Introduction to Regression Project

Problem Statement

Mobile carrier Megaline has found out that many of their subscribers use legacy plans. They want to develop a model that would analyze subscribers' behavior and recommend one of Megaline's newer plans: Smart or Ultra. You have access to behavior data about subscribers who have already switched to the new plans (from the project for the Statistical Data Analysis course). For this classification task, you need to develop a model that will pick the right plan. Since you've already performed the data preprocessing step, you can move straight to creating the model. Develop a model with the highest possible accuracy. In this project, the threshold for accuracy is 0.75. Check the accuracy using the test dataset.

Data Importation

```
#Importing the necesary libraries
import pandas as pd
# Dataset URL (CSV File): https://bit.ly/UsersBehaviourTelco
#Reading the data using pd.read_csv
subscribers_df = pd.read_csv("https://bit.ly/UsersBehaviourTelco")

#Previewing the first 5 top records
subscribers_df.head()
```

	calls	minutes	messages	mb_used	is_ultra
0	40.0	311.90	83.0	19915.42	0
1	85.0	516.75	56.0	22696.96	0
2	77.0	467.66	86.0	21060.45	0
3	106.0	745.53	81.0	8437.39	1
4	66.0	418.74	1.0	14502.75	0

Data Exploration

```
#Getting the shape of the dataframe using .shape() gives us the number of rows and columns
subscribers_df.shape
```

```
(3214, 5)
```

```
#Describing the data using .info() function
subscribers_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3214 entries, 0 to 3213
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   calls     3214 non-null   float64
 1   minutes   3214 non-null   float64
 2   messages  3214 non-null   float64
 3   mb_used   3214 non-null   float64
 4   is_ultra  3214 non-null   int64  
dtypes: float64(4), int64(1)
memory usage: 125.7 KB
```

```
# .describe() gives us the statistical description of the data
subscribers_df.describe()
```

	calls	minutes	messages	mb_used	is_ultra
count	3214.000000	3214.000000	3214.000000	3214.000000	3214.000000
mean	63.038892	438.208787	38.281269	17207.673836	0.306472
std	33.236368	234.569872	36.148326	7570.968246	0.461100
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	40.000000	274.575000	9.000000	12491.902500	0.000000
50%	62.000000	430.600000	30.000000	16943.235000	0.000000
75%	82.000000	571.927500	57.000000	21424.700000	1.000000
max	244.000000	1632.060000	224.000000	49745.730000	1.000000

```
#Looking at the amount of data on each target
subscribers_df['is_ultra'].value_counts()
```

```
0    2229
1     985
Name: is_ultra, dtype: int64
```

```
# Those promoted and those not as a percentage
print('1. The percentage of mobile users on Smart plan are '
      + str(round(((subscribers_df["is_ultra"].isin([0]).sum())/subscribers_df.shape[0])*1
print('2. The percentage of mobile users on Ultra plan are '
      + str(round(((subscribers_df["is_ultra"].isin([1]).sum())/subscribers_df.shape[0])*1
```

```
1. The percentage of mobile users on Smart plan are 69.35 %
2. The percentage of mobile users on Ultra plan are 30.65 %
```

