model-fit-result-comparison

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0.1 Predictive Analysis on Credit Card Defaults Based on Demographic Factors and Payment Behaviour

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2.0 Data Analysis Package Loading

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import StratifiedKFold, cross_val_predict
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score,confusion_matrix, precision_score,␣
↪recall_score
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
import statsmodels.api as sm
```

2.1 Data file loading

[3]:
```
df2=pd.read_csv('/content/card_default_cleaned.csv')
df2
```

[3]:
```
          ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_1  PAY_2  PAY_3  \
0          1      20000    2          2         1   24      2      2      0
1          2     120000    2          2         2   26      0      2      0
2          3      90000    2          2         2   34      0      0      0
3          4      50000    2          2         1   37      0      0      0
4          5      50000    1          2         1   57      0      0      0
…          …          …  …            …         …  …      …      …      …
29927  29996     220000    1          3         1   39      0      0      0
29928  29997     150000    1          3         2   43      0      0      0
```

```
29929  29998      30000    1          2          2  37      4       3       2
29930  29999      80000    1          3          1  41      1       0       0
29931  30000      50000    1          2          1  46      0       0       0

       PAY_4  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
0          0  …          0          0          0         0       689
1          0  …       3272       3455       3261         0      1000
2          0  …      14331      14948      15549      1518      1500
3          0  …      28314      28959      29547      2000      2019
4          0  …      20940      19146      19131      2000     36681
…         …  …          …          …          …         …
29927      0  …      88004      31237      15980      8500     20000
29928      0  …       8979       5190          0      1837      3526
29929      0  …      20878      20582      19357         0         0
29930      0  …      52774      11855      48944     85900      3409
29931      0  …      36535      32428      15313      2078      1800

       PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
0             0         0         0         0                           1
1          1000      1000         0      2000                           1
2          1000      1000      1000      5000                           0
3          1200      1100      1069      1000                           0
4         10000      9000       689       679                           0
…           …         …         …         …                           …
29927      5003      3047      5000      1000                           0
29928      8998       129         0         0                           0
29929     22000      4200      2000      3100                           1
29930      1178      1926     52964      1804                           1
29931      1430      1000      1000      1000                           1

[29932 rows x 25 columns]
```

2.2 Data Normalization

[4]:
```
scaler = MinMaxScaler()
df2_scaled = scaler.fit_transform(df2)
df2_normalized = pd.DataFrame(df2_scaled, columns=df2.columns)
```

2.3 Data Balancing

[5]:
```
features = ['LIMIT_BAL', 'AGE','EDUCATION', 'MARRIAGE', 'PAY_1','PAY_2',␣
 ↪'PAY_3',
            'PAY_4', 'PAY_5', 'PAY_6', 'PAY_AMT1',
            'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']

y = df2_normalized['default payment next month'].copy() #Target variable
X = df2_normalized[features].copy()
```

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
↪random_state=42)

# Apply oversample the minority class
smote = SMOTE(sampling_strategy='auto', random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)

df_train = X_train.join(y_train)
print(df_train['default payment next month'].value_counts())

df_majority = df_train[df_train['default payment next month'] == 0]

df_minority = df_train[df_train['default payment next month'] == 1]


from sklearn.utils import resample

df_minority_upsampled = resample(df_minority,replace=True,␣
↪n_samples=18641,random_state=587)
# Combine majority class with upsampled minority class
df_upsampled= pd.concat([df_majority, df_minority_upsampled])
# Display new class counts
print(df_upsampled['default payment next month'].value_counts())


#Apply downsample to minority class
df_majority_downsampled = resample(df_majority,replace=True,␣
↪n_samples=5304,random_state=587)
# Combine minority class with downsampled majority class
df_downsampled= pd.concat([df_minority, df_majority_downsampled])
# Display new class counts
print(df_downsampled['default payment next month'].value_counts())

#So we have 2 dataset, Upsampled data creates synthetic data and downsampled␣
↪data creates bias.
```

```
0.0    18641
1.0     5304
Name: default payment next month, dtype: int64
0.0    18641
1.0    18641
Name: default payment next month, dtype: int64
1.0    5304
0.0    5304
Name: default payment next month, dtype: int64
```

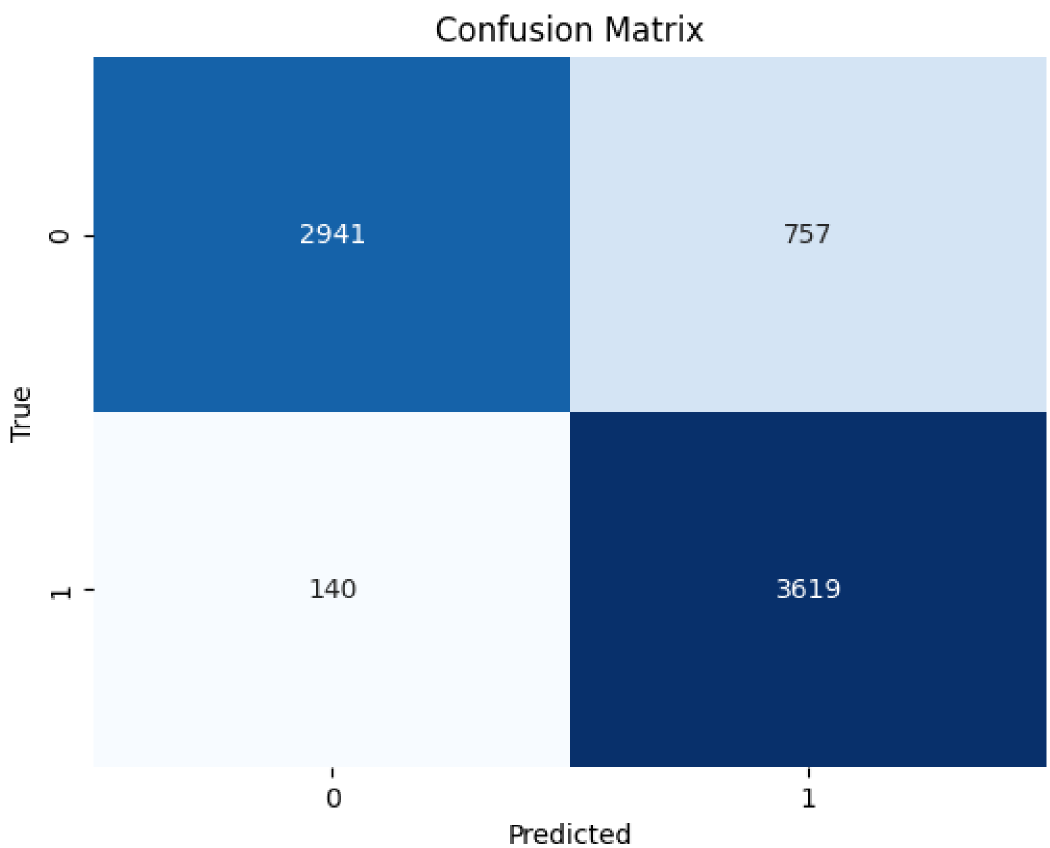
3.0 Data Analysis with three different models-upsampled dataframe

