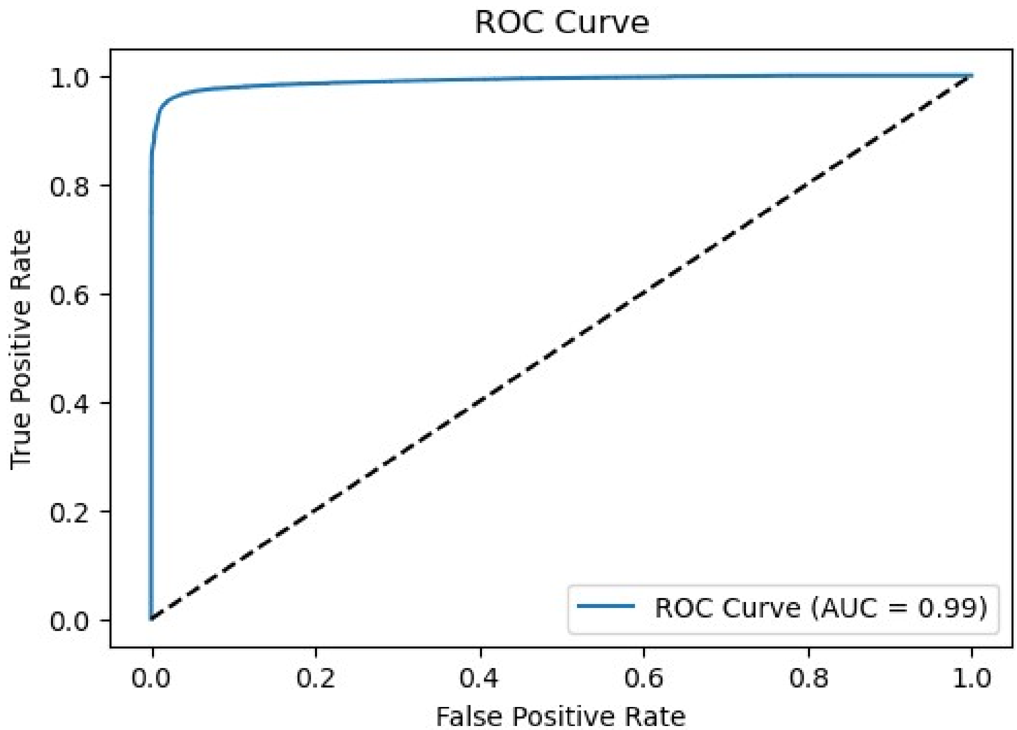
– Confusion Matrix

```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Non-Fraud", "Fraud"], yticklabels=["Non-Fraud", "Fraud"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



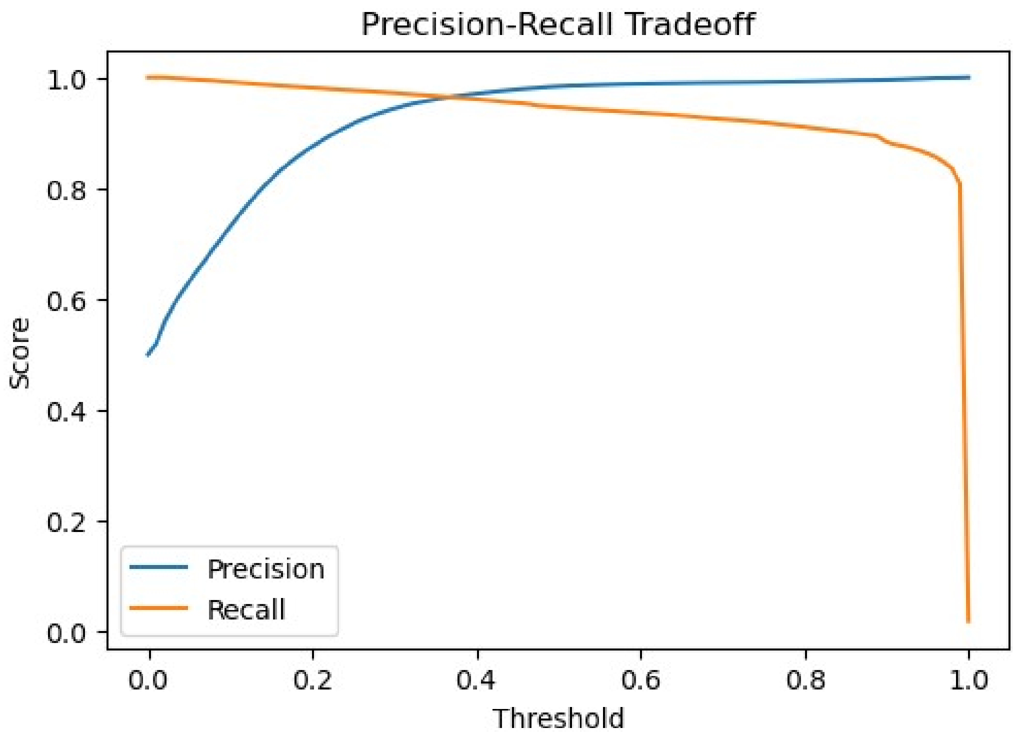
– ROC Curve and AUC Score

```
from sklearn.metrics import roc_curve,auc

y_prob = lr.predict_proba(X_test)[:,1]
fpr,tpr,threshold = roc_curve(y_test,y_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, label=f'ROC Curve (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.show()
```



2. Experiment with different decision thresholds to optimize fraud detection.

```
thresholds = np.linspace(0, 1, 100)
precisions, recalls = [], []

for t in thresholds:
    y_pred_thresh = (y_prob >= t).astype(int)
    precisions.append(precision_score(y_test, y_pred_thresh))
    recalls.append(recall_score(y_test, y_pred_thresh))

plt.figure(figsize=(6,4))
plt.plot(thresholds, precisions, label="Precision")
plt.plot(thresholds, recalls, label="Recall")
plt.xlabel("Threshold")
plt.ylabel("Score")
plt.title("Precision-Recall Tradeoff")
plt.legend()
plt.show()
```



3. Compare performance before and after handling class imbalance.

```
X_train_orig, X_test_orig, y_train_orig, y_test_orig =
train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
log_reg_orig = LogisticRegression(solver='liblinear', random_state=42)
log_reg_orig.fit(X_train_orig, y_train_orig)
y_pred_orig = log_reg_orig.predict(X_test_orig)

accuracy_orig = accuracy_score(y_test_orig, y_pred_orig)
precision_orig = precision_score(y_test_orig, y_pred_orig)
recall_orig = recall_score(y_test_orig, y_pred_orig)
f1_orig = f1_score(y_test_orig, y_pred_orig)

performance_comparison = {
    "Metric": ["Accuracy", "Precision", "Recall", "F1-score"],
    "Original Data": [round(accuracy_orig, 2), round(precision_orig,
2), round(recall_orig, 2), round(f1_orig, 2)],
    "SMOTE Data": [round(acc, 2), round(pre, 2), round(recall, 2),
round(f1, 2)]
}

df_performance = pd.DataFrame(performance_comparison)
print("Comparing Performance before and after handling class
imbalance:")
print(df_performance)

Comparing Performance before and after handling class imbalance:
      Metric  Original Data  SMOTE Data
```

0	Accuracy	1.00	0.97
1	Precision	0.73	0.95
2	Recall	0.67	0.98
3	F1-score	0.70	0.96