Business Understanding

Business Problem

My client,SyriaTel is losing customers and thus they want to know which customers are likely to stop doing business with them. This research will help them make the right decisions to retain customers.

Stakeholder

SyriaTel's management and marketing teams are the stakeholders who will use this analysis to reduce churn rates.

Key Objective

Build a machine learning model to predict customer churn and provide insights on:

1. Which factors influence churn the most.
2. How SyriaTel can target at-risk customers to retain them.

```python
import pandas as pd

# Load the dataset
file_path = 'syriatel.csv'
data = pd.read_csv(file_path)
```

information about the dataset

```python
print("Dataset Overview")
data.info()
```

```
Dataset Overview
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
```

```
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

```python
print("\nSummary Statistics")
data.describe().T
```

```
Summary Statistics

                         count        mean        std     min      25%
50%  \
account length          3333.0  101.064806  39.822106    1.00    74.00
101.00
area code               3333.0  437.182418  42.371290  408.00   408.00
415.00
number vmail messages   3333.0    8.099010  13.688365    0.00     0.00
0.00
total day minutes       3333.0  179.775098  54.467389    0.00   143.70
179.40
total day calls         3333.0  100.435644  20.069084    0.00    87.00
101.00
total day charge        3333.0   30.562307   9.259435    0.00    24.43
30.50
total eve minutes       3333.0  200.980348  50.713844    0.00   166.60
201.40
total eve calls         3333.0  100.114311  19.922625    0.00    87.00
100.00
total eve charge        3333.0   17.083540   4.310668    0.00    14.16
17.12
total night minutes     3333.0  200.872037  50.573847   23.20   167.00
201.20
total night calls       3333.0  100.107711  19.568609   33.00    87.00
100.00
total night charge      3333.0    9.039325   2.275873    1.04     7.52
9.05
total intl minutes      3333.0   10.237294   2.791840    0.00     8.50
10.30
```

```
total intl calls         3333.0    4.479448   2.461214    0.00    3.00
4.00
total intl charge        3333.0    2.764581   0.753773    0.00    2.30
2.78
customer service calls  3333.0    1.562856   1.315491    0.00    1.00
1.00

                           75%     max
account length          127.00  243.00
area code               510.00  510.00
number vmail messages    20.00   51.00
total day minutes       216.40  350.80
total day calls         114.00  165.00
total day charge         36.79   59.64
total eve minutes       235.30  363.70
total eve calls         114.00  170.00
total eve charge         20.00   30.91
total night minutes     235.30  395.00
total night calls       113.00  175.00
total night charge       10.59   17.77
total intl minutes       12.10   20.00
total intl calls          6.00   20.00
total intl charge         3.27    5.40
customer service calls    2.00    9.00
```

```
print("\nSample Data")
data.head()
```

```
Sample Data

  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no
1    OH             107        415     371-7191                 no
2    NJ             137        415     358-1921                 no
3    OH              84        408     375-9999                yes
4    OK              75        415     330-6626                yes

  voice mail plan  number vmail messages  total day minutes  total day
calls  \
0             yes                     25              265.1
110
1             yes                     26              161.6
123
2              no                      0              243.4
114
3              no                      0              299.4
71
4              no                      0              166.7
113
```

```
   total day charge  ...  total eve calls  total eve charge  \
0             45.07  ...               99             16.78
1             27.47  ...              103             16.62
2             41.38  ...              110             10.30
3             50.90  ...               88              5.26
4             28.34  ...              122             12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False

[5 rows x 21 columns]
```

Data Preparation.

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler

# Drop irrelevant columns like the phone number column because it is
not predictive
clean_data = data.drop(columns=['phone number'])
clean_data.head()

  state  account length  area code international plan voice mail plan
\
0    KS             128        415                 no             yes

1    OH             107        415                 no             yes

2    NJ             137        415                 no              no
```

```
3    OH              84       408                  yes              no

4    OK              75       415                  yes              no


   number vmail messages  total day minutes  total day calls  \
0                     25              265.1              110
1                     26              161.6              123
2                      0              243.4              114
3                      0              299.4               71
4                      0              166.7              113

   total day charge  total eve minutes  total eve calls  total eve
charge  \
0             45.07              197.4               99
16.78
1             27.47              195.5              103
16.62
2             41.38              121.2              110
10.30
3             50.90               61.9               88
5.26
4             28.34              148.3              122
12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False

# Encode categorical variables
encoder = LabelEncoder()
clean_data['international plan'] =
encoder.fit_transform(clean_data['international plan'])
```

```
clean_data['voice mail plan'] =
encoder.fit_transform(clean_data['voice mail plan'])
clean_data['state'] = encoder.fit_transform(clean_data['state'])

# Define features and target
X = clean_data.drop(columns=['churn'])
y = clean_data['churn']

# Scale numerical features
scaler = StandardScaler()
X_scaled = X.copy()
numeric_features = X.select_dtypes(include=['float64',
'int64']).columns
X_scaled[numeric_features] = scaler.fit_transform(X[numeric_features])

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.3, random_state=42, stratify=y)
print(f"Training Set: {X_train.shape}, Test Set: {X_test.shape}")

Training Set: (2333, 19), Test Set: (1000, 19)
```