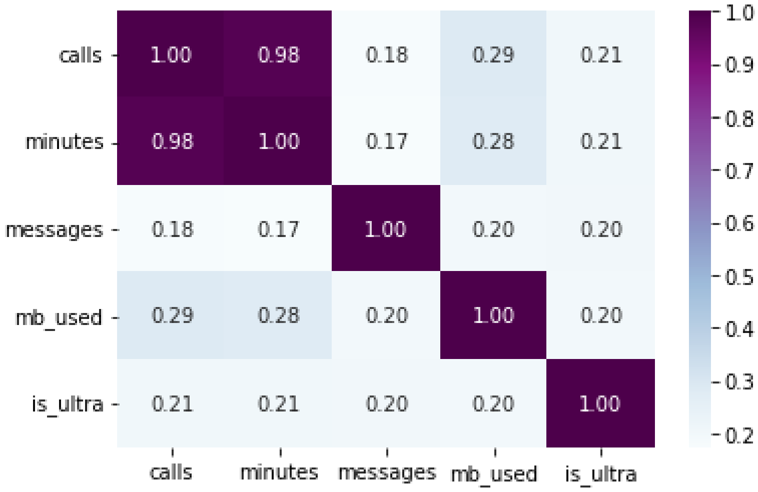
Data Cleaning

Data cleaning has already been done for this data set as per the instructions

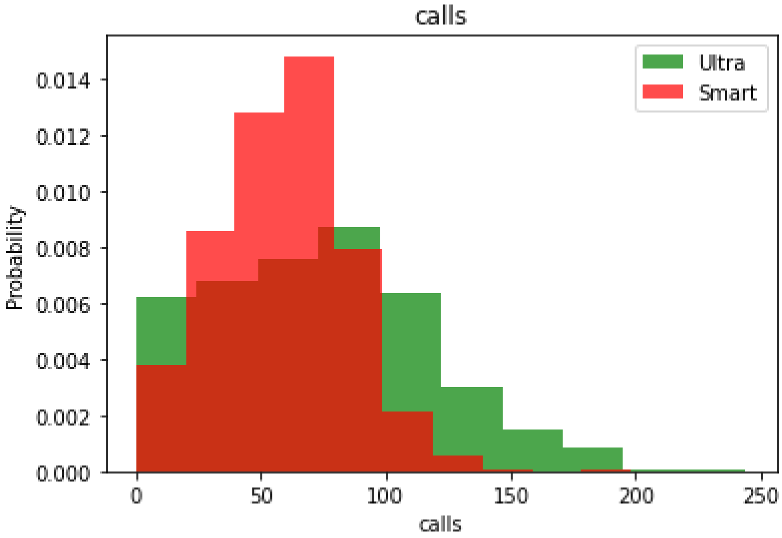
Since you've already performed the data preprocessing step, you can move straight to creating the model

