```
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification report, confusion matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
{\tt from\ imblearn.over\_sampling\ import\ SMOTE}
from sklearn.ensemble import VotingClassifier
# Load the training dataset
train_data = pd.read_csv('/content/Churn_TRAIN.csv')
# Display the first few rows of the training dataset
print(train_data.head())
# Load the test dataset
test_data = pd.read_csv('/content/Churn_TEST.csv')
# Display the first few rows of the test dataset
print(test_data.head())
        Call Failure
                        Complains Subscription Length
                                                          Charge Amount
     0
                                0
                    10
                                                      37
                                                                        1
                                                                        0
                    4
                                0
                                                      36
     1
     2
                    2
                                0
                                                       9
                                                                        1
     3
                    14
                                a
                                                      22
                                                                        5
     4
                     6
                                0
                                                      25
                                                                        a
        Seconds of Use
                         Frequency of use
                                            Frequency of
                                                         SMS
     0
                   6908
                                        76
                                                          117
     1
                  15295
                                       182
                   4390
                                        40
     2
                                                          215
     3
                   3238
                                        53
                                                          48
     4
                    395
                                        19
                                              Tariff Plan
        Distinct Called Numbers
                                  Age Group
                                                            Status
                                                                    Age
     0
                              40
                                                        1
                                                                 1
                                                                     25
     1
                              32
                                           2
                                                        1
                                                                 1
                                                                     25
     2
                              10
                                           3
                                                        1
                                                                 1
                                                                     30
     3
                              25
                                           3
                                                        2
                                                                 1
                                                                     30
     4
                               5
                                           2
                                                                     25
        Customer Value
                         Churn
     0
               840.780
                             0
              1483.965
     1
                             0
              1037.200
     2
                             a
     3
                323,640
                             a
     4
                 32.130
                             a
              Failure
                        Complains
                                    Subscription Length
     0
                     4
                                0
                                                      42
                     3
                                0
                                                      10
                                                                        2
     1
     2
                                0
                                                      27
                                                                        0
                    13
     3
                    5
                                0
                                                      42
                                                                        0
     4
                                                      19
                                                                        2
                    19
                                0
        Seconds of Use
                         Frequency of use
                                            Frequency of
                                                         SMS
     0
                  2315
                                        43
                                                         293
     1
                   2593
                                        35
                                                          16
     2
                    945
                                        28
                                                          12
                    888
                                        17
                                                           24
     4
                   6453
                                       144
                                                          90
        Distinct Called Numbers
                                  Age Group
                                              Tariff Plan
                                                            Status
                                                                    Age
                              22
                                                                     30
                                                        1
                                                                 1
                                           3
                                                                     30
     1
                              13
                                           3
                                                        1
                                                                 1
     2
                               7
                                           3
                                                        1
                                                                 2
                                                                     30
     3
                              10
                                           4
                                                                     45
                                                        1
                                                                 2
     4
                              44
                                           2
                                                        2
                                                                 1
                                                                     25
        Customer Value
              1266.320
     1
                169.120
                             0
                 86.920
     3
                82.625
                             1
     4
               701.865
# Separate features and target variable in the training dataset
```

X_train = train_data.drop(columns=['Churn'])

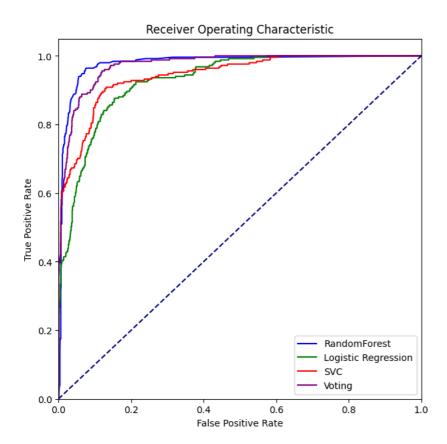
y_train = train_data['Churn']