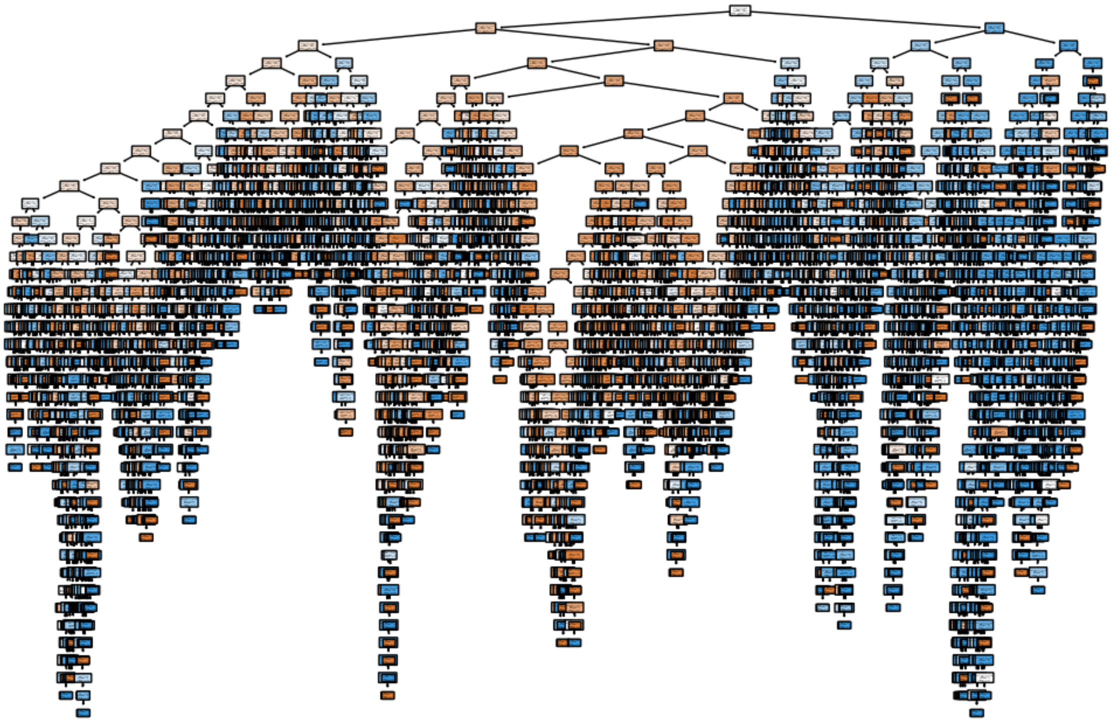
3.1 Decision Tree with upsampled dataframe

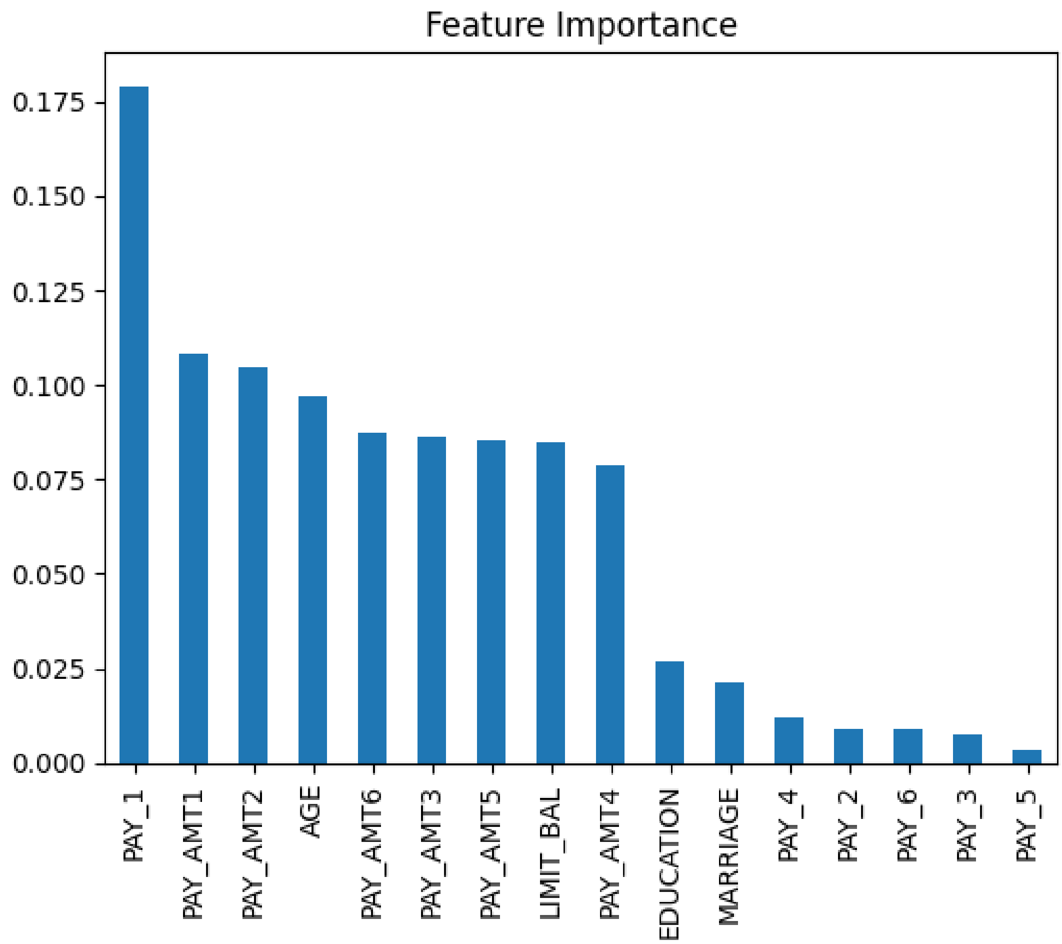
[6]:
```
from sklearn.utils import resample

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score,␣
↪recall_score, f1_score
from sklearn.utils import resample


# Separate features (X) and target variable (y)
X = df_upsampled.drop('default payment next month', axis=1)
y = df_upsampled['default payment next month']
model = DecisionTreeClassifier(random_state=42)


# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Create and fit a Decision Tree model
model = DecisionTreeClassifier(random_state=42)
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
dt_accuracy = accuracy_score(y_test, y_pred)
dt_precision = precision_score(y_test, y_pred)
dt_recall = recall_score(y_test, y_pred)
dt_conf_matrix = confusion_matrix(y_test, y_pred)
dt_f1 = f1_score(y_test, y_pred)

# Print evaluation metrics
print("Accuracy:", dt_accuracy)
print("Precision:", dt_precision)
print("Recall:", dt_recall)
print("Confusion Matrix:")
print(dt_conf_matrix)
print("F1 Score:", dt_f1)

# Plot the confusion matrix using seaborn
sns.heatmap(dt_conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
```

```
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

plt.figure(figsize=(12, 8))
plot_tree(model, feature_names=X.columns, class_names=['0', '1'], filled=True,␣
↪rounded=True)
plt.show()

# Visualize feature importance
feature_importance = pd.Series(model.feature_importances_, index=X.columns)
feature_importance.sort_values(ascending=False).plot(kind='bar')
plt.title('Feature Importance')
plt.show()
```

```
Accuracy: 0.8797103392785303
Precision: 0.8270109689213894
Recall: 0.962756052141527
Confusion Matrix:
[[2941  757]
 [ 140 3619]]
F1 Score: 0.8897357098955132
```







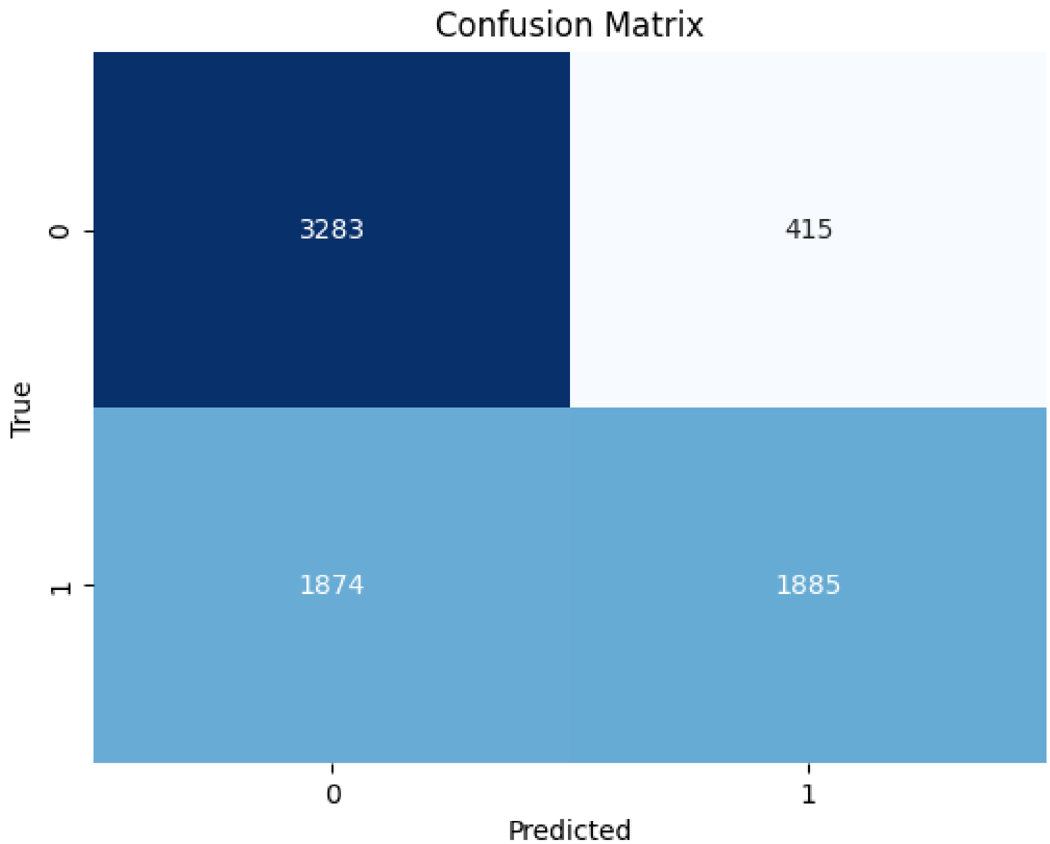
3.2 Support vector machine upsampled dataframe