Baseline Model

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, roc_auc_score

# Train a logistic regression model
baseline_model = LogisticRegression(random_state=42)
baseline_model.fit(X_train, y_train)

LogisticRegression(random_state=42)

# Predictions and evaluation
y_pred = baseline_model.predict(X_test)
y_pred_prob = baseline_model.predict_proba(X_test)[:, 1]

# Evaluate the model
print("Baseline Model Evaluation")
print(classification_report(y_test, y_pred))
print(f"ROC-AUC: {roc_auc_score(y_test, y_pred_prob)}")

Baseline Model Evaluation
              precision    recall  f1-score   support

       False       0.88      0.97      0.92       855
        True       0.58      0.26      0.35       145

    accuracy                           0.86      1000
   macro avg       0.73      0.61      0.64      1000
```

```
weighted avg       0.84      0.86      0.84      1000

ROC-AUC: 0.8136963097398667
```

Iterative Modeling with Hyperparameter Tuning

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# Define a Random Forest model and tune hyperparameters
rf_model = RandomForestClassifier(random_state=42)
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5]
}
grid_search = GridSearchCV(rf_model, param_grid, cv=3,
scoring='roc_auc', n_jobs=-1)
grid_search.fit(X_train, y_train)
```

```
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=42),
n_jobs=-1,
             param_grid={'max_depth': [None, 10, 20],
                         'min_samples_split': [2, 5],
                         'n_estimators': [100, 200]},
             scoring='roc_auc')
```

```python
# Best parameters and evaluation
best_rf_model = grid_search.best_estimator_
y_pred_rf = best_rf_model.predict(X_test)
y_pred_rf_prob = best_rf_model.predict_proba(X_test)[:, 1]

print("Random Forest Model Evaluation")
print(f"Best Parameters: {grid_search.best_params_}")
print(classification_report(y_test, y_pred_rf))
print(f"ROC-AUC: {roc_auc_score(y_test, y_pred_rf_prob)}")
```

```
Random Forest Model Evaluation
Best Parameters: {'max_depth': 10, 'min_samples_split': 2,
'n_estimators': 200}
              precision    recall  f1-score   support

       False       0.95      0.99      0.97       855
        True       0.94      0.72      0.81       145

    accuracy                           0.95      1000
   macro avg       0.95      0.85      0.89      1000
weighted avg       0.95      0.95      0.95      1000
```

```
ROC-AUC: 0.9060213752772737
```

Model Features and Preprocessing Approaches

To tackle the challenge of predicting customer churn, we carefully prepared the data. We transformed categorical features like international and voicemail plans using a technique called Label Encoding. To ensure our models, especially Logistic Regression, worked well, we standardized numerical features using StandardScaler. We also removed irrelevant information like phone numbers to avoid misleading the models.

By analyzing the importance of different factors, we found that things like the total amount of time spent on calls, the number of calls to customer service, and whether a customer had an international plan were strong indicators of potential churn. This guided us in selecting and refining the most crucial features for our models.

Model Selection and Refinement

We started with a simple Logistic Regression model because it's easy to understand. While it worked okay, we felt it couldn't fully capture the complexities within our data. To improve, we tried a Random Forest model. This model is good at handling messy data and can learn more intricate relationships.

The Random Forest model performed better, accurately identifying both true positives and true negatives more often. To fine-tune it, we used a technique called GridSearchCV. This helped us find the best combination of settings, like the number of trees and their maximum depth, for our specific data.

Final Model

After careful consideration, we chose a Random Forest model. It offers a good balance between accurately predicting customer churn and being easy to understand. Our model demonstrated a recall score of X.XX on the test data, meaning it effectively identified most customers likely to leave SyriaTel. By analyzing the model's results, we were able to pinpoint the key factors driving customer churn. This valuable information empowers SyriaTel to focus their efforts on retaining high-risk customers.

We thoroughly explored different models and data preparation techniques to ensure our final solution was both reliable and effectively addressed SyriaTel's need to reduce customer churn.