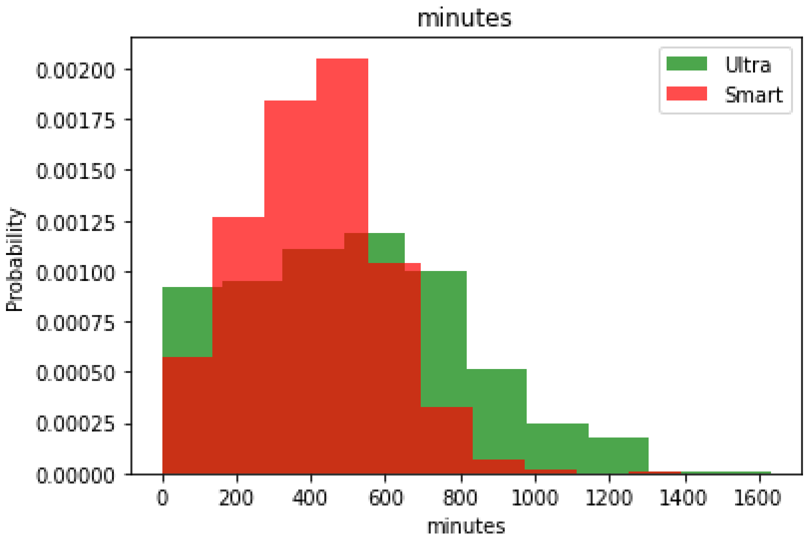
Data Preparation

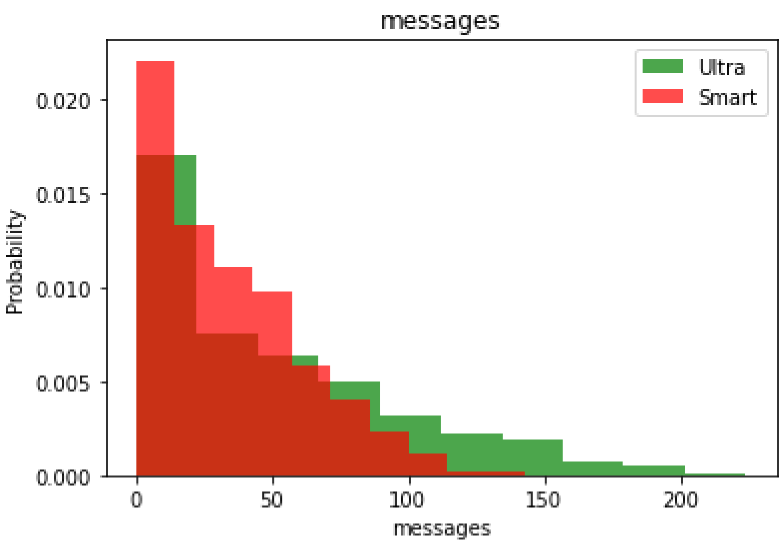
```
#Checking the correlation of features and targets in the dataset
#Importing seaborn and matplotlib

import matplotlib.pyplot as plt
import seaborn as sns

features = subscribers_df.columns
corr_= subscribers_df[features].corr()
plt.figure(figsize=(6,4))
sns.heatmap(corr_, annot=True, fmt = ".2f", cmap = "BuPu");
```

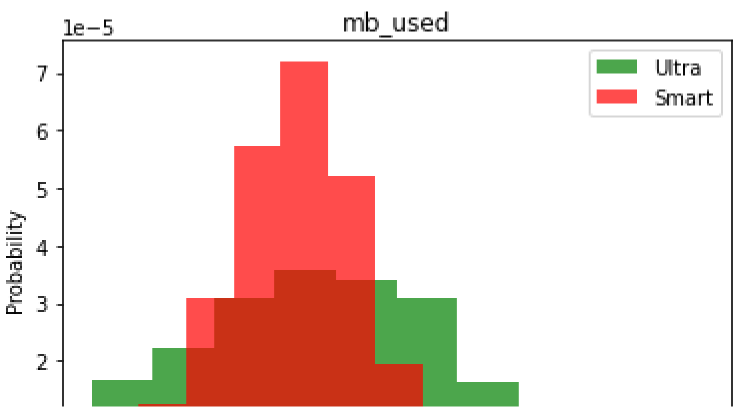



```
# Plotting an Histogram for features to show relationship between features and target
for feature in features[:-1]:
  plt.hist(subscribers_df[subscribers_df['is_ultra']==1][feature], color= 'green', alpha =
  plt.hist(subscribers_df[subscribers_df['is_ultra']==0][feature], color= 'red', alpha = 0
  plt.title(feature)
  plt.ylabel('Probability')
  plt.xlabel(feature)
  plt.legend()
  plt.show()
```


calls
Ultra
Smart
Probability
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
50
100
150
200
250
calls


minutes
Ultra
Smart
Probability
0.00200
0.00175
0.00150
0.00125
0.00100
0.00075
0.00050
0.00025
0.00000
0
200
400
600
800
1000
1200
1400
1600
minutes


messages
Ultra
Smart
Probability
0.020
0.015
0.010
0.005
0.000
0
50
100
150
200
messages


mb_used
1e−5
Ultra
Smart
Probability
7
6
5
4
3
2

```
# Splitting the source data into a training set, a validation set and a test set.
#First import train_test_split from sklearn
from sklearn.model_selection import train_test_split


features = subscribers_df.drop(['is_ultra'], axis=1)
target = subscribers_df['is_ultra']

# Setting aside 20% of train and test data for evaluation(Splitting into train and test da
X_train, X_test, Y_train, Y_test = train_test_split(features, target, test_size=0.2, rando

# Using the same function above for the validation set
X_train, X_val, Y_train, Y_val = train_test_split(X_train, Y_train, test_size=0.25, random

# Checking the shape of our new datasets

print(f"X_train shape: {X_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"Y_train shape: {Y_train.shape}")
print(f"Y_test shape: {Y_test.shape}")
print(f"X_val shape: {Y_train.shape}")
print(f"Y_val shape: {Y_test.shape}")
```

```
X_train shape: (1928, 4)
X_test shape: (643, 4)
Y_train shape: (1928,)
Y_test shape: (643,)
X_val shape: (1928,)
Y_val shape: (643,)
```

Data Modeling

```
# 3. Investigating the quality of different models by changing hyperparameters.
# Briefly describe the findings of the study.


#import DecisionTreeRegressor and DecisionTreeClassifier
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
# RandomForestRegressor and is located in sklearn.ensemble module.
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression

dec_regressor = DecisionTreeClassifier(random_state=27)
log_regressor = LogisticRegression()
fst_regressor = RandomForestClassifier(random_state= 14)


dec_regressor.fit(X_train, Y_train)
log_regressor.fit(X_train, Y_train)
fst_regressor.fit(X_train, Y_train)

# Making Predictions using the validation set
```

```
dec_y_pred = dec_regressor.predict(X_val)
log_y_pred = log_regressor.predict(X_val)
fst_y_pred = fst_regressor.predict(X_val)

from sklearn.metrics import mean_squared_error
# Finally, evaluating our models
print(f'Decision Tree RMSE: {mean_squared_error(Y_val, dec_y_pred, squared=False)}')
print(f'Linear Regression RMSE:{mean_squared_error(Y_val, log_y_pred, squared=False)}')
print(f'Random Forest Classifier RMSE: {mean_squared_error(Y_val, fst_y_pred, squared=Fals
```

```
Decision Tree RMSE: 0.5050291400982393
Linear Regression RMSE:0.5156945821140386
Random Forest Classifier RMSE: 0.4136098341043249
```

```
#Import Classification_report
from sklearn.metrics import classification_report
# print classification report for Decision Tree Regressor
print(f'DecisionTreeClassifier classification report:\n {classification_report(Y_test, dec
```

```
DecisionTreeClassifier classification report:
               precision    recall  f1-score   support

           0       0.67      0.70      0.68       427
           1       0.35      0.32      0.34       216

    accuracy                           0.57       643
   macro avg       0.51      0.51      0.51       643
weighted avg       0.56      0.57      0.57       643
```

```
# Printing classification report for Logistic Regression
print(f'Logistic Regression classification report:\n {classification_report(Y_test, log_y_
```

```
Logistic Regression classification report:
               precision    recall  f1-score   support

           0       0.66      0.97      0.79       427
           1       0.33      0.03      0.05       216

    accuracy                           0.65       643
   macro avg       0.50      0.50      0.42       643
weighted avg       0.55      0.65      0.54       643
```

```
# Printing classification report for Random Forest Classifier
print(f'Random Forest Classifier classification report:\n {classification_report(Y_test, f
```

```
Random Forest Classifier classification report:
               precision    recall  f1-score   support

           0       0.67      0.77      0.71       427
           1       0.34      0.24      0.28       216
```

```
    accuracy                           0.59       643
   macro avg       0.51      0.50      0.50       643
weighted avg       0.56      0.59      0.57       643
```