[7]:
```
# Create and fit an SVM model
model_SVM = SVC(kernel="linear", random_state=42)
model_SVM.fit(X_train, y_train)

# Make predictions on the test set
y_pred1 = model_SVM.predict(X_test)

# Print the trained SVM model parameters
print("Support Vector Machine Model:")
print("Intercept (Bias):", model_SVM.intercept_)
print("Coefficients (Weights):", model_SVM.coef_)
print("Support Vectors:", model_SVM.support_vectors_)

# Print classification report
print("Classification Report:")
print(classification_report(y_test, y_pred1))
```

```python
# Compute confusion matrix
SVM_conf_matrix = confusion_matrix(y_test, y_pred1)

# Calculate accuracy, precision, and recall
SVM_accuracy = accuracy_score(y_test, y_pred1)
SVM_precision = precision_score(y_test, y_pred1)
SVM_recall = recall_score(y_test, y_pred1)
SVM_f1 = f1_score(y_test, y_pred1)
# Print results
print("Confusion Matrix:")
print(SVM_conf_matrix)
print("\nAccuracy:", SVM_accuracy)
print("Precision:", SVM_precision)
print("Recall:", SVM_recall)
print("F1 Score:", SVM_f1)
# Plot the confusion matrix using seaborn
sns.heatmap(SVM_conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()


# Print hyperparameters and support vectors
print("\nSVM Hyperparameters:")
print(model_SVM.get_params())

# Print support vectors
print("\nSupport Vectors:")
print(model_SVM.support_vectors_)
```

```
Support Vector Machine Model:
Intercept (Bias): [-0.99990818]
Coefficients (Weights): [[-6.48081389e-05  3.02948150e-04 -1.80695898e-04
-1.02745900e-04
   7.99901578e+00  3.99778714e+00  1.49372777e-03  6.14769686e-05
   4.96749669e-04  9.91136434e-04 -4.73901913e-04 -1.20659041e-04
   3.06852381e-05  1.13459774e-04  4.03035260e-04 -7.04069566e-05]]
Support Vectors: [[1.21212121e-01 3.62068966e-01 3.33333333e-01 …
6.37681159e-04
  9.28424562e-04 7.49055169e-04]
 [2.42424242e-01 9.31034483e-01 3.33333333e-01 … 8.97262480e-03
  1.86153814e-03 2.23959929e-03]
 [2.02020202e-02 1.37931034e-01 3.33333333e-01 … 0.00000000e+00
  1.94125136e-03 1.60990115e-02]
```

```
 …
 [2.42424242e-01 3.27586207e-01 0.00000000e+00 … 5.24959742e-04
  7.64309109e-04 6.16646427e-04]
 [6.76767677e-01 1.55172414e-01 0.00000000e+00 … 1.18212560e-02
  3.82442929e-01 1.37459190e-02]
 [2.22222222e-01 8.44827586e-01 6.66666667e-01 … 9.76811594e-03
  9.37802588e-03 9.45776729e-03]]
Classification Report:
              precision    recall  f1-score   support

         0.0       0.64      0.89      0.74      3698
         1.0       0.82      0.50      0.62      3759

    accuracy                           0.69      7457
   macro avg       0.73      0.69      0.68      7457
weighted avg       0.73      0.69      0.68      7457

Confusion Matrix:
[[3283  415]
 [1874 1885]]

Accuracy: 0.6930400965535738
Precision: 0.8195652173913044
Recall: 0.5014631550944401
F1 Score: 0.6222148869450405
```




```
SVM Hyperparameters:
{'C': 1.0, 'break_ties': False, 'cache_size': 200, 'class_weight': None,
'coef0': 0.0, 'decision_function_shape': 'ovr', 'degree': 3, 'gamma': 'scale',
'kernel': 'linear', 'max_iter': -1, 'probability': False, 'random_state': 42,
'shrinking': True, 'tol': 0.001, 'verbose': False}

Support Vectors:
[[1.21212121e-01 3.62068966e-01 3.33333333e-01 … 6.37681159e-04
  9.28424562e-04 7.49055169e-04]
 [2.42424242e-01 9.31034483e-01 3.33333333e-01 … 8.97262480e-03
  1.86153814e-03 2.23959929e-03]
 [2.02020202e-02 1.37931034e-01 3.33333333e-01 … 0.00000000e+00
  1.94125136e-03 1.60990115e-02]
 …
 [2.42424242e-01 3.27586207e-01 0.00000000e+00 … 5.24959742e-04
  7.64309109e-04 6.16646427e-04]
 [6.76767677e-01 1.55172414e-01 0.00000000e+00 … 1.18212560e-02
  3.82442929e-01 1.37459190e-02]
 [2.22222222e-01 8.44827586e-01 6.66666667e-01 … 9.76811594e-03
```

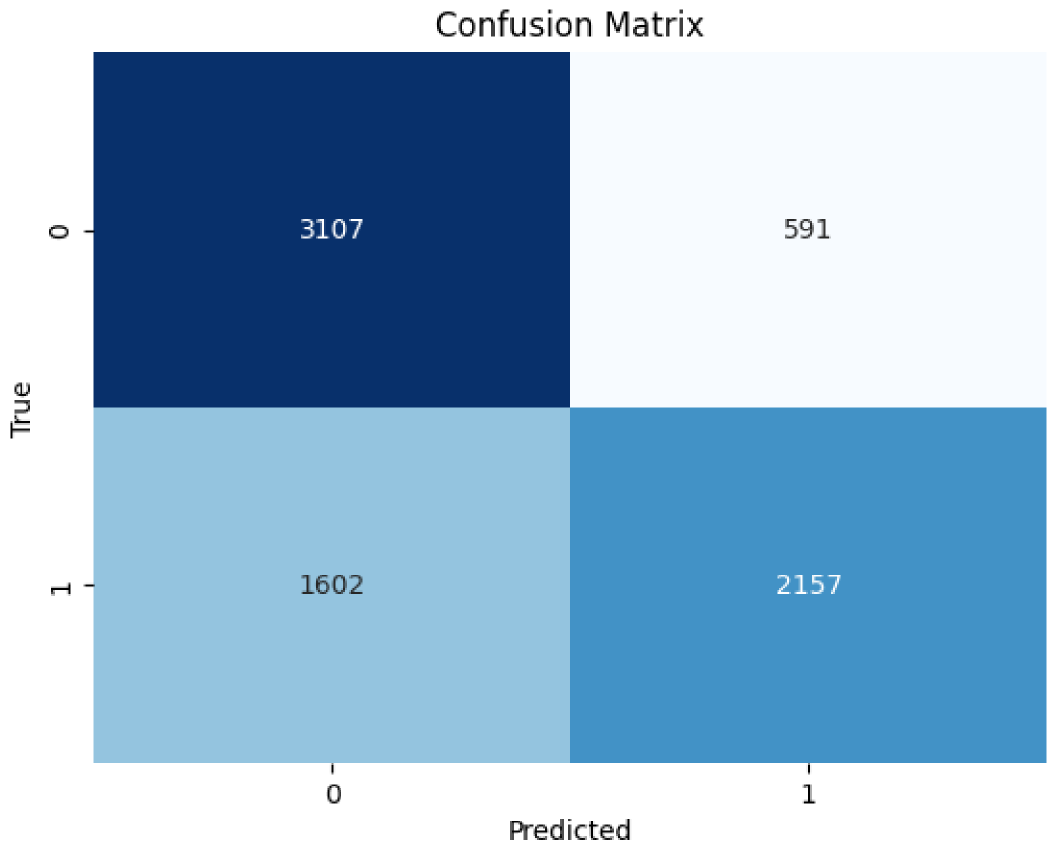
```
 9.37802588e-03 9.45776729e-03]]
```