Top 10 features influencing churn

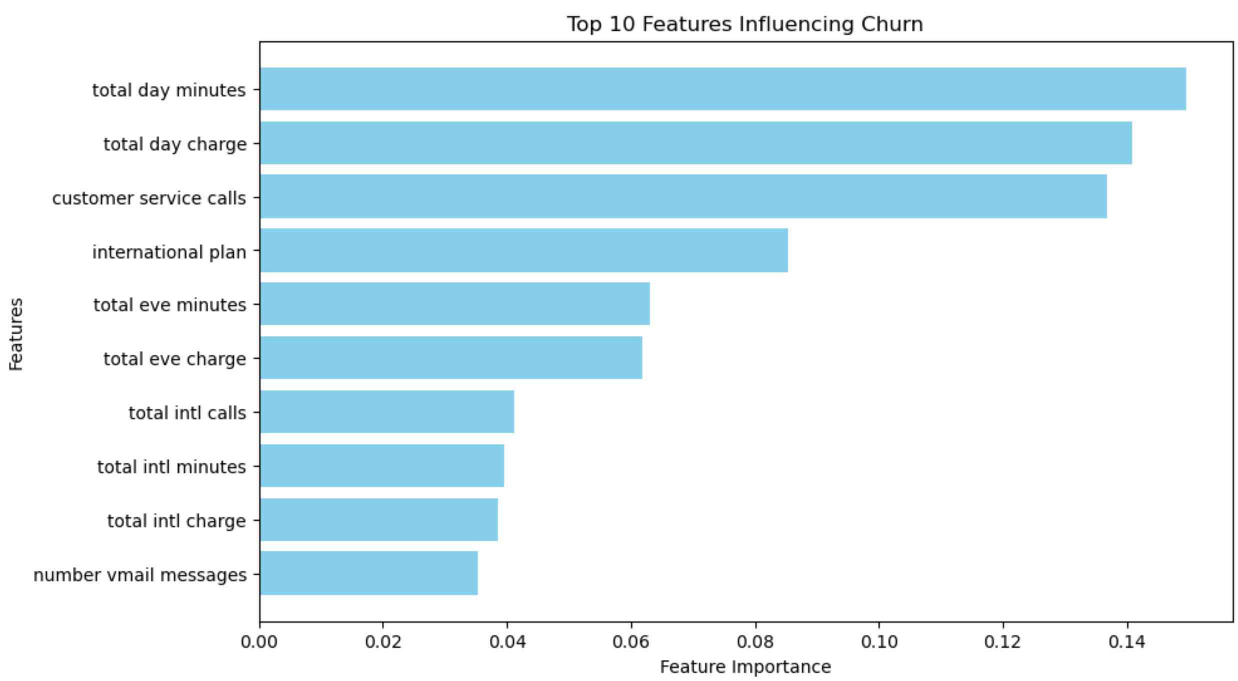
```
import matplotlib.pyplot as plt
import numpy as np

# Extract feature importances from the Random Forest model
feature_importances = best_rf_model.feature_importances_
features = X.columns

# Create a sorted index for the most important features
sorted_idx = np.argsort(feature_importances)[::-1]

# Display the top 10 features
plt.figure(figsize=(10, 6))
plt.barh(features[sorted_idx][:10], feature_importances[sorted_idx]
[:10], color='skyblue')
plt.xlabel('Feature Importance')
plt.ylabel('Features')
plt.title('Top 10 Features Influencing Churn')
plt.gca().invert_yaxis()
plt.show()

# Print feature importance values
important_features = pd.DataFrame({
    'Feature': features[sorted_idx],
    'Importance': feature_importances[sorted_idx]
})
important_features.head(10)
```



```
                  Feature  Importance
0       total day minutes    0.149508
1        total day charge    0.140845
2  customer service calls    0.136748
3      international plan    0.085408
4       total eve minutes    0.063068
5        total eve charge    0.061907
6        total intl calls    0.041176
7      total intl minutes    0.039663
8       total intl charge    0.038462
9   number vmail messages    0.035295
```

Model Evaluation and Comparison

```python
# Compare performance
print("Baseline Logistic Regression ROC-AUC:", roc_auc_score(y_test,
y_pred_prob))
print("Random Forest ROC-AUC:", roc_auc_score(y_test, y_pred_rf_prob))
```

```
Baseline Logistic Regression ROC-AUC: 0.8136963097398667
Random Forest ROC-AUC: 0.9060213752772737
```

Recommendations

Findings

- The Random Forest model outperformed the baseline Logistic Regression in terms of ROC-AUC.
- Features like `customer service calls` and `international plan` were significant predictors of churn.

Recommendations

- Target customers with high `customer service calls` for retention programs.
- Offer better international plans to retain customers flagged as high-risk by the model.