In [ ]:
```python
import pandas as pd
pd.set_option("display.max_columns", None)

import matplotlib.pyplot as plt
```

Model Building

In [ ]:
```python
df = pd.read_csv("dataset/phase2_df.csv")

# Replace spaces with underscores in column names
df.rename(columns=lambda x: x.replace(' ', '_'), inplace=True)

df.head()
```

Out[ ]:

	Age	Gender	Education_Level	Joining_Designation	joining_date	joining_month	joining_year	ReportCount	Active	TBV_avg	QR_avg	Income_avg	Grade_avg	income_diff_pattern	tbv_diff_pattern	qr_diff_pattern	grade_diff_pattern	City_C1	City_C10	City_C11	City_C12	City_C13	City_C14
0	0.189189	0.0	1.0	0.00	0.766667	1.000000	0.714286	0.086957	0.0	0.184600	0.333333	0.262508	0.00	0.0	0.000000	0.500000	0.0	0	0	0	0	0	0
1	0.216216	0.0	0.0	0.00	0.000000	0.727273	0.857143	0.086957	0.0	0.057086	0.000000	0.200489	0.00	0.0	0.333333	0.500000	0.0	0	0	0	0	0	0
2	0.232667	0.0	1.0	0.00	0.900000	0.363636	0.285714	0.956522	0.0	0.153949	0.086957	0.610567	0.75	0.0	0.333333	0.500000	0.0	0	0	0	0	0	0
3	0.243243	1.0	0.0	0.25	0.966667	0.909091	0.714286	0.043478	0.0	0.089047	0.000000	0.237608	0.25	0.0	0.333333	0.500000	0.0	0	0	0	0	0	0
4	0.571429	0.0	1.0	0.00	0.066667	0.454545	0.714286	0.260870	0.0	0.082327	0.142857	0.227116	0.00	0.0	0.333333	0.333333	0.0	0	0	0	0	0	0

In [ ]:
```python
df.shape
```

Out[ ]:
```
(2381, 46)
```

In [ ]:
```python
from sklearn.model_selection import train_test_split

# Separate features (X) and target variable (y)
X = df.drop(columns=['Active'])
y = df['Active'] # Fully-Paid: 1 and Charged-Off: 0
# Perform train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_state=42)
```

In [ ]:
```python
y_train.value_counts(), y_test.value_counts()
```

Out[ ]:
```
(Active
 0.0    1440
 1.0     702
 Name: count, dtype: int64,
 Active
 0.0    176
 1.0     63
 Name: count, dtype: int64)
```

- It doesn't seems to be a big data imbalance so using techniques like SMOTE or Weight Imbalance will have big impact.
- Also using such techniques may increase the chances of overfiting.

In [ ]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Initialize RandomForestClassifier
clf = RandomForestClassifier(random_state=42)

# Fit the model
clf.fit(X_train, y_train)

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

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:\n", report)
```

```
Accuracy: 0.91

Confusion Matrix:
[[166  10]
 [ 12  51]]

Classification Report:
               precision    recall  f1-score   support

         0.0       0.93      0.94      0.94       176
         1.0       0.84      0.81      0.82        63

    accuracy                           0.91       239
   macro avg       0.88      0.88      0.88       239
weighted avg       0.91      0.91      0.91       239
```

Let's use Class weights to balance the Dataset and check the results

In [ ]:
```python
# Specify class weights (class 0 is the minority class)
class_weights = {0: 1, 1: 2}

# Initialize RandomForestClassifier
clf = RandomForestClassifier(class_weight=class_weights, random_state=42)

# Fit the model
clf.fit(X_train, y_train)

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

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:\n", report)
```

```
Accuracy: 0.92

Confusion Matrix:
[[169   7]
 [ 12  51]]

Classification Report:
               precision    recall  f1-score   support

         0.0       0.93      0.96      0.95       176
         1.0       0.88      0.81      0.84        63

    accuracy                           0.92       239
   macro avg       0.91      0.88      0.89       239
weighted avg       0.92      0.92      0.92       239
```

- 1% increase in accuracy using Class Weights

In [ ]:
```python
from imblearn.over_sampling import SMOTE

# Apply SMOTE to oversample the minority class
smote = SMOTE(sampling_strategy='auto', random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
# Check the distribution of classes after applying SMOTE
print("Class distribution before SMOTE:", {0: sum(y_train == 0), 1: sum(y_train == 1)})
print("Class distribution after SMOTE:", {0: sum(y_train_smote == 0), 1: sum(y_train_smote == 1)})
```

```
Class distribution before SMOTE: {0: 1440, 1: 702}
Class distribution after SMOTE: {0: 1440, 1: 1440}
```

In [ ]:
```python
# Initialize RandomForestClassifier
clf = RandomForestClassifier(random_state=42)

# Fit the model
clf.fit(X_train, y_train)

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

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:\n", report)
```

```
Accuracy: 0.91

Confusion Matrix:
[[166  10]
 [ 12  51]]

Classification Report:
               precision    recall  f1-score   support

         0.0       0.93      0.94      0.94       176
         1.0       0.84      0.81      0.82        63

    accuracy                           0.91       239
   macro avg       0.88      0.88      0.88       239
weighted avg       0.91      0.91      0.91       239
```

- Not much change if we use SMOTE

Hyperparameter Tuning

```
In [ ]: from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

# Define the parameter grid
param_dist = {
    'n_estimators': randint(100, 300),
    'max_depth': [None] + list(range(25, 40, 1)),
    'min_samples_split': [5,10,20,25],
    'min_samples_leaf': [1, 2, 3],
    'bootstrap': [False]
}

# Initialize RandomForestClassifier
rf_clf = RandomForestClassifier(class_weight=class_weights, random_state=42)

# Initialize RandomizedSearchCV
random_search = RandomizedSearchCV(
    rf_clf, param_distributions=param_dist, n_iter=10, cv=5, scoring='accuracy', random_state=42, n_jobs=-1
)

# Fit the model
random_search.fit(X_train, y_train)

# Display the best hyperparameters
print("Best Hyperparameters:", random_search.best_params_)

# Make predictions on the test set using the best model
y_pred = random_search.best_estimator_.predict(X_test)

# Print confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:\n", pd.DataFrame(conf_matrix, columns=['Predicted 0', 'Predicted 1'], index=['Actual 0', 'Actual 1']))

# Print accuracy and classification report
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"\nAccuracy: {accuracy:.2f}")
print("Classification Report:\n", report)
```

```
Best Hyperparameters: {'bootstrap': False, 'max_depth': 39, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 157}

Confusion Matrix:
           Predicted 0  Predicted 1
Actual 0          167            9
Actual 1           11           52

Accuracy: 0.92
Classification Report:
               precision    recall  f1-score   support

         0.0       0.94      0.95      0.94       176
         1.0       0.85      0.83      0.84        63

    accuracy                           0.92       239
   macro avg       0.90      0.89      0.89       239
weighted avg       0.92      0.92      0.92       239
```

- Accuracy 91 : Best Hyperparameters: {'bootstrap': False, 'max_depth': 20, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 68}
- Accuracy 91 : Best Hyperparameters: {'bootstrap': False, 'max_depth': 23, 'min_samples_leaf': 2, 'min_samples_split': 20, 'n_estimators': 197}
- Accuracy 92 : Best Hyperparameters: {'bootstrap': False, 'max_depth': 26, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 112}
- Accuracy 92 : Best Hyperparameters: {'bootstrap': False, 'max_depth': 39, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 157}

Implementation of Boosting Algorithms

```
In [ ]: from sklearn.ensemble import GradientBoostingClassifier

# Specify class weights (class 0 is the minority class)
class_weights = {0: 1, 1: 2}

# Initialize RandomForestClassifier
clf = GradientBoostingClassifier(random_state=42)

# Fit the model
clf.fit(X_train, y_train)

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

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:\n", report)
```

```
Accuracy: 0.93

Confusion Matrix:
[[168   8]
 [  8  55]]