3.3 Logistic regression upsampled dataframe

[8]:
```
# Create and fit an Logistic regression model
model_lr = LogisticRegression(random_state=42)
model_lr.fit(X_train, y_train)

# Make predictions on the test set
y_pred2 = model_lr.predict(X_test)

#Add a constant term to the features for intercept
X_train = sm.add_constant(X_train)

# Fit logistic regression model using statsmodels
logreg_model = sm.Logit(y_train, X_train)
result = logreg_model.fit()

# Display model summary
print(result.summary())

# Compute confusion matrix
lr_conf_matrix = confusion_matrix(y_test, y_pred2)

# Calculate accuracy, precision, and recall
lr_accuracy = accuracy_score(y_test, y_pred2)
lr_precision = precision_score(y_test, y_pred2)
lr_recall = recall_score(y_test, y_pred2)
lr_f1 = f1_score(y_test, y_pred2)
# Print results
print("Confusion Matrix:")
print(lr_conf_matrix)
print("\nAccuracy:", lr_accuracy)
print("Precision:", lr_precision)
print("Recall:", lr_recall)
print("F1 Score:", lr_f1)
# Plot the confusion matrix using seaborn
sns.heatmap(lr_conf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Optimization terminated successfully.
         Current function value: 0.580456
         Iterations 6
                           Logit Regression Results
==============================================================================
```

```
======
Dep. Variable:     default payment next month   No. Observations:
29825
Model:                                  Logit   Df Residuals:
29808
Method:                                   MLE   Df Model:
16
Date:                        Sat, 09 Mar 2024   Pseudo R-squ.:
0.1626
Time:                                01:05:13   Log-Likelihood:
-17312.
converged:                               True   LL-Null:
-20673.
Covariance Type:                    nonrobust   LLR p-value:
0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.2946      0.043     -6.897      0.000      -0.378      -0.211
LIMIT_BAL     -1.4783      0.120    -12.348      0.000      -1.713      -1.244
AGE            0.4334      0.090      4.809      0.000       0.257       0.610
EDUCATION     -0.1717      0.056     -3.046      0.002      -0.282      -0.061
MARRIAGE      -0.3264      0.055     -5.891      0.000      -0.435      -0.218
PAY_1          7.3939      0.190     38.963      0.000       7.022       7.766
PAY_2          0.5175      0.188      2.757      0.006       0.150       0.885
PAY_3          1.3676      0.193      7.098      0.000       0.990       1.745
PAY_4          0.7414      0.221      3.359      0.001       0.309       1.174
PAY_5          0.7448      0.244      3.055      0.002       0.267       1.223
PAY_6          1.3558      0.208      6.527      0.000       0.949       1.763
PAY_AMT1      -7.0548      1.208     -5.839      0.000      -9.423      -4.687
PAY_AMT2     -12.8134      2.165     -5.918      0.000     -17.057      -8.570
PAY_AMT3      -0.7247      0.810     -0.895      0.371      -2.312       0.862
PAY_AMT4      -0.7474      0.616     -1.214      0.225      -1.954       0.459
PAY_AMT5      -0.4283      0.427     -1.003      0.316      -1.265       0.409
PAY_AMT6      -0.2265      0.462     -0.490      0.624      -1.133       0.680
==============================================================================
Confusion Matrix:
[[3107  591]
 [1602 2157]]

Accuracy: 0.7059139063966743
Precision: 0.7849344978165939
Recall: 0.5738228252194733
F1 Score: 0.6629783310281235
```



3.4 Comparison of the performance scores

[9]:
```python
comparison_table = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Decision Tree': [dt_accuracy, dt_precision, dt_recall, dt_f1],
    'SVM': [SVM_accuracy, SVM_precision, SVM_recall, SVM_f1],
    'Logistic Regression': [lr_accuracy, lr_precision, lr_recall, lr_f1]
})

# Display the comparison table
print(comparison_table)
```

```
      Metric  Decision Tree       SVM  Logistic Regression
0   Accuracy       0.879710  0.693040             0.705914
1  Precision       0.827011  0.819565             0.784934
2     Recall       0.962756  0.501463             0.573823
3   F1 Score       0.889736  0.622215             0.662978
```

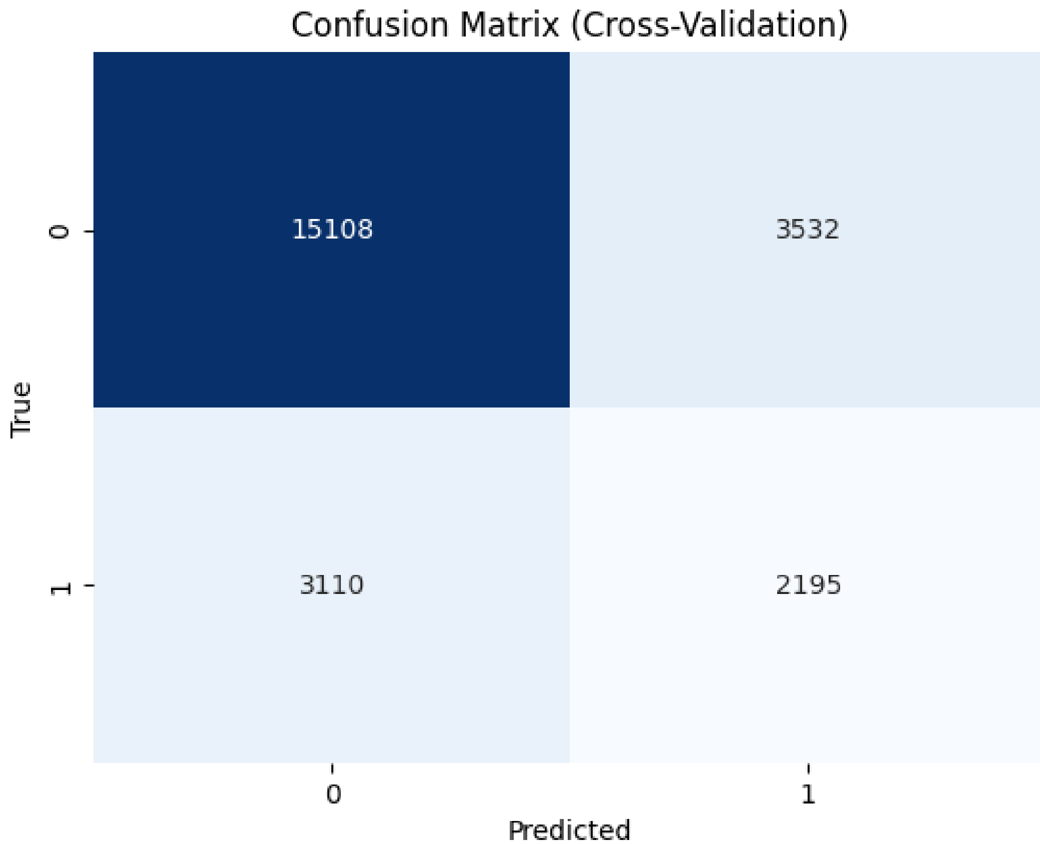
4.0 Cross Validation

4.1 Decision Tree

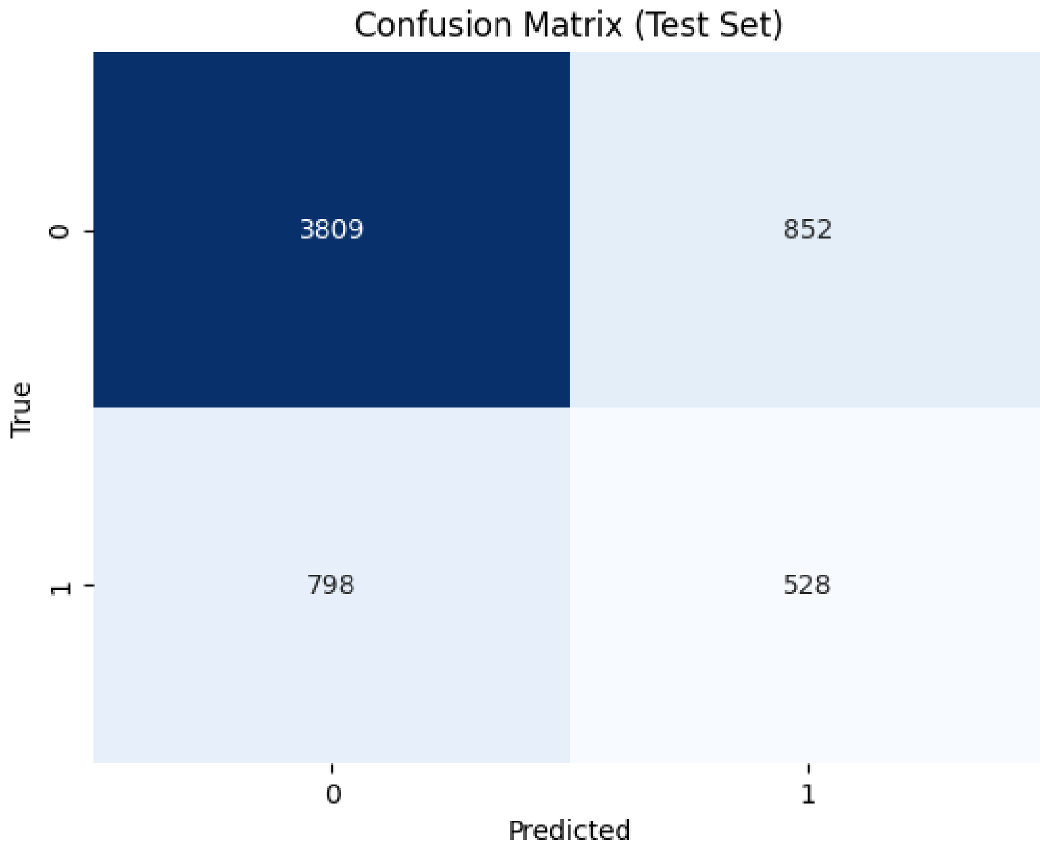
```
[10]: features = ['LIMIT_BAL', 'AGE','EDUCATION', 'MARRIAGE', 'PAY_1','PAY_2',␣
       ↪'PAY_3',
                   'PAY_4', 'PAY_5', 'PAY_6', 'PAY_AMT1',
                   'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']

      y = df2['default payment next month'].copy() #Target variable
      X = df2[features].copy()
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
       ↪random_state=42, stratify=y)

      # Create a Decision Tree model
      dt_model_cv =DecisionTreeClassifier(random_state=42)

      # Perform cross-validation
      stratified_kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

      # Make predictions using cross-validation
      y_pred_cv = cross_val_predict(dt_model_cv, X_train, y_train,␣
       ↪cv=stratified_kfold)

      # Calculate metrics on the training set
      accuracy_dt_cv = accuracy_score(y_train, y_pred_cv)
      precision_dt_cv = precision_score(y_train, y_pred_cv)
      recall_dt_cv = recall_score(y_train, y_pred_cv)
      f1_dt_cv = f1_score(y_train, y_pred_cv)

      # Print metrics
      print("Cross-Validation Metrics:")
      print(f"Accuracy: {accuracy_dt_cv:.4f}")
      print(f"Precision: {precision_dt_cv:.4f}")
      print(f"Recall: {recall_dt_cv:.4f}")
      print(f"F1 Score: {f1_dt_cv:.4f}")

      # Plot confusion matrix
      conf_matrix_dt_cv = confusion_matrix(y_train, y_pred_cv)
      sns.heatmap(conf_matrix_dt_cv, annot=True, fmt='d', cmap='Blues', cbar=False)
      plt.xlabel('Predicted')
      plt.ylabel('True')
      plt.title('Confusion Matrix (Cross-Validation)')
      plt.show()

      # Train the model on the entire training set
      dt_model_cv.fit(X_train, y_train)

      # Make predictions on the test set
      y_pred_test = dt_model_cv.predict(X_test)
```

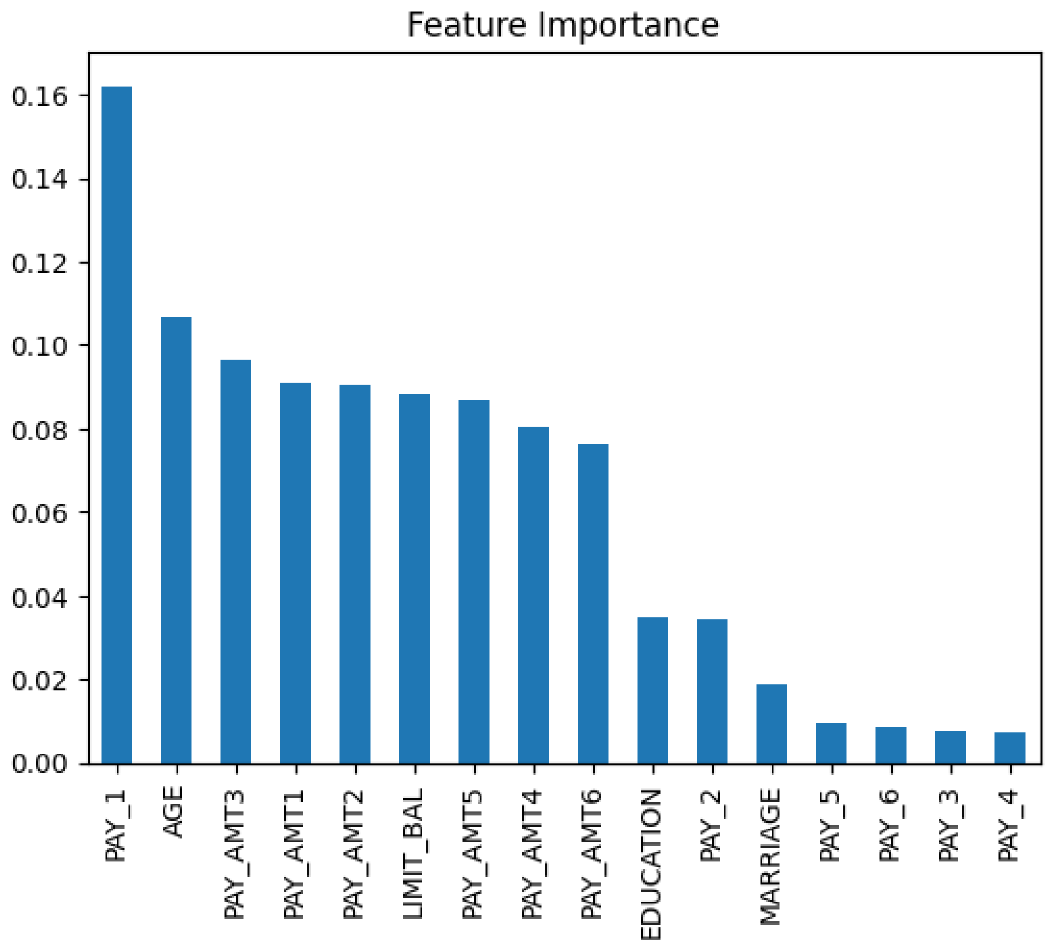
```
# Calculate metrics on the test set
accuracy_test_dt_cv = accuracy_score(y_test, y_pred_test)
precision_test_dt_cv = precision_score(y_test, y_pred_test)
recall_test_dt_cv = recall_score(y_test, y_pred_test)
f1_test_dt_cv = f1_score(y_test, y_pred_test)

# Print test set metrics
print("\nTest Set Metrics:")
print(f"Accuracy: {accuracy_test_dt_cv:.4f}")
print(f"Precision: {precision_test_dt_cv:.4f}")
print(f"Recall: {recall_test_dt_cv:.4f}")
print(f"F1 Score: {f1_test_dt_cv:.4f}")

# Plot confusion matrix for the test set
conf_matrix_test_dt_cv = confusion_matrix(y_test, y_pred_test)
sns.heatmap(conf_matrix_test_dt_cv, annot=True, fmt='d', cmap='Blues',␣
↪cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Test Set)')
plt.show()

# Visualize feature importance
feature_importance = pd.Series(dt_model_cv.feature_importances_, index=X.
↪columns)
feature_importance.sort_values(ascending=False).plot(kind='bar')
plt.title('Feature Importance')
plt.show()
```

```
Cross-Validation Metrics:
Accuracy: 0.7226
Precision: 0.3833
Recall: 0.4138
F1 Score: 0.3979
```




```
Test Set Metrics:
Accuracy: 0.7244
Precision: 0.3826
Recall: 0.3982
F1 Score: 0.3902
```


Confusion Matrix (Test Set)
3809
852
798
528
True
0
1
Predicted
0
1



4.2 Support Vector Machine

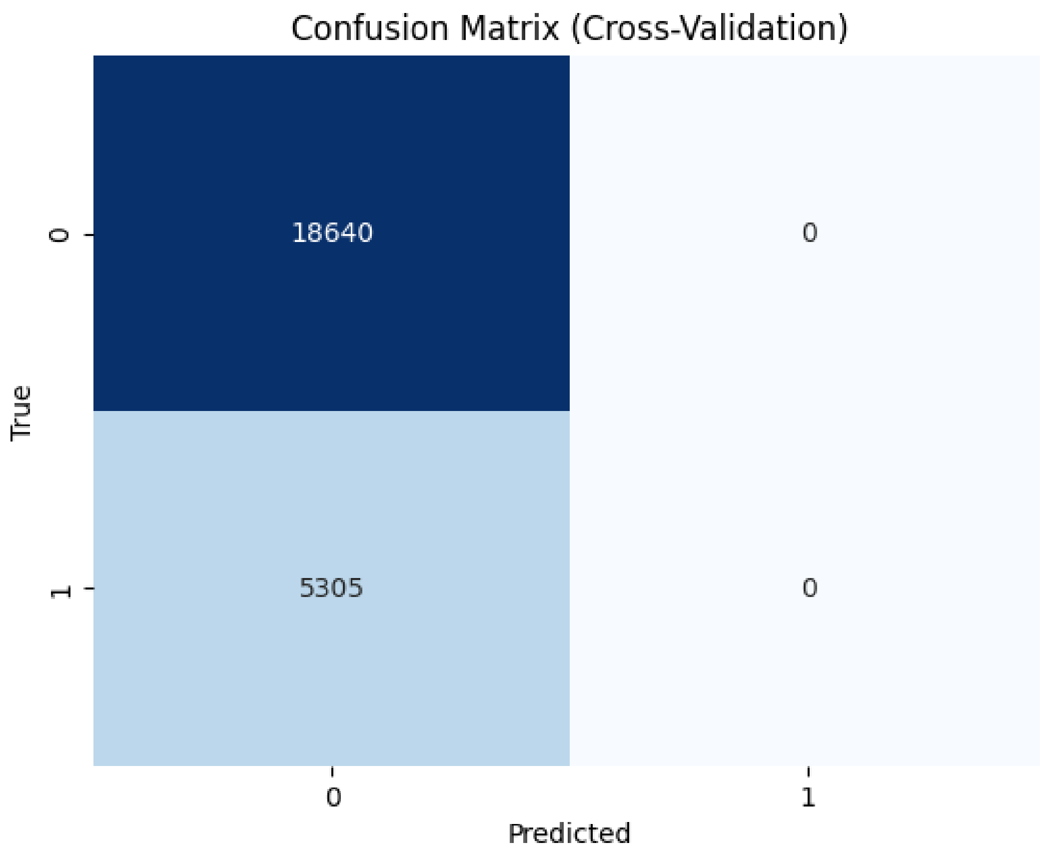
[11]:
```
# Create a Support vector machine
SVC_model_cv = SVC(random_state=42)

# Perform cross-validation
stratified_kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Make predictions using cross-validation
y_pred_cv1 = cross_val_predict(SVC_model_cv, X_train, y_train,␣
↪cv=stratified_kfold)


# Calculate metrics on the training set
accuracy_svc_cv = accuracy_score(y_train, y_pred_cv1)
precision_svc_cv = precision_score(y_train, y_pred_cv1)
recall_svc_cv = recall_score(y_train, y_pred_cv1)
```

```python
f1_svc_cv = f1_score(y_train, y_pred_cv1)

# Print metrics
print("Cross-Validation Metrics:")
print(f"Accuracy: {accuracy_svc_cv:.4f}")
print(f"Precision: {precision_svc_cv:.4f}")
print(f"Recall: {recall_svc_cv:.4f}")
print(f"F1 Score: {f1_svc_cv:.4f}")

# Plot confusion matrix
conf_matrix_svc_cv = confusion_matrix(y_train, y_pred_cv1)
sns.heatmap(conf_matrix_svc_cv, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Cross-Validation)')
plt.show()

# Train the model on the entire training set and make predictions on the test␣
↪set
SVC_model_cv.fit(X_train, y_train)
y_pred_test1 = SVC_model_cv.predict(X_test)

# Calculate metrics on the test set
accuracy_test_svc_cv = accuracy_score(y_test, y_pred_test1)
precision_test_svc_cv = precision_score(y_test, y_pred_test1)
recall_test_svc_cv = recall_score(y_test, y_pred_test1)
f1_test_svc_cv = f1_score(y_test, y_pred_test1)

# Print test set metrics
print("\nTest Set Metrics:")
print(f"Accuracy: {accuracy_test_svc_cv:.4f}")
print(f"Precision: {precision_test_svc_cv:.4f}")
print(f"Recall: {recall_test_svc_cv:.4f}")
print(f"F1 Score: {f1_test_svc_cv:.4f}")

# Plot confusion matrix for the test set
conf_matrix_test_svc_cv = confusion_matrix(y_test, y_pred_test1)
sns.heatmap(conf_matrix_test_svc_cv, annot=True, fmt='d', cmap='Blues',␣
↪cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Test Set)')
plt.show()


from sklearn.model_selection import cross_val_score
```

```
cross_val_results = cross_val_score(SVC_model_cv, X, y, cv=5,
 ↪scoring='accuracy')
print("Cross-Validation Accuracy:", cross_val_results.mean())

# print the support vectors
support_vectors = SVC_model_cv.support_vectors_
print(support_vectors)

decision_function_values = SVC_model_cv.decision_function(X_test)
print(decision_function_values)
```

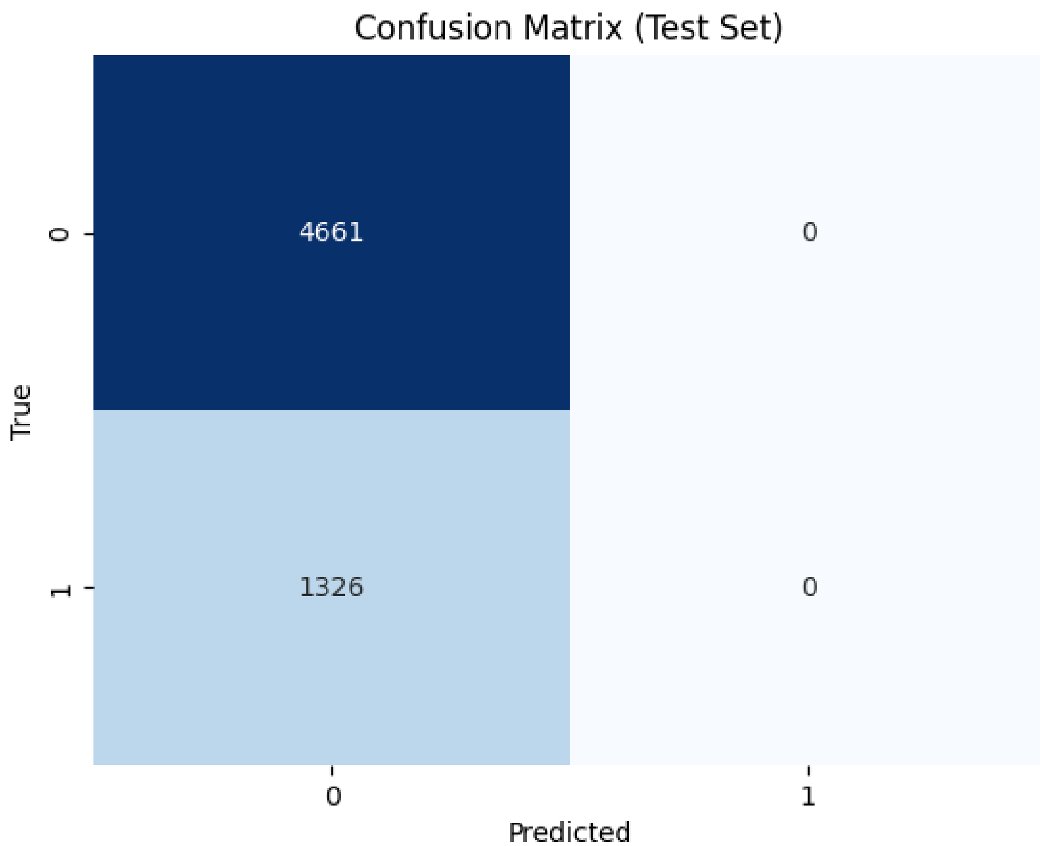
```
Cross-Validation Metrics:
Accuracy: 0.7785
Precision: 0.0000
Recall: 0.0000
F1 Score: 0.0000
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



```
Test Set Metrics:
Accuracy: 0.7785
Precision: 0.0000
Recall: 0.0000
F1 Score: 0.0000
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```




```
Cross-Validation Accuracy: 0.7784645214425218
[[3.0000e+04 3.6000e+01 3.0000e+00 … 0.0000e+00 3.9000e+02 0.0000e+00]
 [9.0000e+04 2.7000e+01 1.0000e+00 … 2.1000e+03 2.5000e+03 2.5000e+03]
 [4.0000e+05 3.2000e+01 2.0000e+00 … 2.8170e+03 2.4100e+03 1.0715e+04]
 …
 [9.0000e+04 2.7000e+01 2.0000e+00 … 4.2000e+03 3.2850e+03 7.7870e+03]
 [6.0000e+04 2.7000e+01 1.0000e+00 … 3.0000e+03 0.0000e+00 9.2300e+02]
```

```
 [1.1000e+05 4.3000e+01 3.0000e+00 … 2.1000e+03 2.5000e+03 2.1000e+03]]
[-0.99988755 -0.99989221 -0.9998649  … -1.00012788 -1.00005984
 -0.99999887]
```

4.3 Logistic Regression

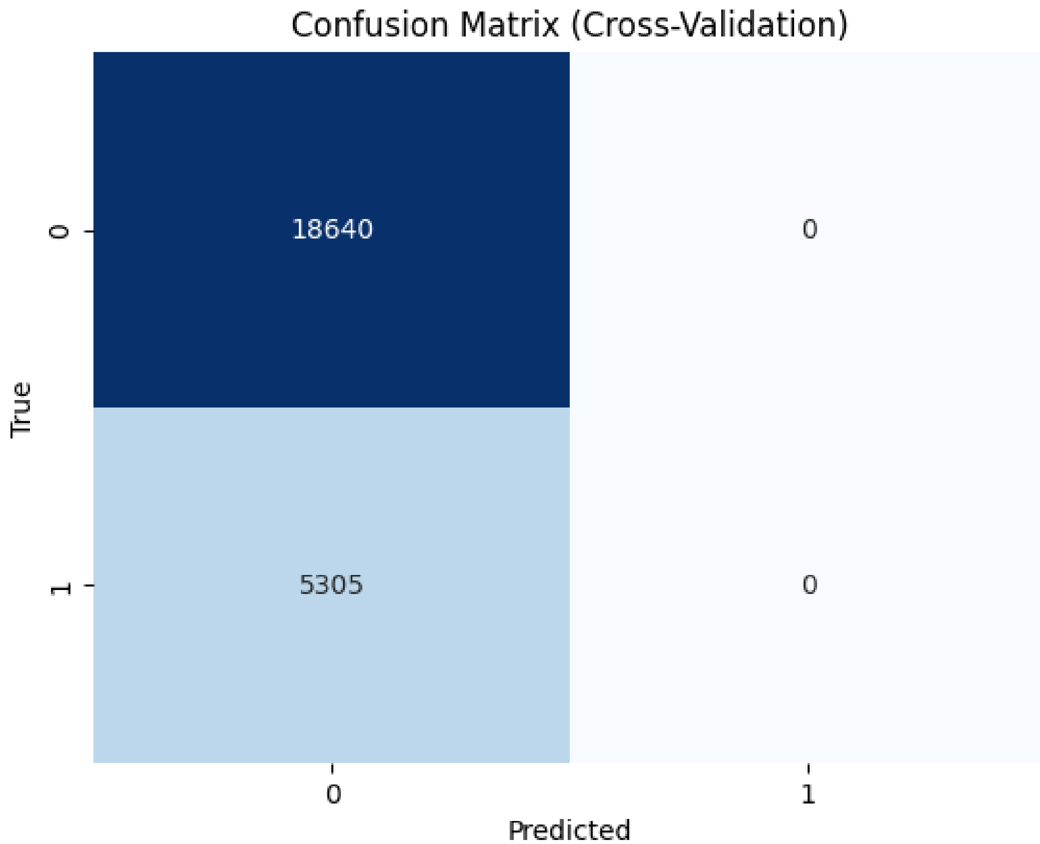
[12]:
```python
# Create a Logistic regression
lr_model_cv = LogisticRegression(random_state=42)

# Perform cross-validation
stratified_kfold = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Make predictions using cross-validation
y_pred_cv2 = cross_val_predict(lr_model_cv, X_train, y_train,␣
 ↪cv=stratified_kfold)

# Fit logistic regression model using statsmodels
logreg_model = sm.Logit(y_train, X_train)
result = logreg_model.fit()

# Display model summary
print(result.summary())


# Calculate metrics on the training set
accuracy_lr_cv = accuracy_score(y_train, y_pred_cv2)
precision_lr_cv = precision_score(y_train, y_pred_cv2)
recall_lr_cv = recall_score(y_train, y_pred_cv2)
f1_lr_cv = f1_score(y_train, y_pred_cv2)

# Print metrics
print("Cross-Validation Metrics:")
print(f"Accuracy: {accuracy_lr_cv:.4f}")
print(f"Precision: {precision_lr_cv:.4f}")
print(f"Recall: {recall_lr_cv:.4f}")
print(f"F1 Score: {f1_lr_cv:.4f}")

# Plot confusion matrix
conf_matrix_lr_cv = confusion_matrix(y_train, y_pred_cv2)
sns.heatmap(conf_matrix_lr_cv, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Cross-Validation)')
plt.show()

# Train the model on the entire training set and make predictions on the test␣
 ↪set
lr_model_cv.fit(X_train, y_train)
```

```python
y_pred_test2 = lr_model_cv.predict(X_test)

# Calculate metrics on the test set
accuracy_test_lr_cv = accuracy_score(y_test, y_pred_test2)
precision_test_lr_cv = precision_score(y_test, y_pred_test2)
recall_test_lr_cv = recall_score(y_test, y_pred_test2)
f1_test_lr_cv = f1_score(y_test, y_pred_test2)

# Print test set metrics
print("\nTest Set Metrics:")
print(f"Accuracy: {accuracy_test_lr_cv:.4f}")
print(f"Precision: {precision_test_lr_cv:.4f}")
print(f"Recall: {recall_test_lr_cv:.4f}")
print(f"F1 Score: {f1_test_lr_cv:.4f}")

# Plot confusion matrix for the test set
conf_matrix_test_lr_cv = confusion_matrix(y_test, y_pred_test2)
sns.heatmap(conf_matrix_test_lr_cv, annot=True, fmt='d', cmap='Blues',␣
 ↪cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Test Set)')
plt.show()

# Get the coefficients (factors) and intercept
coefficients = lr_model_cv.coef_[0]
intercept = lr_model_cv.intercept_[0]

# Display the coefficients and intercept
print("Intercept:", intercept)
print("\nCoefficients:")
for feature, coefficient in zip(X.columns, coefficients):
    print(f"{feature}: {coefficient}")
```

```
Optimization terminated successfully.
         Current function value: 0.447364
         Iterations 7
                           Logit Regression Results
================================================================================
======
Dep. Variable:     default payment next month   No. Observations:
23945
Model:                                  Logit   Df Residuals:
23929
Method:                                   MLE   Df Model:
15
Date:                        Sat, 09 Mar 2024   Pseudo R-squ.:
```

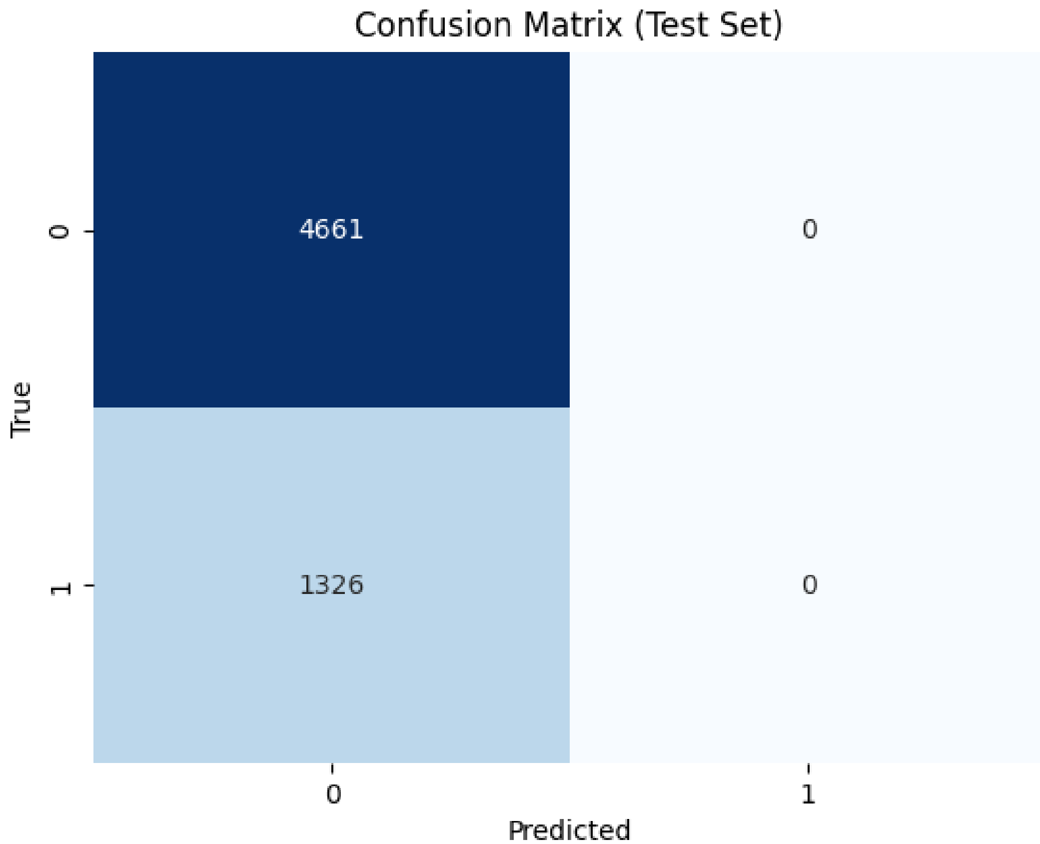
```
0.1541
Time:                            01:09:40   Log-Likelihood:
-10712.
converged:                           True   LL-Null:
-12664.
Covariance Type:                nonrobust   LLR p-value:
0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
LIMIT_BAL  -2.028e-06   1.66e-07    -12.183      0.000   -2.35e-06    -1.7e-06
AGE           -0.0104      0.002     -6.820      0.000      -0.013      -0.007
EDUCATION     -0.1821      0.024     -7.722      0.000      -0.228      -0.136
MARRIAGE      -0.4359      0.024    -18.036      0.000      -0.483      -0.389
PAY_1          0.8888      0.028     31.658      0.000       0.834       0.944
PAY_2          0.0416      0.030      1.411      0.158      -0.016       0.099
PAY_3          0.1029      0.032      3.253      0.001       0.041       0.165
PAY_4          0.0910      0.035      2.604      0.009       0.023       0.159
PAY_5          0.0775      0.038      2.032      0.042       0.003       0.152
PAY_6          0.1640      0.032      5.089      0.000       0.101       0.227
PAY_AMT1     -7.74e-06   2.09e-06     -3.697      0.000   -1.18e-05   -3.64e-06
PAY_AMT2   -7.741e-06   2.03e-06     -3.807      0.000   -1.17e-05   -3.76e-06
PAY_AMT3   -3.505e-06   1.77e-06     -1.976      0.048   -6.98e-06   -2.84e-08
PAY_AMT4   -2.763e-06   1.66e-06     -1.661      0.097   -6.02e-06    4.97e-07
PAY_AMT5   -3.369e-06   1.76e-06     -1.918      0.055   -6.81e-06    7.38e-08
PAY_AMT6   -2.029e-06   1.49e-06     -1.359      0.174   -4.95e-06    8.96e-07
==============================================================================
Cross-Validation Metrics:
Accuracy: 0.7785
Precision: 0.0000
Recall: 0.0000
F1 Score: 0.0000
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```




```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
Test Set Metrics:
Accuracy: 0.7785
Precision: 0.0000
Recall: 0.0000
F1 Score: 0.0000
```




```
Intercept: -0.0004990689904387993

Coefficients:
LIMIT_BAL: -3.069904502567385e-06
AGE: -0.015470214738253375
EDUCATION: -0.0010522746236963586
MARRIAGE: -0.0009097916282728683
PAY_1: 0.0010475253515071818
PAY_2: 0.0008114965405403287
PAY_3: 0.0006827270724640356
PAY_4: 0.0006384821235095486
PAY_5: 0.0005880232009422978
PAY_6: 0.0005469623859297884
PAY_AMT1: -1.6296646832112518e-05
PAY_AMT2: -1.396030263981313e-05
PAY_AMT3: -6.903985615612971e-06
PAY_AMT4: -4.782385998522268e-06
PAY_AMT5: -4.206685515622694e-06
PAY_AMT6: -2.0412890855858295e-06
```

4.4 Comparison of models based on Train set and test set

[13]:

```
comparison_table = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Decision Tree': [accuracy_dt_cv, precision_dt_cv, recall_dt_cv, f1_dt_cv],
    'SVM': [accuracy_svc_cv, precision_svc_cv, recall_svc_cv, f1_svc_cv],
    'Logistic Regression': [accuracy_lr_cv, precision_lr_cv, recall_lr_cv,␣
↪f1_lr_cv]
})

# Display the comparison table
print(comparison_table)


comparison_table1= pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Decision Tree': [accuracy_test_dt_cv, precision_test_dt_cv,␣
↪recall_test_dt_cv, f1_test_dt_cv],
    'SVM': [accuracy_test_svc_cv, precision_test_svc_cv, recall_test_svc_cv,␣
↪f1_test_svc_cv],
    'Logistic Regression': [accuracy_test_lr_cv, precision_test_lr_cv,␣
↪recall_test_lr_cv, f1_test_lr_cv]
})

# Display the comparison table
print(comparison_table1)
```

```
      Metric  Decision Tree       SVM  Logistic Regression
0   Accuracy       0.722614  0.778451             0.778451
1  Precision       0.383272  0.000000             0.000000
2     Recall       0.413761  0.000000             0.000000
3   F1 Score       0.397933  0.000000             0.000000
      Metric  Decision Tree      SVM  Logistic Regression
0   Accuracy       0.724403  0.77852              0.77852
1  Precision       0.382609  0.00000              0.00000
2     Recall       0.398190  0.00000              0.00000
3   F1 Score       0.390244  0.00000              0.00000
```