In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKF
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.metrics import (confusion_matrix, classification_report,roc_auc_scc
import joblib
# imbalanced-learn
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
```

In [2]:
```
df = pd.read_csv(r"C:\Users\veera\Downloads\PRANAV B\docs\projects\Transactional
df.shape, df['Class'].value_counts()
```

Out[2]:
```
((284807, 31),
 Class
 0    284315
 1       492
 Name: count, dtype: int64)
```

In [3]:
```
# Cell 3 — feature engineering
df = df.copy()
# Hour feature (0-23)
df['Hour'] = ((df['Time'] / 3600) % 24).astype(int)
# Log transform amount
df['Amount_log'] = np.log1p(df['Amount'])
# Features list (V1..V28 exist in the dataset)
pca_cols = [c for c in df.columns if c.startswith('V')]
feature_cols = pca_cols + ['Amount_log', 'Hour']
target_col = 'Class'

# Quick check
df[feature_cols + [target_col]].head()
```

Out[3]:

	V1	V2	V3	V4	V5	V6	V7	V8
0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698
1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102
2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676
3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436
4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533

5 rows × 31 columns

In [4]:
```
# Cell 4 — train/test split (stratified)
X = df[feature_cols]
y = df[target_col]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.20, random_state=42, stratify=y
```

```
)

print("Train shape:", X_train.shape, "Test shape:", X_test.shape)
print("Train class distribution:\n", y_train.value_counts(normalize=True))
```

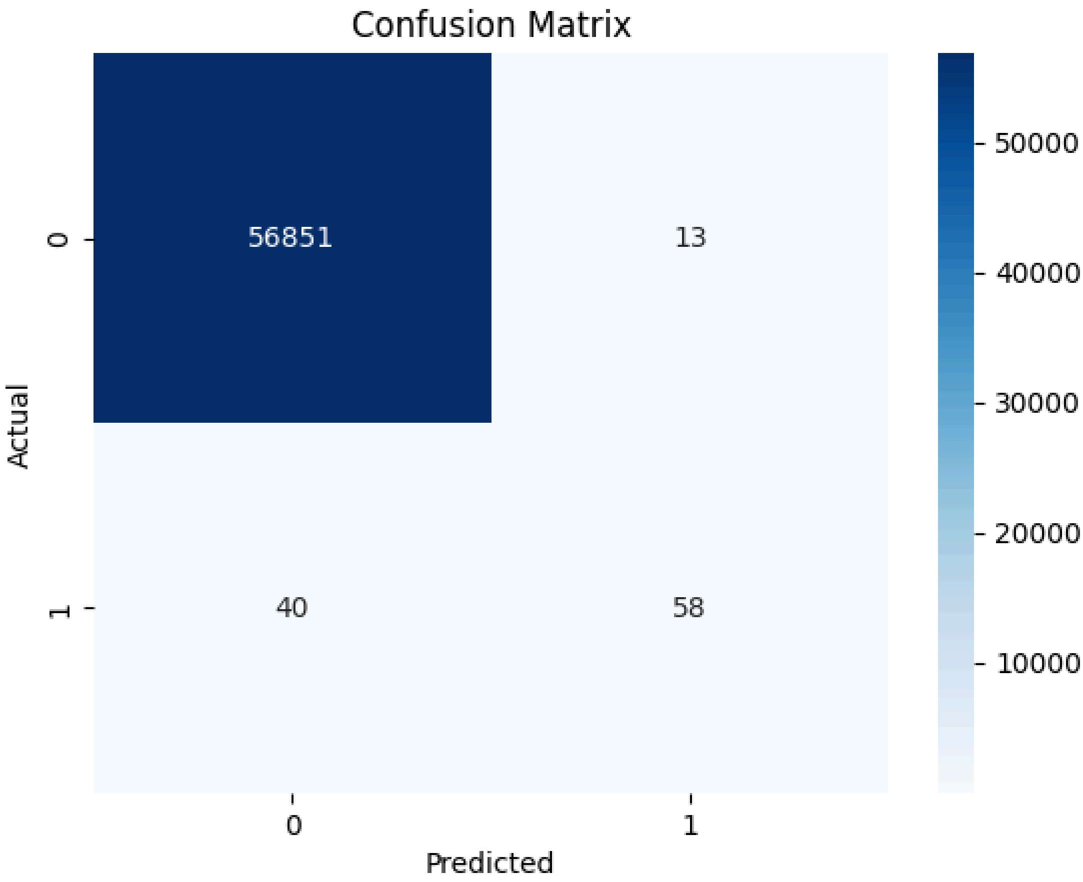
```
Train shape: (227845, 30) Test shape: (56962, 30)
Train class distribution:
 Class
0    0.998271
1    0.001729
Name: proportion, dtype: float64
```

In [6]:
```
# Cell 5 — Baseline pipeline: scaling + logistic regression (class_weight)
pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('clf', LogisticRegression(solver='liblinear', max_iter=1000, random_state=4
])

param_grid = {
    'clf__C': [0.01, 0.1, 1, 10],
    'clf__class_weight': [None, 'balanced']
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

gs = GridSearchCV(pipe, param_grid, cv=cv, scoring='roc_auc', n_jobs=-1, verbose
gs.fit(X_train, y_train)

print("Best params:", gs.best_params_)
print("Best CV ROC-AUC:", gs.best_score_)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
Best params: {'clf__C': 0.01, 'clf__class_weight': None}
Best CV ROC-AUC: 0.9826883575841971
```

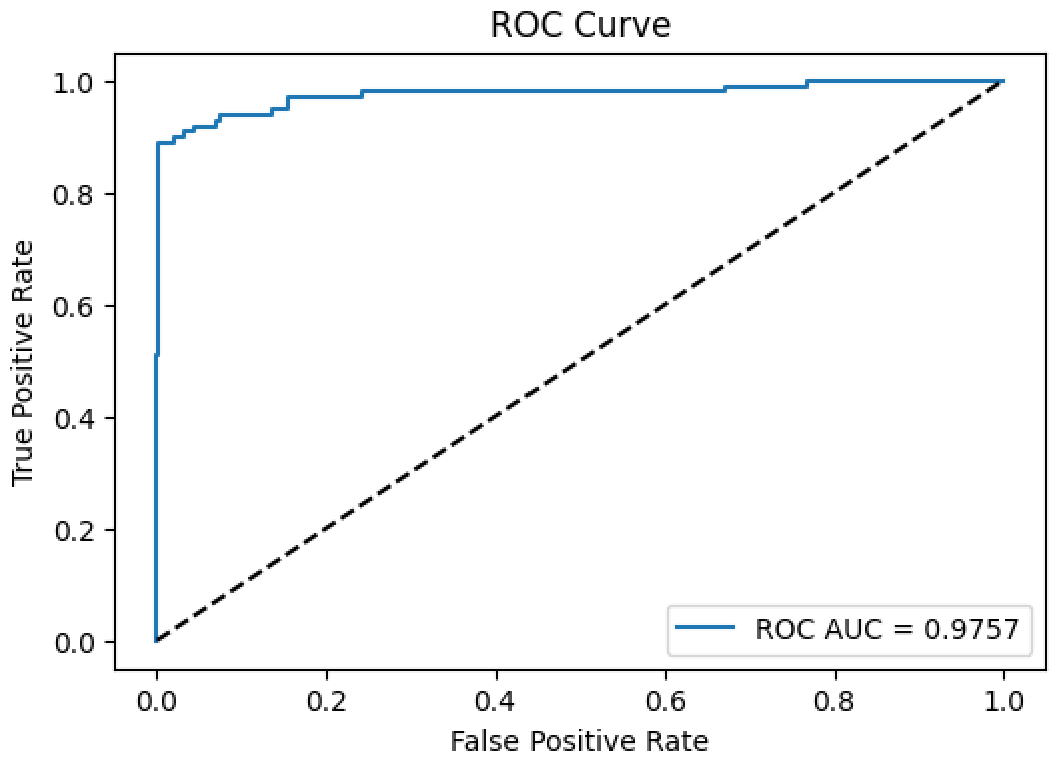
In [7]:
```
# Cell 6 — Evaluate on test set (pipeline with class_weight)
best_pipe = gs.best_estimator_
y_pred = best_pipe.predict(X_test)
y_proba = best_pipe.predict_proba(X_test)[:,1]

print(classification_report(y_test, y_pred, digits=4))

roc_auc = roc_auc_score(y_test, y_proba)
print("Test ROC-AUC:", roc_auc)

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted'); plt.ylabel('Actual'); plt.title('Confusion Matrix')
plt.show()
```

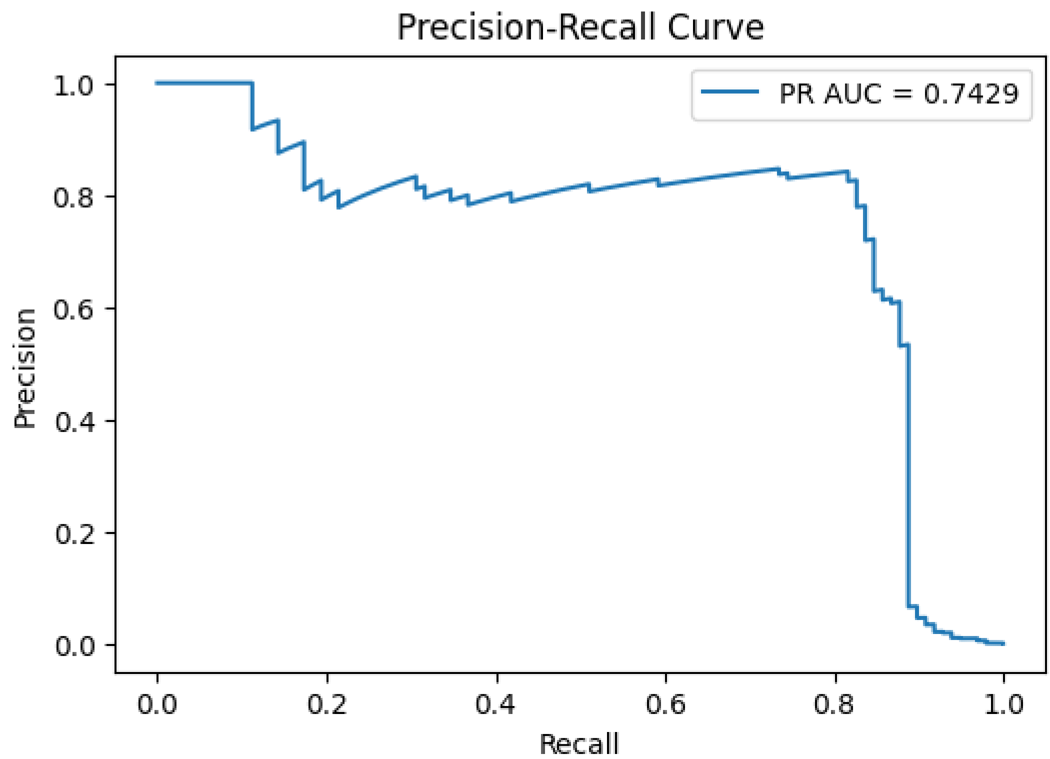
```
              precision    recall  f1-score   support

           0     0.9993    0.9998    0.9995     56864
           1     0.8169    0.5918    0.6864        98

    accuracy                         0.9991     56962
   macro avg     0.9081    0.7958    0.8430     56962
weighted avg     0.9990    0.9991    0.9990     56962

Test ROC-AUC: 0.9756592528682828
```



In [8]:

```
# Cell 7 — ROC & PR curves
fpr, tpr, _ = roc_curve(y_test, y_proba)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, label=f'ROC AUC = {roc_auc:.4f}')
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()

precision, recall, _ = precision_recall_curve(y_test, y_proba)
pr_auc = auc(recall, precision)
plt.figure(figsize=(6,4))
plt.plot(recall, precision, label=f'PR AUC = {pr_auc:.4f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()
plt.show()
```





In [9]:
```
# Cell 8 — Try SMOTE pipeline (only on training set via imblearn pipeline)
from imblearn.pipeline import Pipeline as ImbPipeline
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Cell 8 — Try SMOTE pipeline (only on training set via imblearn pipeline)
smote_pipe = ImbPipeline([
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('clf', LogisticRegression(solver='liblinear', max_iter=1000, random_state=4
```

```
])

param_grid_smote = {
    'clf__C': [0.01, 0.1, 1],
    'clf__class_weight': [None, 'balanced']
}

gs_smote = GridSearchCV(
    smote_pipe,
    param_grid_smote,
    cv=cv,
    scoring='roc_auc',
    n_jobs=-1,
    verbose=1
)
gs_smote.fit(X_train, y_train)

print("Best SMOTE params:", gs_smote.best_params_)
print("Best SMOTE CV ROC-AUC:", gs_smote.best_score_)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
Best SMOTE params: {'clf__C': 0.01, 'clf__class_weight': None}
Best SMOTE CV ROC-AUC: 0.9801339848746947
```

In [10]:

```
# Cell 9 — Evaluate SMOTE model
best_smote = gs_smote.best_estimator_
y_pred_smote = best_smote.predict(X_test)
y_proba_smote = best_smote.predict_proba(X_test)[:,1]

print("SMOTE Model classification report:")
print(classification_report(y_test, y_pred_smote, digits=4))
print("SMOTE Test ROC-AUC:", roc_auc_score(y_test, y_proba_smote))
```

```
SMOTE Model classification report:
              precision    recall  f1-score   support

           0     0.9999    0.9733    0.9864     56864
           1     0.0560    0.9184    0.1056        98

    accuracy                         0.9732     56962
   macro avg     0.5279    0.9459    0.5460     56962
weighted avg     0.9982    0.9732    0.9849     56962

SMOTE Test ROC-AUC: 0.9718148672665465
```

In [11]:

```
# Cell 10 — Choose final model (compare ROC-AUC or preferred metric)
# For demo, pick whichever has higher test ROC-AUC
roc_base = roc_auc_score(y_test, best_pipe.predict_proba(X_test)[:,1])
roc_sm = roc_auc_score(y_test, best_smote.predict_proba(X_test)[:,1])
print("Base ROC:", roc_base, "SMOTE ROC:", roc_sm)

# Pick final pipeline
final_model = best_smote if roc_sm >= roc_base else best_pipe
print("Selected final model:", final_model)
```

```
Base ROC: 0.9756592528682828 SMOTE ROC: 0.9718148672665465
Selected final model: Pipeline(steps=[('scaler', StandardScaler()),
                ('clf',
                 LogisticRegression(C=0.01, max_iter=1000, random_state=42,
                                    solver='liblinear'))])
```

In [12]:
```
# Cell 11 — Save final pipeline
joblib.dump(final_model,"C:/Users/veera/Downloads/PRANAV B/docs/projects/Transac

print("Saved pipeline to ../models/fraud_pipeline_v1.joblib")
```

```
Saved pipeline to ../models/fraud_pipeline_v1.joblib
```

In [14]:
```
!jupyter nbconvert --to html week3_modeling.ipynb
```

```
[NbConvertApp] Converting notebook week3_modeling.ipynb to html
[NbConvertApp] WARNING | Alternative text is missing on 3 image(s).
[NbConvertApp] Writing 382999 bytes to week3_modeling.html
```