Classification Report:
               precision    recall  f1-score   support

         0.0       0.95      0.95      0.95       176
         1.0       0.87      0.87      0.87        63

    accuracy                           0.93       239
   macro avg       0.91      0.91      0.91       239
weighted avg       0.93      0.93      0.93       239
```

XGBoost

```
In [ ]: import xgboost as xgb

# Initialize XGBoost classifier
clf = xgb.XGBClassifier(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)

# Fit the model
clf.fit(X_train, y_train)

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

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:\n", report)
```

```
Accuracy: 0.93

Confusion Matrix:
[[168   8]
 [  8  55]]

Classification Report:
               precision    recall  f1-score   support

         0.0       0.95      0.95      0.95       176
         1.0       0.87      0.87      0.87        63

    accuracy                           0.93       239
   macro avg       0.91      0.91      0.91       239
weighted avg       0.93      0.93      0.93       239
```

```
In [ ]: ## Hyperparameter Tuning
# Define the parameter grid for XGBoost
param_dist = {
    'learning_rate': [0.008, 0.009, 0.01, 0.02],
    'n_estimators': [250, 260, 270, 280, 290],
    'max_depth': [6, 7, 8, 9],
    'subsample': [0.7, 0.8, 0.9, 1.0],
    'colsample_bytree': [0.8, 0.9, 1.0]
}
```

```python
# Initialize XGBoost classifier
xgb_clf = xgb.XGBClassifier(random_state=42)

# Initialize RandomizedSearchCV
random_search = RandomizedSearchCV(
    xgb_clf, param_distributions=param_dist, n_iter=10, cv=5, scoring='accuracy', random_state=42, n_jobs=-1
)

# Fit the model
random_search.fit(X_train, y_train)

# Display the best hyperparameters
print("Best Hyperparameters:", random_search.best_params_)

# Make predictions on the test set using the best model
y_pred = random_search.best_estimator_.predict(X_test)

# Print confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:\n", pd.DataFrame(conf_matrix, columns=['Predicted 0', 'Predicted 1'], index=['Actual 0', 'Actual 1']))

# Print accuracy and classification report
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"\nAccuracy: {accuracy:.2f}")
print("Classification Report:\n", report)
```

```
Best Hyperparameters: {'subsample': 0.8, 'n_estimators': 280, 'max_depth': 6, 'learning_rate': 0.02, 'colsample_bytree': 1.0}

Confusion Matrix:
           Predicted 0  Predicted 1
Actual 0          168            8
Actual 1            8           55

Accuracy: 0.93
Classification Report:
               precision    recall  f1-score   support

         0.0       0.95      0.95      0.95       176
         1.0       0.87      0.87      0.87        63

    accuracy                           0.93       239
   macro avg       0.91      0.91      0.91       239
weighted avg       0.93      0.93      0.93       239
```

- Accuracy 92: Best Hyperparameters: {'subsample': 0.7, 'n_estimators': 200, 'max_depth': 9, 'learning_rate': 0.01, 'colsample_bytree': 1.0}
- Accuracy 93: Best Hyperparameters: {'subsample': 0.9, 'n_estimators': 250, 'max_depth': 7, 'learning_rate': 0.01, 'colsample_bytree': 1.0}
- Accuracy 93: Best Hyperparameters: {'subsample': 0.9, 'n_estimators': 250, 'max_depth': 8, 'learning_rate': 0.01, 'colsample_bytree': 0.8}
- Accuracy 93: Best Hyperparameters: {'subsample': 0.9, 'n_estimators': 280, 'max_depth': 6, 'learning_rate': 0.01, 'colsample_bytree': 0.9}

In [ ]:
```python
import xgboost as xgb

# Initialize XGBoost classifier
clf = xgb.XGBClassifier(subsample= 0.9, n_estimators= 280, max_depth= 6, learning_rate= 0.01, colsample_bytree= 0.9, random_state=42)

# Fit the model
clf.fit(X_train, y_train)

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

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:\n", report)
```

```
Accuracy: 0.93

Confusion Matrix:
[[169   7]
 [ 10  53]]

Classification Report:
               precision    recall  f1-score   support

         0.0       0.94      0.96      0.95       176
         1.0       0.88      0.84      0.86        63

    accuracy                           0.93       239
   macro avg       0.91      0.90      0.91       239
weighted avg       0.93      0.93      0.93       239
```

LightGBM

In [ ]:
```python
import lightgbm as lgb

# Initialize LightGBM classifier
clf = lgb.LGBMClassifier(random_state=42)

# Fit the model
clf.fit(X_train, y_train)

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

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"\nAccuracy: {accuracy:.2f}")
print("\nConfusion Matrix:")
print(conf_matrix)
print("\nClassification Report:\n", report)
```

```
[LightGBM] [Info] Number of positive: 702, number of negative: 1440
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000236 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 1022
[LightGBM] [Info] Number of data points in the train set: 2142, number of used features: 45
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.327731 -> initscore=-0.718465
[LightGBM] [Info] Start training from score -0.718465

Accuracy: 0.94

Confusion Matrix:
[[168   8]
 [  7  56]]

Classification Report:
               precision    recall  f1-score   support

         0.0       0.96      0.95      0.96       176
         1.0       0.88      0.89      0.88        63

    accuracy                           0.94       239
   macro avg       0.92      0.92      0.92       239
weighted avg       0.94      0.94      0.94       239
```

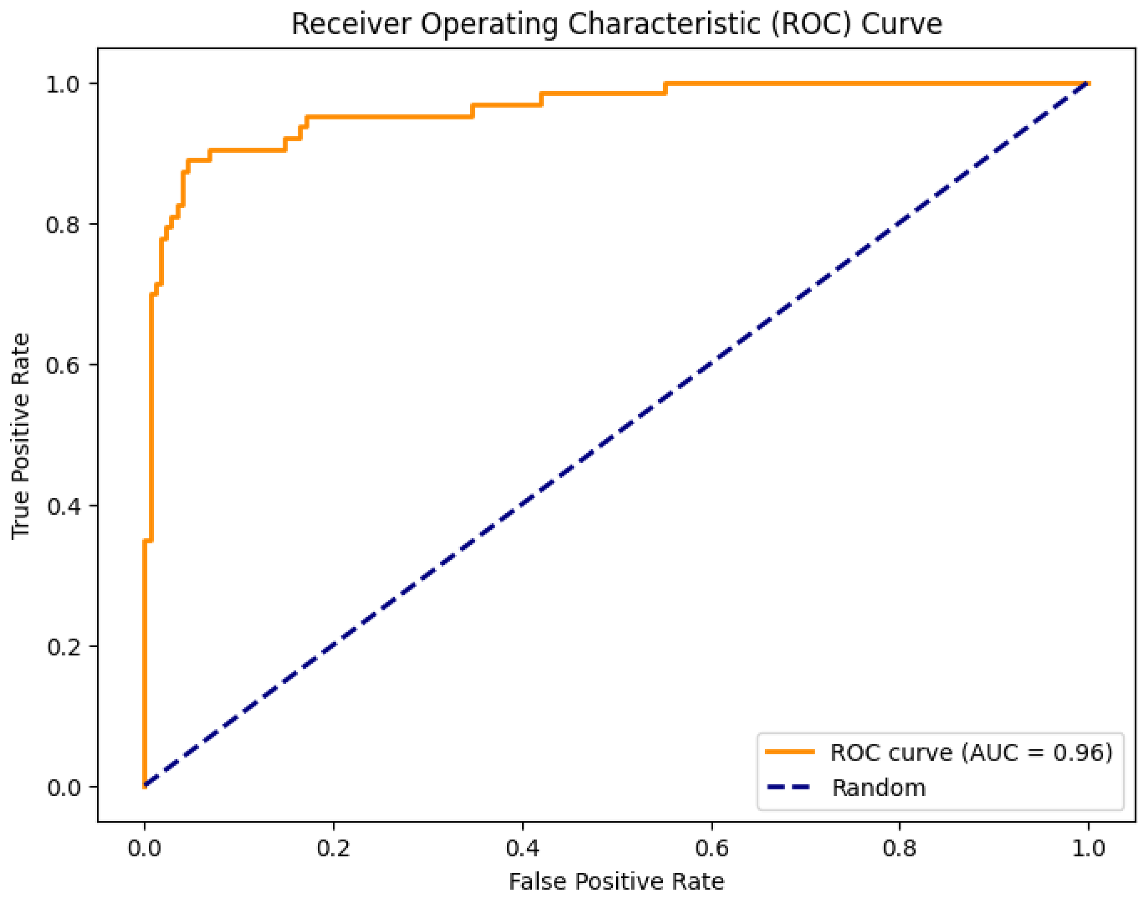
In [ ]:
```python
from sklearn.metrics import roc_curve, auc

# Get predicted probabilities for the positive class (class 1)
y_prob = clf.predict_proba(X_test)[:, 1]

# Compute ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_prob)

# Compute Area Under the Curve (AUC)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



Feature Importance

- Since LightGBM is giving us the best accuracy, we'll be using the LightGBM trained model to extracct feature importance.

In [ ]:
```
# Extract feature importance
feature_importance = clf.feature_importances_

# Create a DataFrame to display feature names and their importance scores
feature_importance_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': feature_importance
})

# Sort the DataFrame by importance score in descending order
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

# Display the feature importance DataFrame
print(feature_importance_df)
```

```
                Feature  Importance
7           ReportCount         451
4          joining_date         404
0                   Age         391
10           Income_avg         339
5         joining_month         298
6          joining_year         233
8               TBV_avg         215
13     tbv_diff_pattern         120
9                QR_avg         117
14      qr_diff_pattern          67
2       Education_Level          55
1                Gender          49
3   Joining_Designation          44
35             City_C27          24
11            Grade_avg          24
37             City_C29          15
18             City_C11          13
40              City_C5          13
29             City_C21          11
24             City_C17          11
16              City_C1          11
34             City_C26          11
20             City_C13           9
26             City_C19           8
25             City_C18           8
36             City_C28           7
38              City_C3           7
30             City_C22           6
42              City_C7           5
27              City_C2           5
41              City_C6           5
19             City_C12           4
31             City_C23           4
32             City_C24           4
33             City_C25           3
28             City_C20           3
17             City_C10           2
44              City_C9           2
43              City_C8           1
23             City_C16           1
12  income_diff_pattern           0
22             City_C15           0
21             City_C14           0
15   grade_diff_pattern           0
39              City_C4           0
```

Results Interpretation & Stakeholder Presentation

Interpreting Model Coefficients: It seems that top features influencing the usecase output includes:

1. ReportCount: Number of time the Driver is reporting.
2. Joining Date: It looks interesting but Joining Date has good incluence on output.
3. Age: Driver's age across the Business has good influence on the output
4. Income_avg: What income the Driver is earning from the Business.
5. Joining_month: Interestingly joining month also has an impact on Driver's attrition.

Feedback Loop

- We should set up a periodic review process to assess the model's relevance and performance.
- Keep on generating more data and analyse the reports on what may impacting out Churing behaviour and handle the same with care and understanding.
- Recommend surveys or feedback mechanisms to collect data on new trends, driver concerns, and customer feedback to refine the model in the future.
- We should have some daily feedback calls form driver, understanding their problems and saving their respective sentiments.

Trade-Off Analysis and Recommendation is in Notebook Phase 2

In [ ]: