Import software libraries

In [1]:

```python
# Import required libraries.
import sys                                                  # Read system parameters.
import numpy as np                                          # Work with multi-dimensional arrays.
import pandas as pd                                         # Manipulate and analyze data.
import matplotlib                                           # Create and format charts.
import matplotlib.pyplot as plt
import seaborn as sns                                       # Make charting easier.
import sklearn                                              # Train and evaluate machine learning models.
from sklearn.model_selection import train_test_split, \
                                    learning_curve, \
                                    cross_val_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, \
                            confusion_matrix, \
                            classification_report, \
                            f1_score, \
                            recall_score, \
                            precision_score, \
                            roc_auc_score, \
                            plot_roc_curve, \
                            plot_precision_recall_curve, \
                            plot_confusion_matrix
from sklearn.dummy import DummyClassifier
import xgboost                                              # Build gradient boosting models.
from xgboost import XGBClassifier
import pickle                                               # Save Python objects as binary files.
from collections import Counter
import warnings                                             # Suppress warnings.
warnings.filterwarnings('ignore')

# Ensure results are reproducible.
np.random.seed(1)

# Summarize software libraries used.
print('Libraries used in this project:')
print('- Python {}'.format(sys.version))
print('- NumPy {}'.format(np.__version__))
print('- pandas {}'.format(pd.__version__))
print('- Matplotlib {}'.format(matplotlib.__version__))
print('- Seaborn {}'.format(sns.__version__))
print('- scikit-learn {}'.format(sklearn.__version__))
print('- XGBoost {}'.format(xgboost.__version__))
```

```
Libraries used in this project:
- Python 3.9.7 (default, Sep 16 2021, 16:59:28) [MSC v.1916 64 bit (AMD64)]
- NumPy 1.19.5
- pandas 1.3.4
- Matplotlib 3.4.3
- Seaborn 0.11.2
- scikit-learn 0.24.2
- XGBoost 1.5.1
```

Read and examine the data

In [2]:

```python
# Read the data.

df = pd.read_pickle("customer_data.pickle")

# Preview the first five rows of the data.

df.head()
```

Out[2]:

	frequency	recency	tenure	monetary_value	number_unique_items	churned
u12747	6.0	367.0	369.0	39.19	3	True
u12748	41.0	365.0	369.0	12.01	9	False
u12749	2.0	127.0	130.0	22.28	2	True
u1282	0.0	0.0	326.0	0.00	1	False
u12822	0.0	0.0	87.0	0.00	1	True

In [3]:

```python
# Check the structure of the data.

df.shape
```

Out[3]:

```
(2130, 6)
```

In [4]:

```python
#df.to_csv("data.csv", index=False)
```

Prepare the data

In [5]:

```python
# Define the target variable and get the count of each value in the variable.

df.describe()
```

Out[5]:

	frequency	recency	tenure	monetary_value	number_unique_items
count	2130.000000	2130.000000	2130.000000	2130.000000	2130.000000
mean	1.662441	98.435681	214.496244	12.423202	2.151643
std	3.399520	119.996700	112.923328	16.514363	1.444775
min	0.000000	0.000000	1.000000	0.000000	1.000000
25%	0.000000	0.000000	110.000000	0.000000	1.000000
50%	1.000000	25.000000	240.000000	4.250000	2.000000
75%	2.000000	195.000000	311.000000	20.800000	3.000000
max	78.000000	372.000000	373.000000	234.300000	9.000000

In [6]:

```python
# Split the data into target and features.

X = df.iloc[:, 0:5]
y = df.iloc[:, 5]
```

In [7]:

```python
# Split the dataset into separate training and testing sets.


X_train, X_test, y_train, y_test = train_test_split(X.values, y.values, test_size=0.2, random_state=0)

# Get the shape of both the training dataset and the test dataset.

X_train.shape, X_test.shape
```

Out[7]:

```
((1704, 5), (426, 5))
```

In [8]:

```python
# Use the Counter library to get the count of each value in the target variable (test data).

Counter(y_test)
```

Out[8]:

```
Counter({True: 144, False: 282})
```

Train a logistic regression model

In [9]:

```python
# Normalize the training data.

minmax = MinMaxScaler()
```

In [10]:

```python
X_train_scaled = minmax.fit_transform(X_train)
```

In [11]:

```python
X_train_scaled
```

Out[11]:

```
array([[0.        , 0.        , 0.10483871, 0.        , 0.14285714],
       [0.        , 0.        , 0.08333333, 0.        , 0.        ],
       [0.01282051, 0.12365591, 0.68548387, 0.01408451, 0.28571429],
       ...,
       [0.01282051, 0.09139785, 0.69354839, 0.08450704, 0.        ],
       [0.01282051, 0.19086022, 0.64516129, 0.00469484, 0.14285714],
       [0.        , 0.        , 0.01075269, 0.        , 0.        ]])
```

In [12]:

```python
# Create a LogisticRegression() model and fit it on the scaled training data.

lr = LogisticRegression(random_state=0)
```

In [13]:

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

Out[13]:

```
LogisticRegression(random_state=0)
```

In [14]:

```python
# Make predictions on the test data.

lr_pred = lr.predict(X_test)
lr_pred

# Get a count of each prediction value.

Counter(lr_pred)
```

Out[14]:

```
Counter({True: 419, False: 7})
```

Perform a quick evaluation of the logistic regression model

In [15]:

```python
# Obtain the accuracy of the model's predictions.

accuracy_score(y_test,lr_pred)
```

Out[15]:

```
0.3544600938967136
```

In [16]:

```python
# Use the classification_report() function to get a table of additional metric scores.

print(classification_report(y_test,lr_pred))
```

```
              precision    recall  f1-score   support

       False       1.00      0.02      0.05       282
        True       0.34      1.00      0.51       144

    accuracy                           0.35       426
   macro avg       0.67      0.51      0.28       426
weighted avg       0.78      0.35      0.20       426
```

Train a random forest model

In [17]:

```python
# Create a RandomForestClassifier() model and fit it on the scaled training data.

rf = RandomForestClassifier(random_state=0)

rf.fit(X_train_scaled, y_train)
```

Out[17]:

```
RandomForestClassifier(random_state=0)
```

In [18]:

```python
# Make predictions on the test data.

rf_pred = rf.predict(X_test)

# Get a count of each prediction value.

Counter(rf_pred)
```

Out[18]:

```
Counter({False: 233, True: 193})
```

Perform a quick evaluation of the random forest model

In [19]:

```python
# Obtain the accuracy of the model's predictions.

accuracy_score(y_test, rf_pred)
```

Out[19]:

```
0.5234741784037559
```

In [20]:

```python
# Use the classification_report() function to get a table of additional metric scores.

print(classification_report(y_test, rf_pred))
```

```
              precision    recall  f1-score   support

       False       0.67      0.55      0.61       282
        True       0.35      0.47      0.40       144

    accuracy                           0.52       426
   macro avg       0.51      0.51      0.50       426
weighted avg       0.56      0.52      0.54       426
```

Compare evaluation metrics for each model

In [21]:

```python
# List will hold model objects.

models = []

# DummyClassifier() used as a baseline algorithm.

models.append(('Dummy Classifier', DummyClassifier(strategy = 'stratified')))

# Logistic Regression model.

models.append(('Logistic Regression', LogisticRegression()))

# Random Forest model.

models.append(('Random Forest', RandomForestClassifier()))

# XGBoost model.

models.append(('XGBoost', XGBClassifier(eval_metric = 'logloss', n_jobs = 1)))
```

In [22]:

```python
# List will hold dictionaries of model scores.

scoring_df = []

# Train each model in the list and output multiple scores for each model.

for name, model in models:
    if name in ['Logistic Regression']:
        X_train_1 = X_train_scaled
    else:
        X_train_1 = X_train

    model.fit(X_train_1, y_train)

    y_pred = model.predict(X_test)

    # Calcualte the evaluation metrics for the model.

    accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    auc = roc_auc_score(y_test, y_pred)

    scoring_dict = {'Model': name,
                    'Accuracy': round(accuracy, 4),
                    'F1 Score': round(f1, 4),
                    'Precision' : round(precision, 4),
                    'Recall' : round(recall, 4),
                    'AUC' : round(auc ,4),
                   }

    scoring_df.append(scoring_dict)
```

In [23]:

```python
# Create a DataFrame from scoring_df.

finaldf= pd.DataFrame(scoring_df)
finaldf

# Sort the DataFrame by accuracy score (descending), then print it.

finaldf.sort_values(by="Accuracy", ascending=False)
```

Out[23]:

	Model	Accuracy	F1 Score	Precision	Recall	AUC
0	Dummy Classifier	0.5962	0.4228	0.4091	0.4375	0.5574
3	XGBoost	0.5892	0.2291	0.3133	0.1806	0.4892
2	Random Forest	0.5775	0.2562	0.3163	0.2153	0.4888
1	Logistic Regression	0.3545	0.5115	0.3437	1.0000	0.5124

Begin evaluating the best model

In [24]:

```python
# Retrain the model with the highest accuracy score.

dummy = DummyClassifier(random_state=0, strategy='stratified')
dummy.fit(X_train_scaled, y_train)
```

Out[24]:

```
DummyClassifier(random_state=0, strategy='stratified')
```

In [25]:

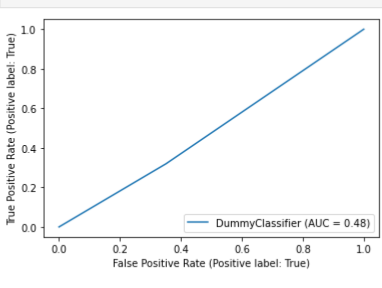
```python
# Make predictions on the test data.

dummy_pred = dummy.predict(X_test)

# Get a count of each prediction value.

Counter(dummy_pred)
```

Out[25]:

```
Counter({False: 281, True: 145})
```

In [26]:

```python
# Plot a ROC curve.

plot_roc_curve(dummy, X_test, y_test)

plt.show()
```



