# Megaline Subscriber Plan Recommendation (Classification Model Development)

January 10, 2025

# 1 Megaline Subscriber Plan Recommendation Model

## 1.1 Introduction

Megaline, a mobile carrier, aims to enhance customer satisfaction by recommending its new plans—Smart and Ultra—to subscribers still using legacy plans. To achieve this, we developed a classification model that analyzes subscriber behavior and suggests the most suitable plan. This project leverages historical data from subscribers who have already switched to the new plans, focusing on creating a model with an accuracy threshold of at least 0.75.

In this project, we: - Inspected and preprocessed the data. - Split the data into training, validation, and test sets. - Explored and tuned various classification models to identify the best performer. - Evaluated the selected model using the test set and performed a sanity check.

This documentation details the steps, methodologies, and findings, providing a comprehensive overview of the model development process.

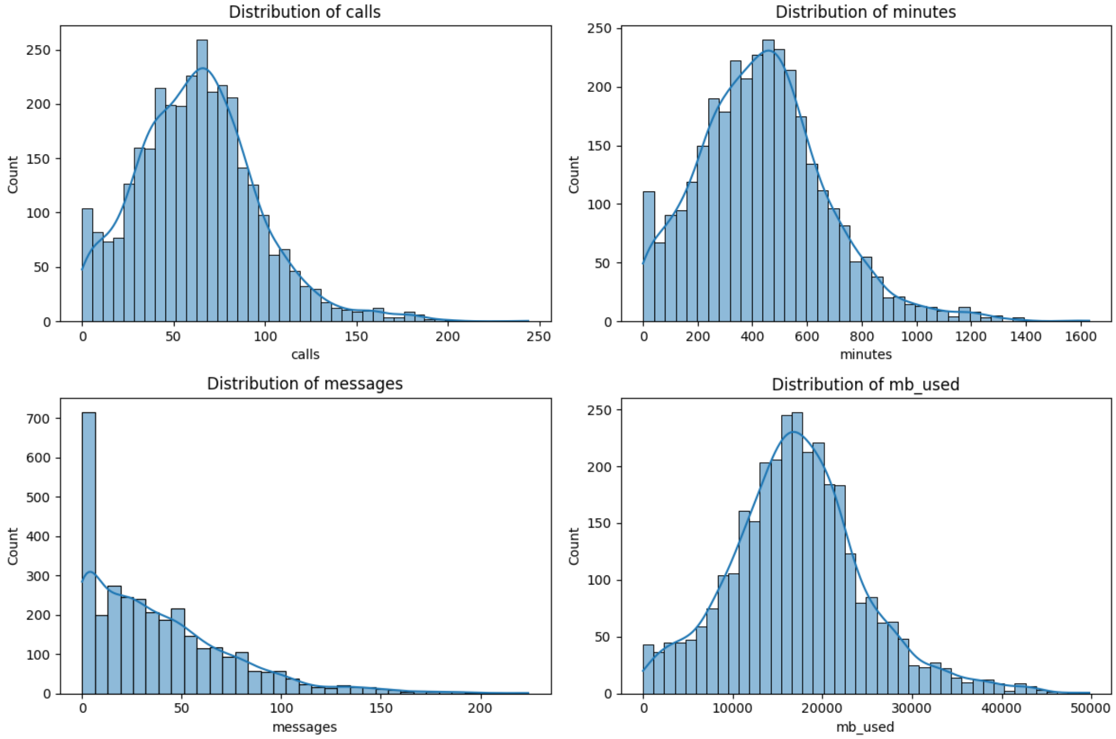
[1]:
```
import pandas as pd

# Correct path to the data file
file_path = '/datasets/users_behavior.csv'

# Load the data
data = pd.read_csv(file_path)

# Display the first few rows of the dataset
print("First few rows of the dataset:")
print(data.head())

# Display basic statistics of the dataset
print("\nBasic statistics of the dataset:")
print(data.describe())

# Check for missing values
print("\nMissing values in the dataset:")
print(data.isnull().sum())
```