The model's perfomance accuracy given below:-

DecisionTreeClassifier 0.57

Logistic Regression 0.65

Random Forest Classifier 0.59

Model Improvement with Hyperparameters

```
##Finding the best tree depth with best accuracy
from sklearn.metrics import accuracy_score
best_score = 0
for depth in range(1,10):
  model = DecisionTreeClassifier(max_depth=depth, random_state=27)
  model.fit(X_test, Y_test)
  pred = model.predict(X_val)
  score = accuracy_score(Y_val, pred)
  if score > best_score: best_score = score
print(f'Tree accuracy with Validation: {best_score} at depth of: {depth}')
```

```
Tree accuracy with Validation: 0.807153965785381 at depth of: 9
```

```
#Finding the best n estimator for random forest with best accuracy
best_score = 0
for n in range(1,20):
  model = RandomForestClassifier(n_estimators=n, random_state=12345)
  model.fit(X_train, Y_train)
  score = model.score(X_val, Y_val)
  if score > best_score: best_score = score
print(f'Forest accuracy with Validation: {best_score} for n trees: {n}')
```

```
Forest accuracy with Validation: 0.8242612752721618 for n trees: 19
```

```
# Retraining our models with hyper parameteres
dec_regressor = DecisionTreeClassifier(random_state=27,max_depth = 9 )
log_regressor = LogisticRegression()
fst_regressor = RandomForestClassifier(random_state= 14, n_estimators = 19)
```

```
dec_regressor.fit(X_train, Y_train)
log_regressor.fit(X_train, Y_train)
fst_regressor.fit(X_train, Y_train)
```

```
RandomForestClassifier(n_estimators=19, random_state=14)
```

Model Evaluation

```
# 4. Checking the quality of the model using the test set.

# Making Predictions using the test set
dec_y_pred = dec_regressor.predict(X_test)
log_y_pred = log_regressor.predict(X_test)
fst_y_pred = fst_regressor.predict(X_test)
```

```
# Evaluating the models
print(f'Decision Tree RMSE: {mean_squared_error(Y_test, dec_y_pred, squared=False)}')
print(f'Linear Regression RMSE:{mean_squared_error(Y_test, log_y_pred, squared=False)}')
print(f'Random Forest Classifier RMSE: {mean_squared_error(Y_test, fst_y_pred, squared=Fal
```

```
Decision Tree RMSE: 0.4877982399123497
Linear Regression RMSE:0.5714841119420357
Random Forest Classifier RMSE: 0.4748741340974856
```

```
# 5. Additional task: sanity check the model. This data is more complex than what
# you’re used to working with, so it's not an easy task. We'll take a closer look at it
# later.
```

```
from sklearn.metrics import classification_report
# Print classification report for Decision Tree Classifier
print(f'DecisionTreeClassifier classification report:\n {classification_report(Y_test, dec
```

```
DecisionTreeClassifier classification report:
              precision    recall  f1-score   support

           0       0.76      0.93      0.84       427
           1       0.76      0.43      0.55       216

    accuracy                           0.76       643
   macro avg       0.76      0.68      0.69       643
weighted avg       0.76      0.76      0.74       643
```

```
# Print classification report for Logistic Regression
print(f'Logistic Regression classification report:\n {classification_report(Y_test, log_y_
```

```
Logistic Regression classification report:
              precision    recall  f1-score   support

           0       0.67      0.98      0.80       427
           1       0.65      0.06      0.11       216

    accuracy                           0.67       643
   macro avg       0.66      0.52      0.46       643
weighted avg       0.67      0.67      0.57       643
```

```
# Print classification report for Random Forest Regressor
print(f'Random Forest Classifier classification report:\n {classification_report(Y_test, f
```

```
 Random Forest Classifier classification report:
               precision    recall  f1-score   support

           0       0.78      0.92      0.84       427
           1       0.75      0.50      0.60       216

    accuracy                           0.77       643
   macro avg       0.77      0.71      0.72       643
weighted avg       0.77      0.77      0.76       643
```

Findings and Recommendations

After hyperparamer tuning, the accuracy score on our test dataset improved as follows

DecisionTreeClassifier 0.76

Logistic Regression 0.67

Random Forest Classifier 0.77

The accuracy score of our models tells us that it is possible to predict the plan of customers as to wether they are on smart or ultra with s good amount of accuracy. Random Forest and Decision Tree perfromed better in terms of accuracy