[#] Separate features and target variable in the test dataset

```
X_test = test_data.drop(columns=['Churn'])
y_test = test_data['Churn']
# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
# Train a RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
# Train a LogisticRegression
lr = LogisticRegression(max_iter=1000)
lr.fit(X train, y train)
# Train a SVC
svc = SVC(probability=True)
svc.fit(X_train, y_train)
               SVC
     SVC(probability=True)
\hbox{\tt\# Make predictions using the RandomForestClassifier}\\
rf_predictions = rf.predict(X_test)
# Evaluate the RandomForestClassifier
print('Classification Report for RandomForestClassifier:')
print(classification_report(y_test, rf_predictions))
print('Confusion Matrix for RandomForestClassifier:')
print(confusion_matrix(y_test, rf_predictions))
# Make predictions using the LogisticRegression
lr_predictions = lr.predict(X_test)
# Evaluate the LogisticRegression
\verb"print('Classification Report for Logistic Regression:')
print(classification_report(y_test, lr_predictions))
print('Confusion Matrix for LogisticRegression:')
print(confusion_matrix(y_test, lr_predictions))
# Make predictions using the SVC
svc_predictions = svc.predict(X_test)
# Evaluate the SVC
print('Classification Report for SVC:')
print(classification_report(y_test, svc_predictions))
print('Confusion Matrix for SVC:')
print(confusion_matrix(y_test, svc_predictions))
     Classification Report for RandomForestClassifier:
                                recall f1-score
                   precision
                                                   support
                0
                                  0.98
                                                      1324
                        0.96
                                            0.97
                1
                        0.89
                                  0.77
                                            0.83
                                                       251
                                            0.95
                                                      1575
         accuracy
                        0.92
                                  0.88
                                            0.90
                                                      1575
        macro avg
     weighted avg
                        0.95
                                  0.95
                                            0.95
                                                      1575
     Confusion Matrix for RandomForestClassifier:
     [[1299 25]
      [ 57 194]]
     Classification Report for LogisticRegression:
                   precision
                               recall f1-score
                                                   support
                0
                        9.99
                                  0.97
                                            0.94
                                                      1324
                1
                        0.76
                                  0.43
                                            0.55
                                                       251
                                            0.89
                                                      1575
         accuracy
                        0.83
                                  0.70
                                            0.74
        macro avg
                                                      1575
     weighted avg
                        0.88
                                  0.89
                                            0.87
                                                      1575
     Confusion Matrix for LogisticRegression:
     [[1290 34]
      [ 143 108]]
     Classification Report for SVC:
                   precision recall f1-score
```

```
0.92
                                  0.99
                                            0.95
                                                      1324
                0
                        0.94
                                  0.54
                                            0.68
                                                       251
                                                      1575
         accuracy
                                            0.92
                        0.93
                                  0.77
                                            0.82
                                                      1575
        macro avg
                                                      1575
                                            0.91
     weighted avg
                        0.92
                                  0.92
     Confusion Matrix for SVC:
     [[1315
      [ 116 135]]
# Hyperparameter tuning for RandomForestClassifier
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10]
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='roc_auc')
grid_search.fit(X_train, y_train)
print('Best parameters for RandomForestClassifier:', grid_search.best_params_)
print('Best score for RandomForestClassifier:', grid_search.best_score_)
# Ensemble learning using VotingClassifier
voting_clf = VotingClassifier(estimators=[
    ('lr', LogisticRegression(max_iter=1000)),
    ('rf', RandomForestClassifier()),
    ('svc', SVC(probability=True))],
    voting='soft')
voting_clf.fit(X_train, y_train)
voting_predictions = voting_clf.predict(X_test)
print('Classification Report for VotingClassifier:')
print(classification_report(y_test, voting_predictions))
print('Confusion Matrix for VotingClassifier:')
print(confusion_matrix(y_test, voting_predictions))
# Handling imbalanced data using SMOTE
smote = SMOTE()
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
     Best parameters for RandomForestClassifier: {'max_depth': 30, 'min_samples_split': 5, 'n_estimators': 300}
     Best score for RandomForestClassifier: 0.980417347446427
     Classification Report for VotingClassifier:
                   precision
                                recall f1-score
                0
                        0.93
                                  0.99
                                            0.96
                                                      1324
                                            0.73
                1
                        0.90
                                  0.62
                                                       251
                                            0.93
                                                      1575
         accuracy
                        0.91
                                  0.80
                                            0.84
        macro avg
                                                      1575
     weighted avg
                        0.93
                                  0.93
                                            0.92
                                                      1575
     Confusion Matrix for VotingClassifier:
     [[1306 18]
      [ 96 155]]
# Import necessary libraries
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_auc_score, roc_curve, precision_recall_curve, auc
# Calculate the ROC AUC scores
rf_roc_auc = roc_auc_score(y_test, rf.predict(X_test))
lr_roc_auc = roc_auc_score(y_test, lr.predict(X_test))
svc_roc_auc = roc_auc_score(y_test, svc.predict(X_test))
voting_roc_auc = roc_auc_score(y_test, voting_clf.predict(X_test))
print('ROC AUC score for RandomForestClassifier: ', rf_roc_auc)
print('ROC AUC score for LogisticRegression: ', lr_roc_auc)
print('ROC AUC score for SVC: ', svc_roc_auc)
print('ROC AUC score for VotingClassifier: ', voting_roc_auc)
     ROC AUC score for RandomForestClassifier: 0.8770130956536392
     ROC AUC score for LogisticRegression: 0.7022995630769973
     ROC AUC score for SVC: 0.7655255112480591
     ROC AUC score for VotingClassifier: 0.8019673571574727
# Plot the ROC curves
plt.figure(figsize=(7, 7))
for model, name, color in zip([rf, lr, svc, voting_clf], ['RandomForest', 'Logistic Regression', 'SVC', 'Voting'], ['blue', 'green', 'rec
    fpr, tpr, _ = roc_curve(y_test, model.predict_proba(X_test)[:, 1])
    plt.plot(fpr, tpr, color=color, label=name)
```

```
plt.plot([0, 1], [0, 1], color='navy', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```



```
# Cost analysis
# Please replace the values for cost_fp and cost_fn with your actual costs
cost_fp = 1 # Cost of a false positive
cost_fn = 1 # Cost of a false negative
cm_rf = confusion_matrix(y_test, rf_predictions)
cm_lr = confusion_matrix(y_test, lr_predictions)
cm_svc = confusion_matrix(y_test, svc_predictions)
cm_voting = confusion_matrix(y_test, voting_predictions)
cost_rf = cm_rf[0, 1] * cost_fp + cm_rf[1, 0] * cost_fn
cost_lr = cm_lr[0, 1] * cost_fp + cm_lr[1, 0] * cost_fn
cost\_svc = cm\_svc[0, 1] * cost\_fp + cm\_svc[1, 0] * cost\_fn
cost_voting = cm_voting[0, 1] * cost_fp + cm_voting[1, 0] * cost_fn
print('Total cost for RandomForestClassifier: ', cost_rf)
print('Total cost for LogisticRegression: ', cost_lr)
print('Total cost for SVC: ', cost_svc)
print('Total cost for VotingClassifier: ', cost_voting)
     Total cost for RandomForestClassifier: 82
     Total cost for LogisticRegression: 177
     Total cost for SVC: 125
     Total cost for VotingClassifier: 114
# Import necessary libraries
from sklearn.metrics import precision_score, recall_score, f1_score, log_loss, matthews_corrcoef
# Calculate metrics for RandomForestClassifier
rf_precision = precision_score(y_test, rf_predictions)
rf_recall = recall_score(y_test, rf_predictions)
rf_f1 = f1_score(y_test, rf_predictions)
rf_log_loss = log_loss(y_test, rf.predict_proba(X_test))
rf_matthews = matthews_corrcoef(y_test, rf_predictions)
print('RandomForestClassifier:')
```

```
print('Precision: ', rf_precision)
print('Recall: ', rf_recall)
print('F1-score: ', rf_f1)
print('Log Loss: ', rf log loss)
print('Matthews Correlation Coefficient: ', rf_matthews)
# Calculate metrics for LogisticRegression
lr_precision = precision_score(y_test, lr_predictions)
lr_recall = recall_score(y_test, lr_predictions)
lr_f1 = f1_score(y_test, lr_predictions)
lr_log_loss = log_loss(y_test, lr.predict_proba(X_test))
lr_matthews = matthews_corrcoef(y_test, lr_predictions)
print('\nLogisticRegression:')
print('Precision: ', lr_precision)
print('Recall: ', lr_recall)
print('F1-score: ', lr_f1)
print('Log Loss: ', lr_log_loss)
print('Matthews Correlation Coefficient: ', lr_matthews)
# Calculate metrics for SVC
svc_precision = precision_score(y_test, svc_predictions)
svc_recall = recall_score(y_test, svc_predictions)
svc_f1 = f1_score(y_test, svc_predictions)
svc_log_loss = log_loss(y_test, svc.predict_proba(X_test))
svc_matthews = matthews_corrcoef(y_test, svc_predictions)
print('\nSVC:')
print('Precision: ', svc_precision)
print('Recall: ', svc_recall)
print('F1-score: ', svc_f1)
print('Log Loss: ', svc_log_loss)
print('Matthews Correlation Coefficient: ', svc_matthews)
# Calculate metrics for VotingClassifier
voting_precision = precision_score(y_test, voting_predictions)
voting_recall = recall_score(y_test, voting_predictions)
voting\_f1 = f1\_score(y\_test, \ voting\_predictions)
voting_log_loss = log_loss(y_test, voting_clf.predict_proba(X_test))
voting_matthews = matthews_corrcoef(y_test, voting_predictions)
print('\nVotingClassifier:')
print('Precision: ', voting_precision)
print('Recall: ', voting_recall)
print('F1-score: ', voting_f1)
print('Log Loss: ', voting_log_loss)
print('Matthews Correlation Coefficient: ', voting_matthews)
     RandomForestClassifier:
     Precision: 0.8858447488584474
      Recall: 0.7729083665338645
     F1-score: 0.825531914893617
Log Loss: 0.220508289503508
     Matthews Correlation Coefficient: 0.7976555339516986
     {\tt LogisticRegression:}
     Precision: 0.7605633802816901
     Recall: 0.4302788844621514
      F1-score: 0.549618320610687
      Log Loss: 0.2300518912407888
     Matthews Correlation Coefficient: 0.5170571241823865
      Precision: 0.9375
     Recall: 0.5378486055776892
     F1-score: 0.6835443037974683
Log Loss: 0.21601221478887933
     Matthews Correlation Coefficient: 0.6743976367376933
     VotingClassifier:
     Precision: 0.8959537572254336
      Recall: 0.6175298804780877
      F1-score: 0.7311320754716981
     Log Loss: 0.1665534415242046
      Matthews Correlation Coefficient: 0.7069257293672487
# Convert numpy arrays back into dataframes
X_train = pd.DataFrame(X_train, columns=train_data.drop(columns=['Churn']).columns)
X_test = pd.DataFrame(X_test, columns=train_data.drop(columns=['Churn']).columns)
```

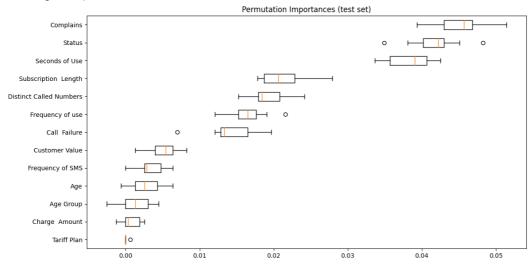
```
from sklearn.inspection import permutation_importance
import matplotlib.pyplot as plt

# Calculate permutation importance for RandomForestClassifier
result = permutation_importance(rf, X_test, y_test, n_repeats=10, random_state=0, n_jobs=-1)

# Sort features by importance
sorted_idx = result.importances_mean.argsort()

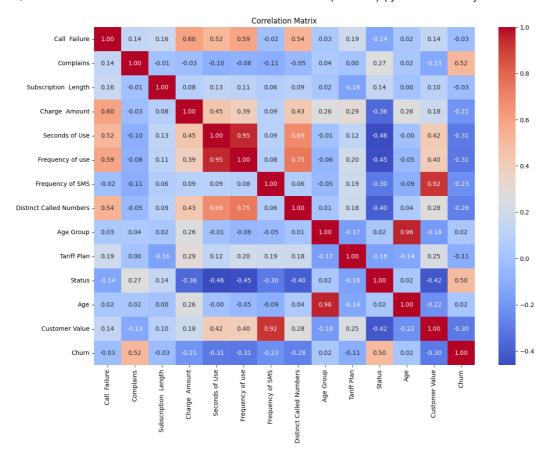
# Plot
fig, ax = plt.subplots(figsize=(12, 6))
ax.boxplot(result.importances[sorted_idx].T, vert=False, labels=X_test.columns[sorted_idx])
ax.set_title("Permutation Importances (test set)")
fig.tight_layout()
plt.show()
```

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but Ranc warnings.warn(



```
# Define cost values
cost_tp = -100 # Cost of true positive (retention cost)
cost_fp = -100 # Cost of false positive (unnecessary retention cost)
cost_tn = 0 # Cost of true negative (no cost)
cost_fn = -2300 # Cost of false negative (lost revenue + cost of acquiring a new customer)
# Calculate total cost for RandomForestClassifier
 \texttt{cost\_rf} = \texttt{cm\_rf[0, 1]} * \texttt{cost\_fp} + \texttt{cm\_rf[1, 0]} * \texttt{cost\_fn} + \texttt{cm\_rf[1, 1]} * \texttt{cost\_tp} + \texttt{cm\_rf[0, 0]} * \texttt{cost\_tn} 
# Calculate total cost for LogisticRegression
# Calculate total cost for SVC
cost\_svc = cm\_svc[0, 1] * cost\_fp + cm\_svc[1, 0] * cost\_fn + cm\_svc[1, 1] * cost\_tp + cm\_svc[0, 0] * cost\_tn + cm\_svc[0
# Calculate total cost for VotingClassifier
cost\_voting = cm\_voting[0, 1] * cost\_fp + cm\_voting[1, 0] * cost\_fn + cm\_voting[1, 1] * cost\_tp + cm\_voting[0, 0] * cost\_tn + cm\_voting[0, 0
\verb|print('Total cost for RandomForestClassifier: ', cost\_rf)|\\
print('Total cost for LogisticRegression: ', cost_lr)
print('Total cost for SVC: ', cost_svc)
print('Total cost for VotingClassifier: ', cost_voting)
                     Total cost for RandomForestClassifier: -153000
                     Total cost for LogisticRegression: -343100
                      Total cost for SVC: -281200
                      Total cost for VotingClassifier: -238100
```

```
# Define profit values
profit_tn = 1000 # Profit from true negative (customer correctly identified as not churning)
profit_tp = 1000 # Profit from true positive (customer correctly identified as churning and retained)
# Calculate total profit for RandomForestClassifier
profit_rf = cm_rf[0, 0] * profit_tn + cm_rf[1, 1] * profit_tp
# Calculate total profit for LogisticRegression
profit_lr = cm_lr[0, 0] * profit_tn + cm_lr[1, 1] * profit_tp
# Calculate total profit for SVC
profit_svc = cm_svc[0, 0] * profit_tn + cm_svc[1, 1] * profit_tp
# Calculate total profit for VotingClassifier
profit_voting = cm_voting[0, 0] * profit_tn + cm_voting[1, 1] * profit_tp
print('Total profit for RandomForestClassifier: ', profit_rf)
print('Total profit for LogisticRegression: ', profit_lr)
print('Total profit for SVC: ', profit_svc)
print('Total profit for VotingClassifier: ', profit_voting)
     Total profit for RandomForestClassifier: 1493000
     Total profit for LogisticRegression: 1398000
     Total profit for SVC: 1450000
     Total profit for VotingClassifier: 1461000
import numpy as np
from sklearn.model_selection import cross_val_score
# Perform cross-validation on RandomForestClassifier
rf_cv_scores = cross_val_score(rf, X_train, y_train, cv=5)
print('Cross-validation scores for RandomForestClassifier: ', rf_cv_scores)
print('Mean cross-validation score for RandomForestClassifier: ', np.mean(rf_cv_scores))
# Perform cross-validation on LogisticRegression
lr_cv_scores = cross_val_score(lr, X_train, y_train, cv=5)
print('\nCross-validation scores for LogisticRegression: ', lr_cv_scores)
print('Mean cross-validation score for LogisticRegression: ', np.mean(lr_cv_scores))
# Perform cross-validation on SVC
svc_cv_scores = cross_val_score(svc, X_train, y_train, cv=5)
print('\nCross-validation scores for SVC: ', svc_cv_scores)
print('Mean cross-validation score for SVC: ', np.mean(svc_cv_scores))
# Perform cross-validation on VotingClassifier
voting_cv_scores = cross_val_score(voting_clf, X_train, y_train, cv=5)
print('\nCross-validation scores for VotingClassifier: ', voting_cv_scores)
print('Mean cross-validation score for VotingClassifier: ', np.mean(voting_cv_scores))
     Cross-validation scores for RandomForestClassifier: [0.95555556 0.93650794 0.95238095 0.93333333 0.95555556]
     Mean cross-validation score for RandomForestClassifier: 0.9466666666666666666
     Cross-validation scores for LogisticRegression: [0.9047619 0.9015873 0.87619048 0.85714286 0.92063492]
     Mean cross-validation score for LogisticRegression: 0.8920634920634921
     Cross-validation scores for SVC: [0.92063492 0.93015873 0.89206349 0.88253968 0.93333333]
     Mean cross-validation score for SVC: 0.9117460317460317
     Cross-validation scores for VotingClassifier: [0.94920635 0.93015873 0.92698413 0.8984127 0.94285714]
     Mean cross-validation score for VotingClassifier: 0.9295238095238094
import seaborn as sns
# Calculate correlation matrix
corr = train_data.corr()
# Plot the heatmap
plt.figure(figsize=(14, 10))
sns.heatmap(corr, annot=True, fmt=".2f", cmap='coolwarm', cbar=True)
plt.title('Correlation Matrix')
plt.show()
```



```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
# Define the model with n_init specified
kmeans = KMeans(n_clusters=3, n_init=10, random_state=0)
# Define data for clustering (only numerical variables)
cluster_data = train_data.select_dtypes(include=[np.number])
# Scale the data
scaler = StandardScaler()
cluster_data_scaled = scaler.fit_transform(cluster_data)
# Define the model
kmeans = KMeans(n_clusters=3, random_state=0) # we choose 3 clusters, but this could be any number
# Fit the model
kmeans.fit(cluster_data_scaled)
# Get cluster labels
train_data['cluster'] = kmeans.labels_
# Check the size of each cluster
print(train_data['cluster'].value_counts())
# Explore the mean values in each cluster
cluster_summary = train_data.groupby('cluster').mean()
print(cluster_summary)
     /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
       warnings.warn(
     0
          878
          363
          334
```

```
Name: cluster, dtype: int64
              Call Failure Complains Subscription Length Charge Amount \
     cluster
                            0.119590
                                                   32.082005
     0
                  15.209581
                             0.029940
                                                   33.979042
                                                                    2.407186
     1
                             0.019284
                                                   31.016529
                                                                    0.947658
     2
                   6.093664
              Seconds of Use \mbox{ Frequency of use }\mbox{ Frequency of SMS }\ \
     cluster
     0
                2089,438497
                                     38.136674
                                                       13.514806
                10603.736527
                                   151.011976
                                                       50.538922
     1
     2
                 5003.107438
                                    75.451791
                                                      241.440771
              Distinct Called Numbers Age Group Tariff Plan
                                                                 Status
                                                                               Age \
     cluster
                            15.480638
                                       2.769932
                                                    1.001139 1.439636 30.461276
     0
                            44.224551
                                       3.245509
                                                    1.095808 1.000000 35.284431
     1
                            23.988981 2.490358
                                                    1.253444 1.000000 27.410468
     2
              Customer Value
                                 Churn
     cluster
     0
                 137.852215 0.275626
     1
                  575.416317 0.000000
                 1222.589518 0.005510
from sklearn.model_selection import learning_curve
# Define a function to plot the learning curves
def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None, n_jobs=None):
    plt.figure()
    plt.title(title)
    if ylim is not None:
       plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()
    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                    train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1, color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")
    plt.legend(loc="best")
    return plt
# Generate learning curves
plot_learning_curve(rf, 'Learning curve for RandomForestClassifier', X_train, y_train, cv=5)
```

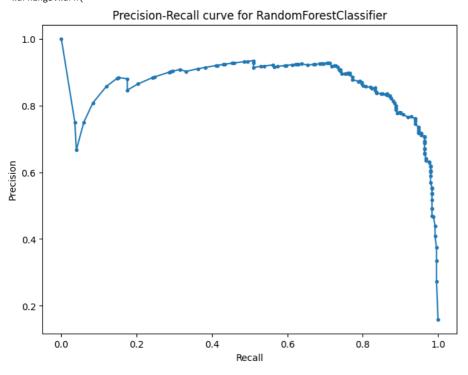
Learning curve for RandomForestClassifier

```
from sklearn.metrics import precision_recall_curve

# Calculate precision and recall
precision, recall, _ = precision_recall_curve(y_test, rf.predict_proba(X_test)[:, 1])

# Plot the precision-recall curve
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, marker='.')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall curve for RandomForestClassifier')
plt.show()
```

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but Ranc warnings.warn(



```
# Binning the 'Age' column into three categories
train_data['Age_bin'] = pd.cut(train_data['Age'], bins=[0, 30, 60, 100], labels=['Young', 'Middle-aged', 'Senior'])
from imblearn.over_sampling import SMOTE
# Initialize SMOTE
smote = SMOTE()
# Fit SMOTE to the data
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
import xgboost as xgb
# Initialize XGBClassifier
xgb_clf = xgb.XGBClassifier()
# Train the model
xgb_clf.fit(X_train, y_train)
# Make predictions
y_pred_xgb = xgb_clf.predict(X_test)
# Evaluate the model
print(classification_report(y_test, y_pred_xgb))
                                recall f1-score
                   precision
                                                   support
```

1324

0.97

0.96

0.98

```
0.88
                                  0.78
                                            0.83
                                                       251
                                            0.95
                                                      1575
         accuracy
        macro avg
                        0.92
                                  0.88
                                            0.90
                                                      1575
                        0.95
                                  0.95
                                            0.95
                                                      1575
     weighted avg
# Make predictions using multiple models
y_pred_rf = rf.predict_proba(X_test)[:, 1]
y_pred_lr = lr.predict_proba(X_test)[:, 1]
y_pred_xgb = xgb_clf.predict_proba(X_test)[:, 1]
# Average the predictions
y_pred_ensemble = (y_pred_rf + y_pred_lr + y_pred_xgb) / 3
# Convert probabilities to class labels
y_pred_ensemble = [1 if prob > 0.5 else 0 for prob in y_pred_ensemble]
# Evaluate the ensemble
print(classification_report(y_test, y_pred_ensemble))
     /usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but RandomForestClassifier was fitte
       warnings.warn(
     /usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but LogisticRegression was fitted wi
       warnings.warn(
                   precision
                                recall f1-score
                                                   support
                0
                        0.95
                                  0.98
                                            0.97
                                                      1324
                        0.88
                                            0.81
                                                       251
                1
                                  0.75
         accuracy
                                            0.94
                                                      1575
        macro avg
                        0.92
                                  0.87
                                            0.89
                                                      1575
     weighted avg
                        0.94
                                  0.94
                                            0.94
                                                      1575
    4
import joblib
joblib.dump(rf, 'model.joblib')
     ['model.joblib']
!pip install shap
     Collecting shap
       Downloading shap-0.42.0-cp310-cp310-manylinux_2_12_x86_64.manylinux2010_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_64.whl (54
                                                - 547.1/547.1 kB 14.2 MB/s eta 0:00:00
     Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from shap) (1.22.4)
     Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from shap) (1.10.1)
     Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (from shap) (1.2.2)
     Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from shap) (1.5.3)
     Requirement already satisfied: tqdm>=4.27.0 in /usr/local/lib/python3.10/dist-packages (from shap) (4.65.0)
     Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.10/dist-packages (from shap) (23.1)
     Collecting slicer==0.0.7 (from shap)
       Downloading slicer-0.0.7-py3-none-any.whl (14 kB)
     Requirement already satisfied: numba in /usr/local/lib/python3.10/dist-packages (from shap) (0.56.4)
     Requirement already satisfied: cloudpickle in /usr/local/lib/python3.10/dist-packages (from shap) (2.2.1)
     Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/lib/python3.10/dist-packages (from numba->shap) (0.39.1)
     Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from numba->shap) (67.7.2)
     Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas->shap) (2.8.2)
     Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->shap) (2022.7.1)
     Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->shap) (1.3.1)
     Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->shap) (3.1.0)
     Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas->shap) (1.1
     Installing collected packages: slicer, shap
     Successfully installed shap-0.42.0 slicer-0.0.7
from sklearn.ensemble import RandomForestClassifier
# Define your RandomForestClassifier
rf = RandomForestClassifier(n estimators=100, random state=42)
# Fit the classifier to your training data
# (Substitute X_train and y_train with your actual training data)
rf.fit(Churn_TRAIN, Churn_TEST)
```

① 0s completed at 01:03

```
NameError

Traceback (most recent call last)

sipython-input-7-5c1ce8ec3bbf> in <cell line: 8>()

6 # Fit the classifier to your training data

7 # (Substitute X_train and y_train with your actual training data)

---> 8 rf.fit(Churn_TRAIN, Churn_TEST)

NameError: name 'Churn_TRAIN' is not defined
```

https://colab.research.google.com/drive/1YwLnwl_5qSnwL1-Uzg8_5GIK-n2XpfNL#scrollTo=bPshiwNNX734&printMode=true