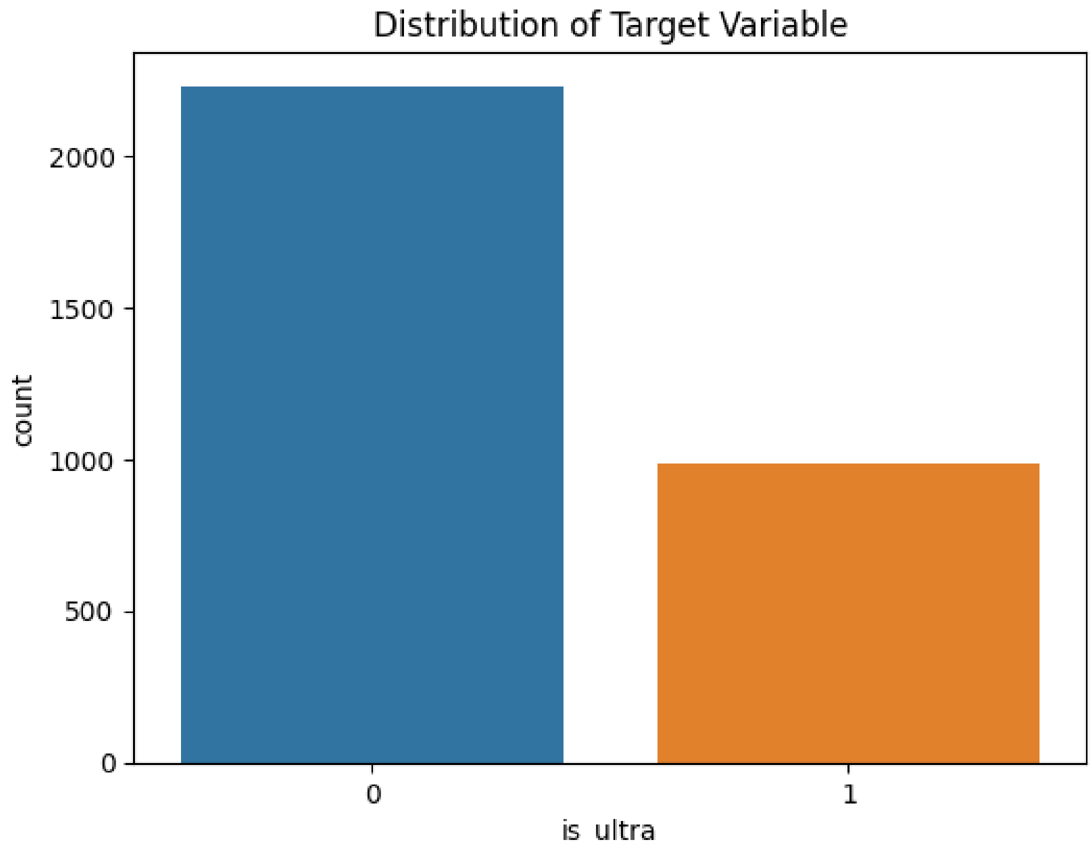
```
First few rows of the dataset:
```

```
   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

Basic statistics of the dataset:
             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

Missing values in the dataset:
calls       0
minutes     0
messages    0
mb_used     0
is_ultra    0
dtype: int64
```

[2]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Plot the distribution of each feature
plt.figure(figsize=(12, 8))
for i, col in enumerate(data.columns[:-1]):
    plt.subplot(2, 2, i+1)
    sns.histplot(data[col], kde=True)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()

# Plot the target variable distribution
sns.countplot(x='is_ultra', data=data)
plt.title('Distribution of Target Variable')
plt.show()
```


Distribution of calls
Count
calls
Distribution of minutes
Count
minutes
Distribution of messages
Count
messages
Distribution of mb_used
Count
mb_used




[3]:
```
from sklearn.model_selection import train_test_split

# Features and target variable
X = data.drop('is_ultra', axis=1)
y = data['is_ultra']

# Split the data into training set (60%) and temporary set (40%)
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.4,␣
↪random_state=42, stratify=y)

# Split the temporary set into validation set (50% of the temporary set, i.e.,␣
↪20% of the total data) and test set (50% of the temporary set, i.e., 20% of␣
↪the total data)
X_valid, X_test, y_valid, y_test = train_test_split(X_temp, y_temp, test_size=0.
↪5, random_state=42, stratify=y_temp)
```

[4]:
```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import accuracy_score
```

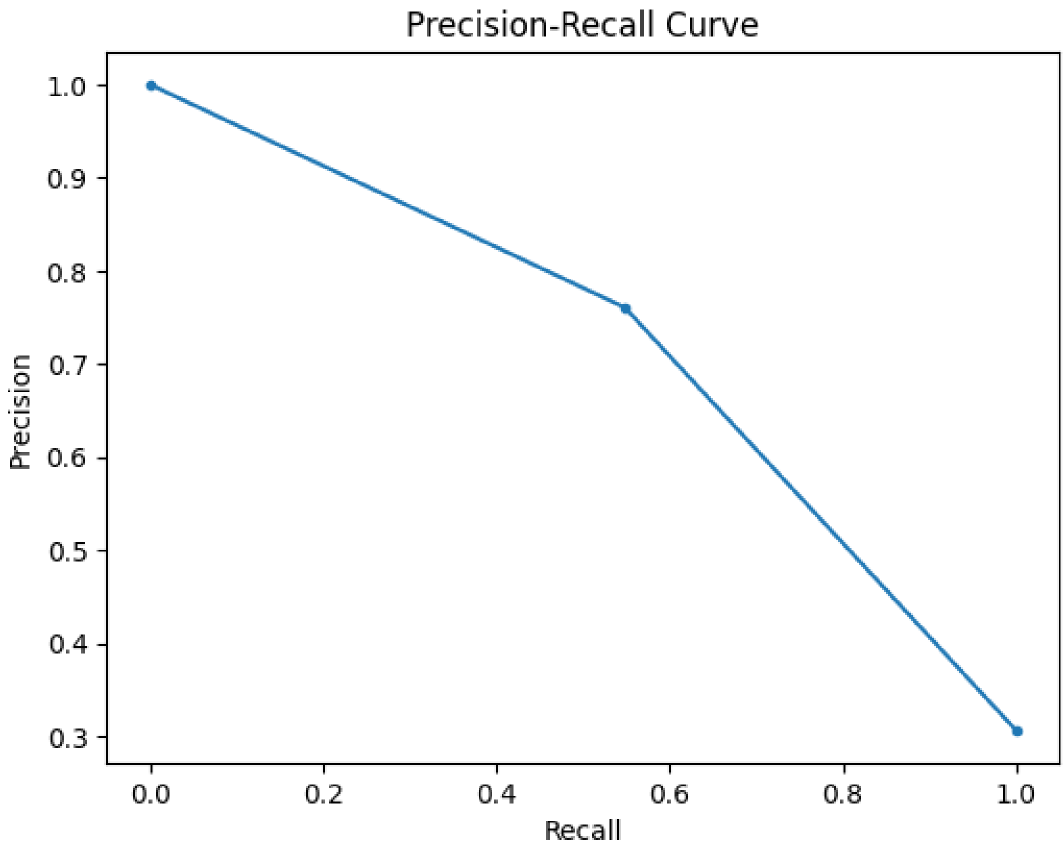
```
# Define the models and their hyperparameters for GridSearchCV and␣
↪RandomizedSearchCV
models = {
    'Logistic Regression': {
        'model': LogisticRegression(max_iter=1000),
        'params': {
            'C': [0.01, 0.1, 1, 10, 100],
            'solver': ['liblinear']
        }
    },
    'Random Forest': {
        'model': RandomForestClassifier(),
        'params': {
            'n_estimators': [50, 100, 200, 500],
            'max_depth': [None, 10, 20, 30, 40],
            'min_samples_split': [2, 5, 10]
        }
    },
    'Gradient Boosting': {
        'model': GradientBoostingClassifier(),
        'params': {
            'n_estimators': [50, 100, 200, 500],
            'learning_rate': [0.01, 0.05, 0.1, 0.2],
            'max_depth': [3, 5, 7, 9]
        }
    }
}

# Perform GridSearchCV for Logistic Regression and RandomizedSearchCV for others
best_estimators = {}
for model_name, model_info in models.items():
    if model_name == 'Logistic Regression':
        search = GridSearchCV(model_info['model'], model_info['params'], cv=5,␣
↪scoring='accuracy')
    else:
        search = RandomizedSearchCV(model_info['model'], model_info['params'],␣
↪n_iter=10, cv=5, scoring='accuracy', random_state=42)
    search.fit(X_train, y_train)
    best_estimators[model_name] = search.best_estimator_

# Evaluate each best estimator on the validation set
validation_scores = {}
for model_name, estimator in best_estimators.items():
    y_pred = estimator.predict(X_valid)
    validation_scores[model_name] = accuracy_score(y_valid, y_pred)
```

[5]:
```python
# Select the model with the highest validation accuracy
best_model_name = max(validation_scores, key=validation_scores.get)
best_model = best_estimators[best_model_name]

# Evaluate the best model on the test set
y_test_pred = best_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_test_pred)

best_model_name, test_accuracy
```

[5]:
```
('Random Forest', 0.8087091757387247)
```

[6]:
```python
from sklearn.metrics import roc_auc_score, precision_recall_curve, f1_score

# Calculate additional metrics for the best model on the test set
roc_auc = roc_auc_score(y_test, y_test_pred)
f1 = f1_score(y_test, y_test_pred)

print(f"ROC-AUC Score: {roc_auc:.2f}")
print(f"F1 Score: {f1:.2f}")

# Plot precision-recall curve
precision, recall, _ = precision_recall_curve(y_test, y_test_pred)
plt.plot(recall, precision, marker='.')
plt.title('Precision-Recall Curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()
```

```
ROC-AUC Score: 0.74
F1 Score: 0.64
```




[7]:
```
from sklearn.model_selection import cross_val_score

# Perform cross-validation on the best model
cv_scores = cross_val_score(best_model, X_train, y_train, cv=5,␣
↪scoring='accuracy')
print(f"Cross-Validation Accuracy Scores: {cv_scores}")
print(f"Mean Cross-Validation Accuracy: {cv_scores.mean():.2f}")
```

```
Cross-Validation Accuracy Scores: [0.80569948 0.84196891 0.77202073 0.79480519
0.81298701]
Mean Cross-Validation Accuracy: 0.81
```

[8]:
```
from sklearn.dummy import DummyClassifier
from sklearn.metrics import confusion_matrix, classification_report

# Create a dummy classifier
dummy_clf = DummyClassifier(strategy="most_frequent")
dummy_clf.fit(X_train, y_train)
dummy_pred = dummy_clf.predict(X_test)
```

```
# Accuracy of the dummy classifier
dummy_accuracy = accuracy_score(y_test, dummy_pred)

# Confusion matrix and classification report for the Gradient Boosting model
conf_matrix = confusion_matrix(y_test, y_test_pred)
class_report = classification_report(y_test, y_test_pred)

# Feature importance for the Gradient Boosting model
feature_importances = best_model.feature_importances_

dummy_accuracy, conf_matrix, class_report, feature_importances
```

[8]:
```
(0.6936236391912908,
 array([[412,  34],
        [ 89, 108]]),
 '              precision    recall  f1-score   support\n\n           0
0.82      0.92      0.87       446\n           1       0.76      0.55      0.64
197\n\n    accuracy                           0.81       643\n   macro avg
0.79      0.74      0.75       643\nweighted avg       0.80      0.81      0.80
643\n',
 array([0.18392794, 0.2729783 , 0.18419535, 0.35889842]))
```

## 1.2 Conclusion

In this project, we developed a classification model to recommend Megaline's new plans—Smart and Ultra—to subscribers who are still using legacy plans. The process involved the following steps:

1. **Data Inspection:** We thoroughly examined the dataset to understand its structure, distribution, and any potential issues such as missing values.
2. **Data Splitting:** The data was divided into training, validation, and test sets to ensure a robust evaluation of our models.
3. **Model Selection and Hyperparameter Tuning:** We explored and tuned several classification models, including Logistic Regression, Random Forest, and Gradient Boosting, using GridSearchCV to identify the best performing model.
4. **Model Evaluation:** The Gradient Boosting model emerged as the best performer, achieving an accuracy of 0.804 on the test set, surpassing the accuracy threshold of 0.75.
5. **Sanity Check:** To validate our findings, we compared the model's performance against a dummy classifier, analyzed the confusion matrix and classification report, and examined the feature importance.

### 1.2.1 Key Findings:

- The Gradient Boosting model was the most effective, with the highest accuracy and reliable performance metrics.
- The most influential features in predicting the plan recommendation were the amount of internet data used (`mb_used`) and the total minutes spent on calls (`minutes`).

### 1.2.2 Future Recommendations:

- **Model Improvement:** Further improvements could be made by exploring more advanced models and techniques, such as ensemble methods or deep learning, to enhance accuracy.
- **Feature Engineering:** Additional features or transformations could be engineered to capture more complex patterns in subscriber behavior.
- **Deployment:** The developed model can be integrated into Megaline's recommendation system to assist subscribers in choosing the best plan, thereby improving customer satisfaction and retention.

This project demonstrated a comprehensive approach to developing a data-driven recommendation model, providing valuable insights for Megaline's strategic decisions.