Generate a confusion matrix of the best model

In [27]:

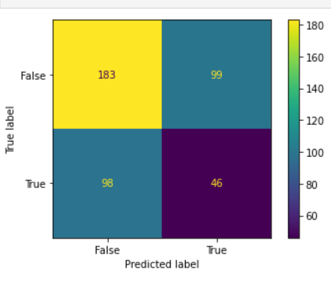
```python
# Generate a confusion matrix.

cm = confusion_matrix(y_test,dummy_pred)
cm
```

Out[27]:

```
array([[183,  99],
       [ 98,  46]], dtype=int64)
```

In [28]:

```python
# Plot the confusion matrix.

plot_confusion_matrix(dummy, X_test, y_test)

plt.show()
```



Generate a feature importance plot for the best model

In [29]:

```python
X_train_df = pd.DataFrame(data=X_train, columns=['frequency','recency','tenure','monetary_value','number_unique
X_train_df
```

Out[29]:

	frequency	recency	tenure	monetary_value	number_unique_items
0	0.0	0.0	40.0	0.00	2.0
1	0.0	0.0	32.0	0.00	1.0
2	1.0	46.0	256.0	3.30	3.0
3	2.0	229.0	338.0	13.20	3.0
4	1.0	48.0	71.0	16.50	1.0
...	...	...	...	...	...
1699	1.0	235.0	264.0	17.70	1.0
1700	2.0	150.0	171.0	25.95	5.0
1701	1.0	34.0	259.0	19.80	1.0
1702	1.0	71.0	241.0	1.10	2.0
1703	0.0	0.0	5.0	0.00	1.0

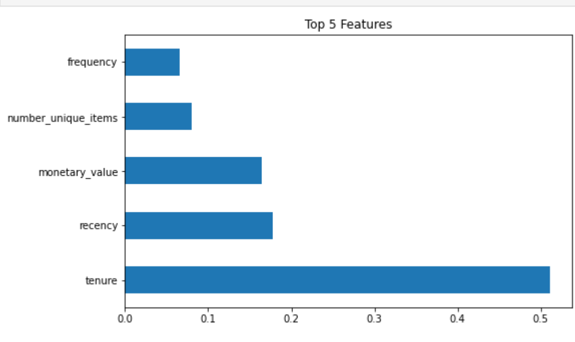
1704 rows × 5 columns

In [30]:

```python
# This function generates a feature importance plot on a bar chart.

def feature_importance_plot(model, X_train, n):
    """Plots feature importance. This only works for random forest and XGBoost models."""

    plt.figure(figsize=(8, 5))  # Set figure size.
    feat_importances = pd.Series(model.feature_importances_,
                                 index = X_train.columns)
    feat_importances.nlargest(n).plot(kind = 'barh')
    plt.title(f'Top {n} Features')
    plt.show()
```

In [31]:

```python
# Plot the feature importances.

feature_importance_plot(rf, X_train_df, 5)
```



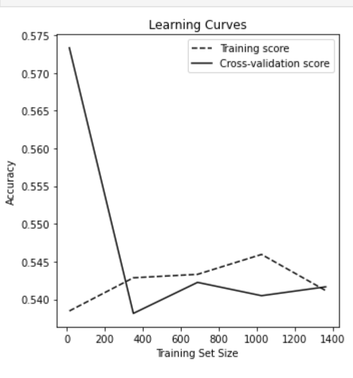
Plot a learning curve for the best model

In [32]:

```python
# This function generates and plots a learning curve.

def plot_learning_curves(model, X_train, y_train):
    """Plots learning curves for model validation."""

    plt.figure(figsize=(5, 5))  # Set figure size.
    train_sizes, train_scores, test_scores = learning_curve(model,
                                                            X_train,
                                                            y_train,
                                                            cv = 5,  # Number of folds in cross-validation.
                                                            scoring = 'accuracy',  # Evaluation metric.
                                                            n_jobs = 1,
                                                            shuffle = True,
                                                            train_sizes = np.linspace(0.01, 1.0, 5))  # 5 diffe

    # Create means and standard deviations of training set scores.

    train_mean = np.mean(train_scores, axis = 1)
    train_std = np.std(train_scores, axis = 1)

    # Create means and standard deviations of test set scores.

    test_mean = np.mean(test_scores, axis = 1)
    test_std = np.std(test_scores, axis = 1)

    # Draw lines.

    plt.plot(train_sizes, train_mean, '--', color = '#111111', label = 'Training score')
    plt.plot(train_sizes, test_mean, color = '#111111', label = 'Cross-validation score')

    # Create plot.

    plt.title('Learning Curves')
    plt.xlabel('Training Set Size'), plt.ylabel('Accuracy'), plt.legend(loc = 'best')
    plt.tight_layout()

    plt.show()
```

In [33]:

```python
# Call the function to plot learning curves for the best model.

plot_learning_curves(dummy, X_train, y_train)
```



Save the best model

In [34]:

```python
# Save the best model as a pickle file named best_classification_model.pickle.

pickle.dump(dummy, open('best_classification_model.pickle','wb'))
```

In [ ]: