# MXN_442_Assigment2-Copy1

October 24, 2025

# 1 Modern Computing Techniques MXN 442

## 1.1 Assesment 2

**Manuela Posso Baena**

- Logistic Regression
- Decision Trees
- Neural Network

[1]:
```
pip install ISLP
```

```
Requirement already satisfied: ISLP in /opt/conda/lib/python3.12/site-packages
(0.4.0)
Requirement already satisfied: numpy>=1.7.1 in /opt/conda/lib/python3.12/site-
packages (from ISLP) (2.3.2)
Requirement already satisfied: scipy>=0.9 in /opt/conda/lib/python3.12/site-
packages (from ISLP) (1.15.2)
Requirement already satisfied: pandas>=0.20 in /opt/conda/lib/python3.12/site-
packages (from ISLP) (2.3.1)
Requirement already satisfied: lxml in /opt/conda/lib/python3.12/site-packages
(from ISLP) (6.0.2)
Requirement already satisfied: scikit-learn>=1.2 in
/opt/conda/lib/python3.12/site-packages (from ISLP) (1.7.1)
Requirement already satisfied: joblib in /opt/conda/lib/python3.12/site-packages
(from ISLP) (1.5.1)
Requirement already satisfied: statsmodels>=0.13 in
/opt/conda/lib/python3.12/site-packages (from ISLP) (0.14.5)
Requirement already satisfied: lifelines in /opt/conda/lib/python3.12/site-
packages (from ISLP) (0.30.0)
Requirement already satisfied: pygam in /opt/conda/lib/python3.12/site-packages
(from ISLP) (0.10.1)
Requirement already satisfied: torch in /opt/conda/lib/python3.12/site-packages
(from ISLP) (2.7.1)
Requirement already satisfied: pytorch-lightning in
/opt/conda/lib/python3.12/site-packages (from ISLP) (2.5.5)
Requirement already satisfied: torchmetrics in /opt/conda/lib/python3.12/site-
packages (from ISLP) (1.8.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
```

```
/opt/conda/lib/python3.12/site-packages (from pandas>=0.20->ISLP) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.12/site-
packages (from pandas>=0.20->ISLP) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /opt/conda/lib/python3.12/site-
packages (from pandas>=0.20->ISLP) (2025.2)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.12/site-
packages (from python-dateutil>=2.8.2->pandas>=0.20->ISLP) (1.17.0)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/opt/conda/lib/python3.12/site-packages (from scikit-learn>=1.2->ISLP) (3.6.0)
Requirement already satisfied: patsy>=0.5.6 in /opt/conda/lib/python3.12/site-
packages (from statsmodels>=0.13->ISLP) (1.0.1)
Requirement already satisfied: packaging>=21.3 in
/opt/conda/lib/python3.12/site-packages (from statsmodels>=0.13->ISLP) (25.0)
Requirement already satisfied: matplotlib>=3.0 in
/opt/conda/lib/python3.12/site-packages (from lifelines->ISLP) (3.10.3)
Requirement already satisfied: autograd>=1.5 in /opt/conda/lib/python3.12/site-
packages (from lifelines->ISLP) (1.8.0)
Requirement already satisfied: autograd-gamma>=0.3 in
/opt/conda/lib/python3.12/site-packages (from lifelines->ISLP) (0.5.0)
Requirement already satisfied: formulaic>=0.2.2 in
/opt/conda/lib/python3.12/site-packages (from lifelines->ISLP) (1.2.1)
Requirement already satisfied: interface-meta>=1.2.0 in
/opt/conda/lib/python3.12/site-packages (from formulaic>=0.2.2->lifelines->ISLP)
(1.3.0)
Requirement already satisfied: narwhals>=1.17 in /opt/conda/lib/python3.12/site-
packages (from formulaic>=0.2.2->lifelines->ISLP) (2.9.0)
Requirement already satisfied: typing-extensions>=4.2.0 in
/opt/conda/lib/python3.12/site-packages (from formulaic>=0.2.2->lifelines->ISLP)
(4.14.1)
Requirement already satisfied: wrapt>=1.0 in /opt/conda/lib/python3.12/site-
packages (from formulaic>=0.2.2->lifelines->ISLP) (2.0.0)
Requirement already satisfied: contourpy>=1.0.1 in
/opt/conda/lib/python3.12/site-packages (from matplotlib>=3.0->lifelines->ISLP)
(1.3.3)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.12/site-
packages (from matplotlib>=3.0->lifelines->ISLP) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/conda/lib/python3.12/site-packages (from matplotlib>=3.0->lifelines->ISLP)
(4.59.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/opt/conda/lib/python3.12/site-packages (from matplotlib>=3.0->lifelines->ISLP)
(1.4.8)
Requirement already satisfied: pillow>=8 in /opt/conda/lib/python3.12/site-
packages (from matplotlib>=3.0->lifelines->ISLP) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/opt/conda/lib/python3.12/site-packages (from matplotlib>=3.0->lifelines->ISLP)
(3.2.3)
Requirement already satisfied: progressbar2<5,>=4.2.0 in
```

```
/opt/conda/lib/python3.12/site-packages (from pygam->ISLP) (4.5.0)
Requirement already satisfied: python-utils>=3.8.1 in
/opt/conda/lib/python3.12/site-packages (from
progressbar2<5,>=4.2.0->pygam->ISLP) (3.9.1)
Requirement already satisfied: tqdm>=4.57.0 in /opt/conda/lib/python3.12/site-
packages (from pytorch-lightning->ISLP) (4.67.1)
Requirement already satisfied: PyYAML>5.4 in /opt/conda/lib/python3.12/site-
packages (from pytorch-lightning->ISLP) (6.0.2)
Requirement already satisfied: fsspec>=2022.5.0 in
/opt/conda/lib/python3.12/site-packages (from fsspec[http]>=2022.5.0->pytorch-
lightning->ISLP) (2025.7.0)
Requirement already satisfied: lightning-utilities>=0.10.0 in
/opt/conda/lib/python3.12/site-packages (from pytorch-lightning->ISLP) (0.15.2)
Requirement already satisfied: aiohttp!=4.0.0a0,!=4.0.0a1 in
/opt/conda/lib/python3.12/site-packages (from fsspec[http]>=2022.5.0->pytorch-
lightning->ISLP) (3.12.14)
Requirement already satisfied: aiohappyeyeballs>=2.5.0 in
/opt/conda/lib/python3.12/site-packages (from
aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP)
(2.6.1)
Requirement already satisfied: aiosignal>=1.4.0 in
/opt/conda/lib/python3.12/site-packages (from
aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP)
(1.4.0)
Requirement already satisfied: attrs>=17.3.0 in /opt/conda/lib/python3.12/site-
packages (from aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-
lightning->ISLP) (25.3.0)
Requirement already satisfied: frozenlist>=1.1.1 in
/opt/conda/lib/python3.12/site-packages (from
aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP)
(1.7.0)
Requirement already satisfied: multidict<7.0,>=4.5 in
/opt/conda/lib/python3.12/site-packages (from
aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP)
(6.6.3)
Requirement already satisfied: propcache>=0.2.0 in
/opt/conda/lib/python3.12/site-packages (from
aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP)
(0.3.1)
Requirement already satisfied: yarl<2.0,>=1.17.0 in
/opt/conda/lib/python3.12/site-packages (from
aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-lightning->ISLP)
(1.20.1)
Requirement already satisfied: idna>=2.0 in /opt/conda/lib/python3.12/site-
packages (from
yarl<2.0,>=1.17.0->aiohttp!=4.0.0a0,!=4.0.0a1->fsspec[http]>=2022.5.0->pytorch-
lightning->ISLP) (3.10)
Requirement already satisfied: setuptools in /opt/conda/lib/python3.12/site-
```

```
packages (from lightning-utilities>=0.10.0->pytorch-lightning->ISLP) (80.9.0)
Requirement already satisfied: filelock in /opt/conda/lib/python3.12/site-
packages (from torch->ISLP) (3.18.0)
Requirement already satisfied: sympy>=1.13.3 in /opt/conda/lib/python3.12/site-
packages (from torch->ISLP) (1.14.0)
Requirement already satisfied: networkx in /opt/conda/lib/python3.12/site-
packages (from torch->ISLP) (3.5)
Requirement already satisfied: jinja2 in /opt/conda/lib/python3.12/site-packages
(from torch->ISLP) (3.1.6)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.6.77 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (12.6.77)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.6.77 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (12.6.77)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.6.80 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (12.6.80)
Requirement already satisfied: nvidia-cudnn-cu12==9.5.1.17 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (9.5.1.17)
Requirement already satisfied: nvidia-cublas-cu12==12.6.4.1 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (12.6.4.1)
Requirement already satisfied: nvidia-cufft-cu12==11.3.0.4 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (11.3.0.4)
Requirement already satisfied: nvidia-curand-cu12==10.3.7.77 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (10.3.7.77)
Requirement already satisfied: nvidia-cusolver-cu12==11.7.1.2 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (11.7.1.2)
Requirement already satisfied: nvidia-cusparse-cu12==12.5.4.2 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (12.5.4.2)
Requirement already satisfied: nvidia-cusparselt-cu12==0.6.3 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (0.6.3)
Requirement already satisfied: nvidia-nccl-cu12==2.26.2 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (2.26.2)
Requirement already satisfied: nvidia-nvtx-cu12==12.6.77 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (12.6.77)
Requirement already satisfied: nvidia-nvjitlink-cu12==12.6.85 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (12.6.85)
Requirement already satisfied: nvidia-cufile-cu12==1.11.1.6 in
/opt/conda/lib/python3.12/site-packages (from torch->ISLP) (1.11.1.6)
Requirement already satisfied: triton==3.3.1 in /opt/conda/lib/python3.12/site-
packages (from torch->ISLP) (3.3.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/opt/conda/lib/python3.12/site-packages (from sympy>=1.13.3->torch->ISLP)
(1.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/opt/conda/lib/python3.12/site-packages (from jinja2->torch->ISLP) (3.0.2)
Note: you may need to restart the kernel to use updated packages.
```

[2]:
```
!pip install imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in
/opt/conda/lib/python3.12/site-packages (0.14.0)
Requirement already satisfied: numpy<3,>=1.25.2 in
/opt/conda/lib/python3.12/site-packages (from imbalanced-learn) (2.3.2)
Requirement already satisfied: scipy<2,>=1.11.4 in
/opt/conda/lib/python3.12/site-packages (from imbalanced-learn) (1.15.2)
Requirement already satisfied: scikit-learn<2,>=1.4.2 in
/opt/conda/lib/python3.12/site-packages (from imbalanced-learn) (1.7.1)
Requirement already satisfied: joblib<2,>=1.2.0 in
/opt/conda/lib/python3.12/site-packages (from imbalanced-learn) (1.5.1)
Requirement already satisfied: threadpoolctl<4,>=2.0.0 in
/opt/conda/lib/python3.12/site-packages (from imbalanced-learn) (3.6.0)
```

[3]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in /opt/conda/lib/python3.12/site-
packages (3.1.1)
Requirement already satisfied: numpy in /opt/conda/lib/python3.12/site-packages
(from xgboost) (2.3.2)
Requirement already satisfied: nvidia-nccl-cu12 in
/opt/conda/lib/python3.12/site-packages (from xgboost) (2.26.2)
Requirement already satisfied: scipy in /opt/conda/lib/python3.12/site-packages
(from xgboost) (1.15.2)
Note: you may need to restart the kernel to use updated packages.
```

[4]:
```
from ISLP import confusion_table
from ISLP.models import contrast
from sklearn.discriminant_analysis import \
     (LinearDiscriminantAnalysis as LDA,
      QuadraticDiscriminantAnalysis as QDA)
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.neural_network import MLPClassifier
import seaborn as sns
```

```python
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score
import numpy as np
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
↪roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
from matplotlib.pyplot import subplots
import statsmodels.api as sm
from ISLP import load_data
from ISLP.models import (ModelSpec as MS,
                         summarize)
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
↪recall_score, f1_score, roc_auc_score
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
↪recall_score, f1_score, roc_auc_score
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.model_selection import GridSearchCV, cross_validate,␣
↪train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
↪recall_score, f1_score, roc_auc_score
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, cross_validate
from sklearn.metrics import classification_report, confusion_matrix,␣
↪roc_auc_score
```

```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import GridSearchCV, cross_val_score, KFold
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score, make_scorer
import numpy as np
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_auc_score, confusion_matrix
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV, cross_validate, KFold
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import make_scorer, accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_validate, StratifiedKFold
from sklearn.metrics import make_scorer, recall_score, precision_score, f1_score, roc_auc_score, accuracy_score
import numpy as np
```

# 2 Customer Churn Prediction

## 2.1 Introduction & Objective

**Customer churn** refers to the phenomenon where customers stop using a company's products or services.
For telecommunication companies, churn is a major business problem because acquiring new customers is far more expensive than retaining existing ones. A reliable churn prediction model allows businesses to identify at-risk customers early and take proactive retention measures, such as targeted offers or improved customer service. It is important: - Reducing churn increases profitability and customer lifetime value (CLV). - Retaining customers costs significantly less than acquiring new ones. - Understanding drivers of churn provides actionable insights for customer experience teams.

**Research context:** The baseline study Churn prediction in telecommunication industry using kernel Support Vector Machines (2022) by *Nguyen, Tran & Dao (2022)* applied **Support Vector Machines (SVMs)** for churn prediction in the telecommunication industry. While effective, SVMs may struggle with scalability, interpretability, and handling imbalanced datasets.

**Objective of this project:** To extend the baseline by implementing and comparing multiple machine learning models for churn prediction, including: - Logistic Regression
- Decision Tree (with hyperparameter tuning)
- Random Forest
- Gradient Boosting
- Neural Network (MLP)
- XGBoost (as an industry-standard extension suggested via GenAI)

Evaluation will be based on multiple metrics (Accuracy, Precision, Recall, F1, AUC), with particular emphasis on **Recall**, since missing churners (false negatives) is more costly than targeting some non-churners (false positives).

## 2.2 Data Description & Summary

## 2.3 Data Source

The dataset used in this project comes from **Kaggle**, specifically the https://www.kaggle.com/datasets/mnassrib/telecom-churn-datasets/discussion?sort=undefined

It contains customer-level data from a telecommunication company, including demographic details, account information, subscribed services, and financial attributes.

This dataset is widely used for churn prediction tasks in research and practice.

The dataset used in this project combines customer records from the telecommunication industry, with approximately **3,300 customers** and **20 predictor variables**. The target variable is **Churn**, encoded as a binary label:

- **0 = No Churn** (customer stayed)
- **1 = Churn** (customer left)

### 2.3.1 Key Features:

- **Demographic attributes**: Gender, SeniorCitizen, Partner, Dependents
- **Account information**: Tenure, Contract type, PaperlessBilling, PaymentMethod
- **Service-related features**: InternetService, OnlineSecurity, TechSupport, StreamingTV, StreamingMovies
- **Financial attributes**: MonthlyCharges, TotalCharges

### 2.3.2 Target Distribution:

The dataset is imbalanced: - ~85% of customers did not churn
- ~15% of customers churned

This imbalance means that **accuracy alone is not a sufficient metric** for evaluating models. Metrics such as **Recall, Precision, F1-score, and AUC** will be used to better assess predictive performance.

[5]:
```
#Import Datasets

df1 = pd.read_csv("data/churn-bigml-20.csv")
df2 = pd.read_csv("data/churn-bigml-80.csv")

print(df1.shape, df2.shape)
```

```
(667, 20) (2666, 20)
```

[6]:
```
df = pd.concat([df1, df2], axis=0).reset_index(drop=True)
```

[7]:
```
df.to_csv("telecom_churn_final.csv", index=False)
```

[8]:
```
print(df.shape)
print(df.info())

# Descriptive statistics
df.describe(include='all')
```

```
(3333, 20)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 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   International plan      3333 non-null   object
 4   Voice mail plan         3333 non-null   object
 5   Number vmail messages   3333 non-null   int64
 6   Total day minutes       3333 non-null   float64
 7   Total day calls         3333 non-null   int64
 8   Total day charge        3333 non-null   float64
 9   Total eve minutes       3333 non-null   float64
 10  Total eve calls         3333 non-null   int64
 11  Total eve charge        3333 non-null   float64
 12  Total night minutes     3333 non-null   float64
 13  Total night calls       3333 non-null   int64
 14  Total night charge      3333 non-null   float64
 15  Total intl minutes      3333 non-null   float64
 16  Total intl calls        3333 non-null   int64
 17  Total intl charge       3333 non-null   float64
 18  Customer service calls  3333 non-null   int64
 19  Churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(3)
memory usage: 498.1+ KB
None
```

[8]:

| | State | Account length | Area code | International plan | Voice mail plan |
|---|---|---|---|---|---|
| count | 3333 | 3333.000000 | 3333.000000 | 3333 | 3333 |
| unique | 51 | NaN | NaN | 2 | 2 |
| top | WV | NaN | NaN | No | No |
| freq | 106 | NaN | NaN | 3010 | 2411 |
| mean | NaN | 101.064806 | 437.182418 | NaN | NaN |
| std | NaN | 39.822106 | 42.371290 | NaN | NaN |
| min | NaN | 1.000000 | 408.000000 | NaN | NaN |
| 25% | NaN | 74.000000 | 408.000000 | NaN | NaN |
| 50% | NaN | 101.000000 | 415.000000 | NaN | NaN |
| 75% | NaN | 127.000000 | 510.000000 | NaN | NaN |
| max | NaN | 243.000000 | 510.000000 | NaN | NaN |

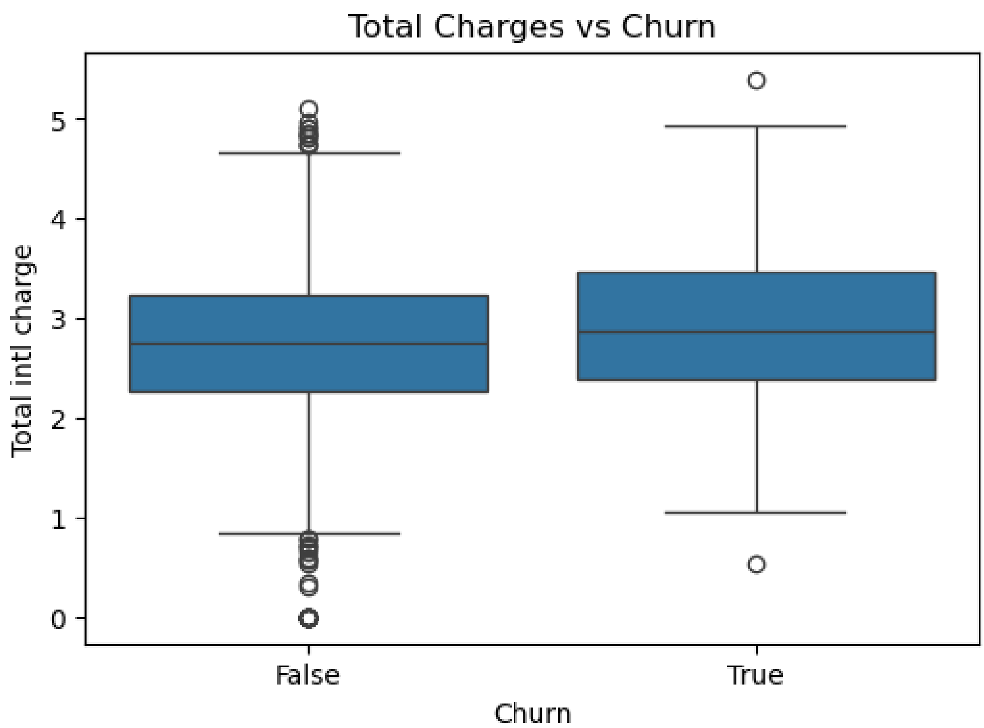
| | Number vmail messages | Total day minutes | Total day calls |
|---|---|---|---|
| count | 3333.000000 | 3333.000000 | 3333.000000 |
| unique | NaN | NaN | NaN |
| top | NaN | NaN | NaN |
| freq | NaN | NaN | NaN |
| mean | 8.099010 | 179.775098 | 100.435644 |
| std | 13.688365 | 54.467389 | 20.069084 |
| min | 0.000000 | 0.000000 | 0.000000 |
| 25% | 0.000000 | 143.700000 | 87.000000 |
| 50% | 0.000000 | 179.400000 | 101.000000 |
| 75% | 20.000000 | 216.400000 | 114.000000 |
| max | 51.000000 | 350.800000 | 165.000000 |

| | Total day charge | Total eve minutes | Total eve calls |
|---|---|---|---|
| count | 3333.000000 | 3333.000000 | 3333.000000 |
| unique | NaN | NaN | NaN |
| top | NaN | NaN | NaN |
| freq | NaN | NaN | NaN |
| mean | 30.562307 | 200.980348 | 100.114311 |
| std | 9.259435 | 50.713844 | 19.922625 |
| min | 0.000000 | 0.000000 | 0.000000 |
| 25% | 24.430000 | 166.600000 | 87.000000 |
| 50% | 30.500000 | 201.400000 | 100.000000 |
| 75% | 36.790000 | 235.300000 | 114.000000 |
| max | 59.640000 | 363.700000 | 170.000000 |

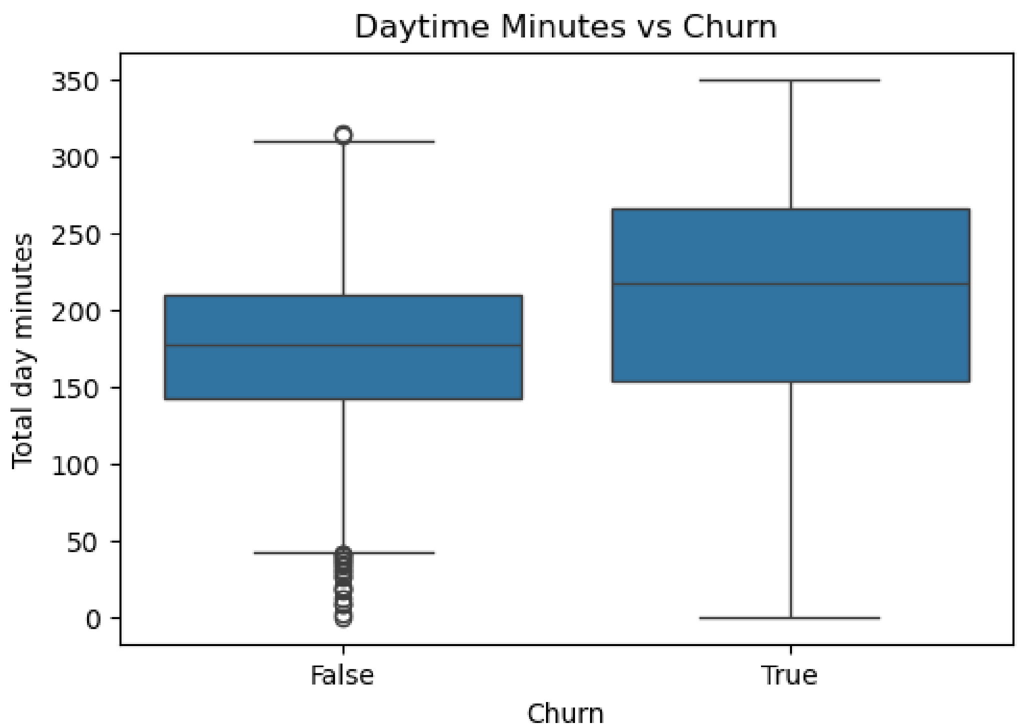
| | Total eve charge | Total night minutes | Total night calls |
|---|---|---|---|
| count | 3333.000000 | 3333.000000 | 3333.000000 |
| unique | NaN | NaN | NaN |
| top | NaN | NaN | NaN |
| freq | NaN | NaN | NaN |
| mean | 17.083540 | 200.872037 | 100.107711 |
| std | 4.310668 | 50.573847 | 19.568609 |
| min | 0.000000 | 23.200000 | 33.000000 |

```
25%              14.160000            167.000000           87.000000
50%              17.120000            201.200000          100.000000
75%              20.000000            235.300000          113.000000
max              30.910000            395.000000          175.000000

        Total night charge  Total intl minutes  Total intl calls  \
count          3333.000000         3333.000000       3333.000000
unique                 NaN                 NaN               NaN
top                    NaN                 NaN               NaN
freq                   NaN                 NaN               NaN
mean              9.039325           10.237294          4.479448
std               2.275873            2.791840          2.461214
min               1.040000            0.000000          0.000000
25%               7.520000            8.500000          3.000000
50%               9.050000           10.300000          4.000000
75%              10.590000           12.100000          6.000000
max              17.770000           20.000000         20.000000

        Total intl charge  Customer service calls  Churn
count         3333.000000             3333.000000   3333
unique                NaN                     NaN      2
top                   NaN                     NaN  False
freq                  NaN                     NaN   2850
mean             2.764581                1.562856    NaN
std              0.753773                1.315491    NaN
min              0.000000                0.000000    NaN
25%              2.300000                1.000000    NaN
50%              2.780000                1.000000    NaN
75%              3.270000                2.000000    NaN
max              5.400000                9.000000    NaN
```

[9]:
```
plt.figure(figsize=(6,4))
sns.boxplot(data=df, x="Churn", y="Total intl charge")
plt.title("Total Charges vs Churn")
plt.show()
```



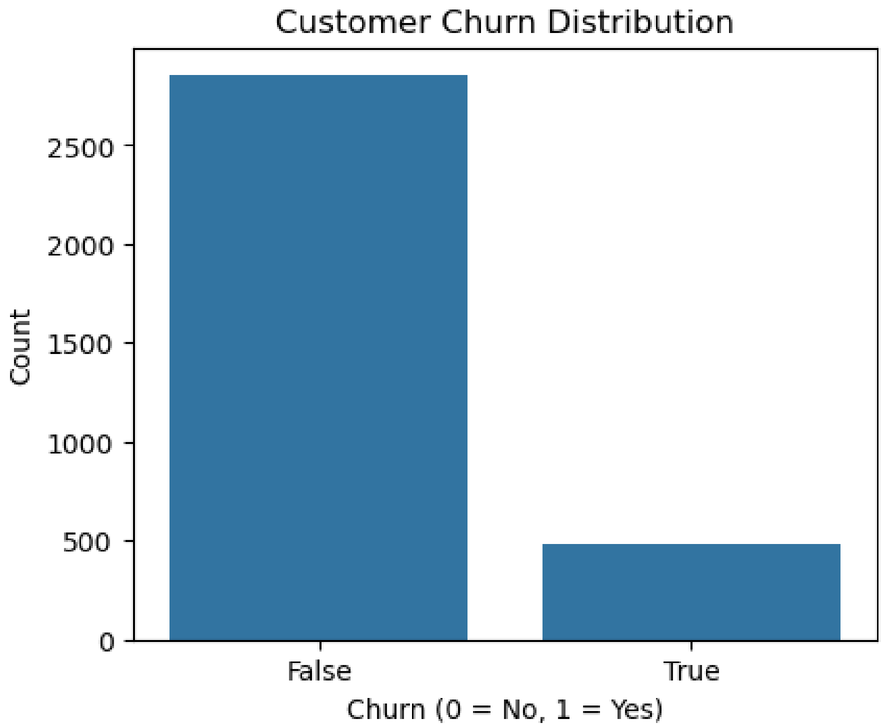

[10]:
```
plt.figure(figsize=(6,4))
sns.boxplot(data=df, x="Churn", y="Total day minutes")
plt.title("Daytime Minutes vs Churn")
plt.show()
```




```
[11]: print(df['Churn'].unique())
      print(df['Churn'].value_counts())
```

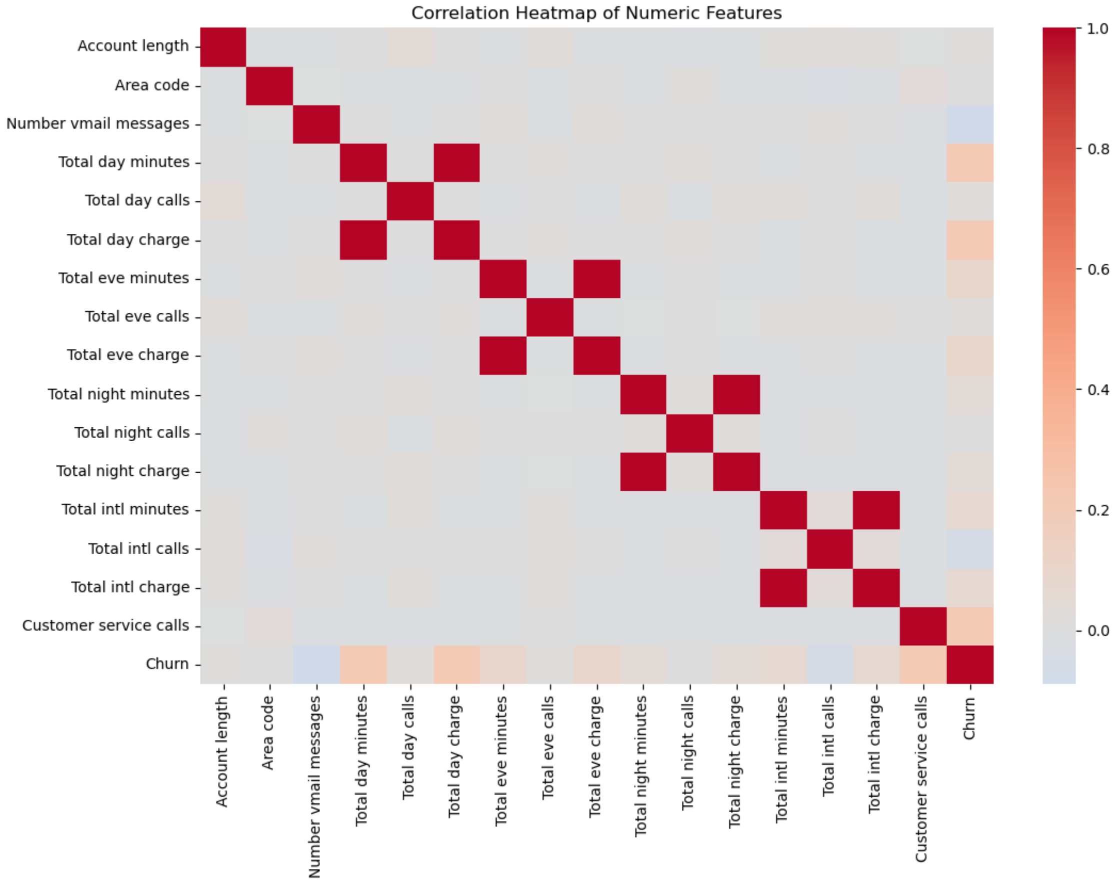
```
[False  True]
Churn
False    2850
True      483
Name: count, dtype: int64
```

```
[12]: plt.figure(figsize=(5,4))
      sns.countplot(x="Churn", data=df)
      plt.title("Customer Churn Distribution")
      plt.xlabel("Churn (0 = No, 1 = Yes)")
      plt.ylabel("Count")
      plt.show()

      # Percentage
      print(df["Churn"].value_counts(normalize=True)*100)
```




```
Churn
False    85.508551
True     14.491449
Name: proportion, dtype: float64
```

[13]:
```
plt.figure(figsize=(12,8))
corr = df.corr(numeric_only=True)
sns.heatmap(corr, annot=False, cmap="coolwarm", center=0)
plt.title("Correlation Heatmap of Numeric Features")
plt.show()
```




# 3 Pre process data

[14]:
```
X = df.drop(['Churn'], axis=1)    # drop churn + ID
X = pd.get_dummies(X, drop_first=True)    # convert categorical → numeric

y = df['Churn'].astype(int)    # convert True/False to 1/0

X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.3,
    random_state=42,
    stratify=y
)

print("Train set distribution:\n", y_train.value_counts())
print("Test set distribution:\n", y_test.value_counts())
```

```
Train set distribution:
 Churn
```

```
0    1995
1     338
Name: count, dtype: int64
Test set distribution:
 Churn
0    855
1    145
Name: count, dtype: int64
```

[15]:

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

# 4 1. Logistic Regression

The Logistic Regression model was implemented as a baseline classifier to predict customer churn. It estimates the probability of churn using the sigmoid function. The "balanced" class weight was applied to adjust for class imbalance and prevent bias toward the majority (non-churn) class.

### 4.0.1 Model Implementation

[16]:

```
# Scale the data (important for convergence)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize model
log_reg = LogisticRegression(
    solver='liblinear',
    max_iter=10000,
    class_weight='balanced',
    random_state=42
)

# Fit model
log_reg.fit(X_train_scaled, y_train)

# Predictions
y_pred = log_reg.predict(X_test_scaled)
y_prob = log_reg.predict_proba(X_test_scaled)[:, 1]

# Cross-validation (5-fold) using recall
cv_scores = cross_val_score(log_reg, X_train_scaled, y_train, cv=5,␣
↪scoring='recall', n_jobs=-1)

print("Cross-validation Recall:", np.mean(cv_scores).round(4), "+/-", np.
↪std(cv_scores).round(4))
```

```
Cross-validation Recall: 0.7103 +/- 0.0758
```

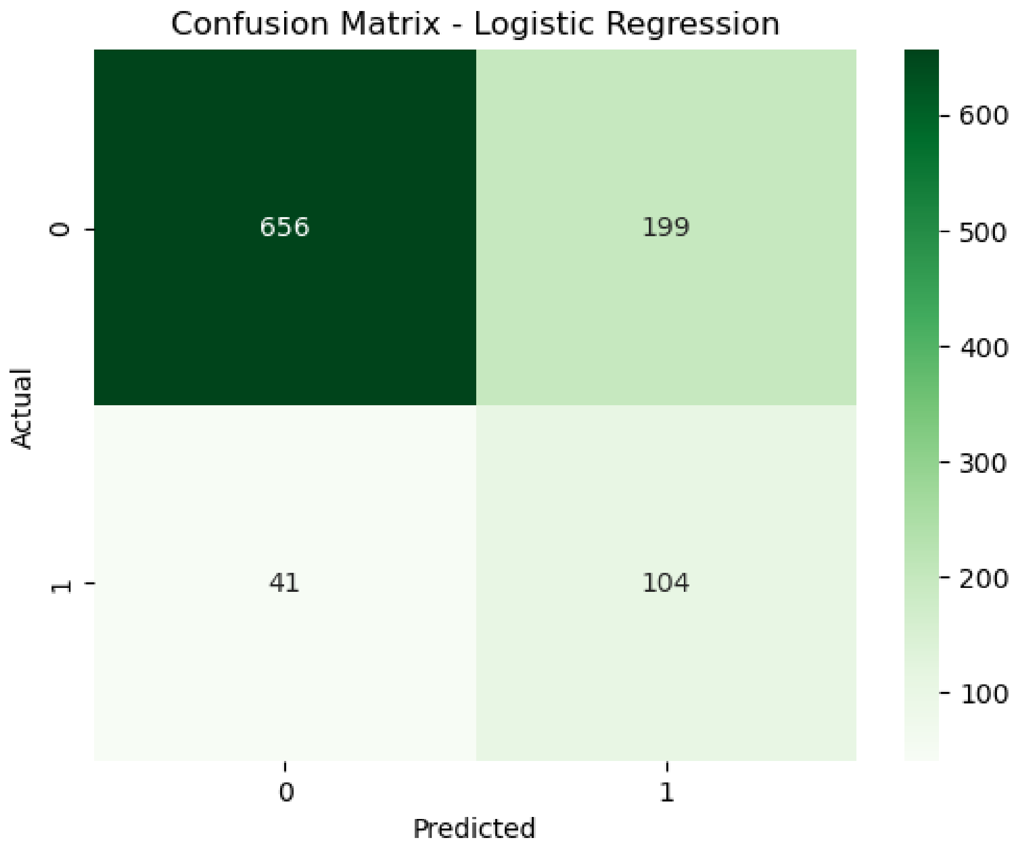
#### 4.0.2 Evaluation (Cross-validation results)

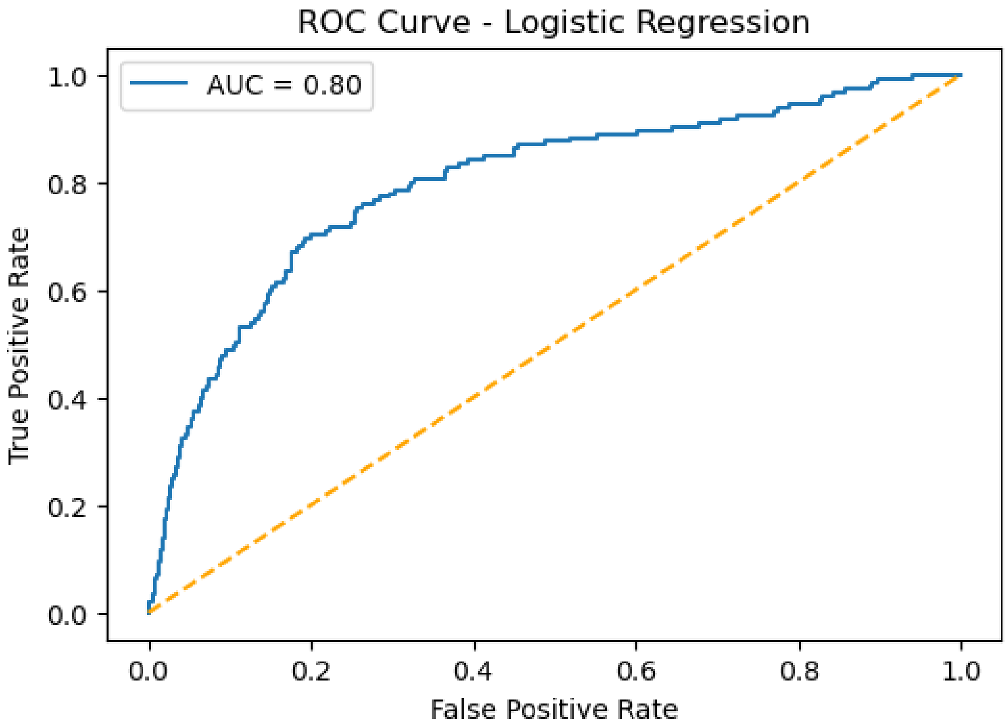
[17]:
```python
from sklearn.model_selection import cross_validate
from sklearn.metrics import (
    make_scorer, accuracy_score, precision_score, recall_score, f1_score,␣
 ↪roc_auc_score
)
import numpy as np

scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': make_scorer(roc_auc_score)
}

cv_results = cross_validate(log_reg, X_train_scaled, y_train, cv=5,␣
 ↪scoring=scoring, n_jobs=-1)

# Print results in a clean, formatted way
print("Cross-validation results (5-fold):")
for metric in scoring.keys():
    mean_score = np.mean(cv_results[f'test_{metric}'])
    std_score = np.std(cv_results[f'test_{metric}'])
    print(f"  {metric.capitalize():<10}: {mean_score:.3f} ± {std_score:.3f}")
```

```
Cross-validation results (5-fold):
  Accuracy  : 0.766 ± 0.013
  Precision : 0.348 ± 0.024
  Recall    : 0.710 ± 0.076
  F1        : 0.467 ± 0.038
  Roc_auc   : 0.743 ± 0.038
```

[18]:
```python
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Greens')
plt.title("Confusion Matrix - Logistic Regression")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

fpr, tpr, _ = roc_curve(y_test, y_prob)
plt.figure(figsize=(6,4))
plt.plot(fpr, tpr, label=f"AUC = {roc_auc_score(y_test, y_prob):.2f}")
plt.plot([0,1], [0,1], '--', color='orange')
plt.xlabel("False Positive Rate")
```

```python
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - Logistic Regression")
plt.legend()
plt.show()
```






The Logistic Regression model demonstrated moderate recall ( 0.71), indicating a reasonable ability to identify customers likely to churn while maintaining interpretability and simplicity. This baseline performance establishes a reference point for comparing more complex models such as Decision Trees, Random Forests, and Neural Networks.

---

# 5 2. Decision Tree

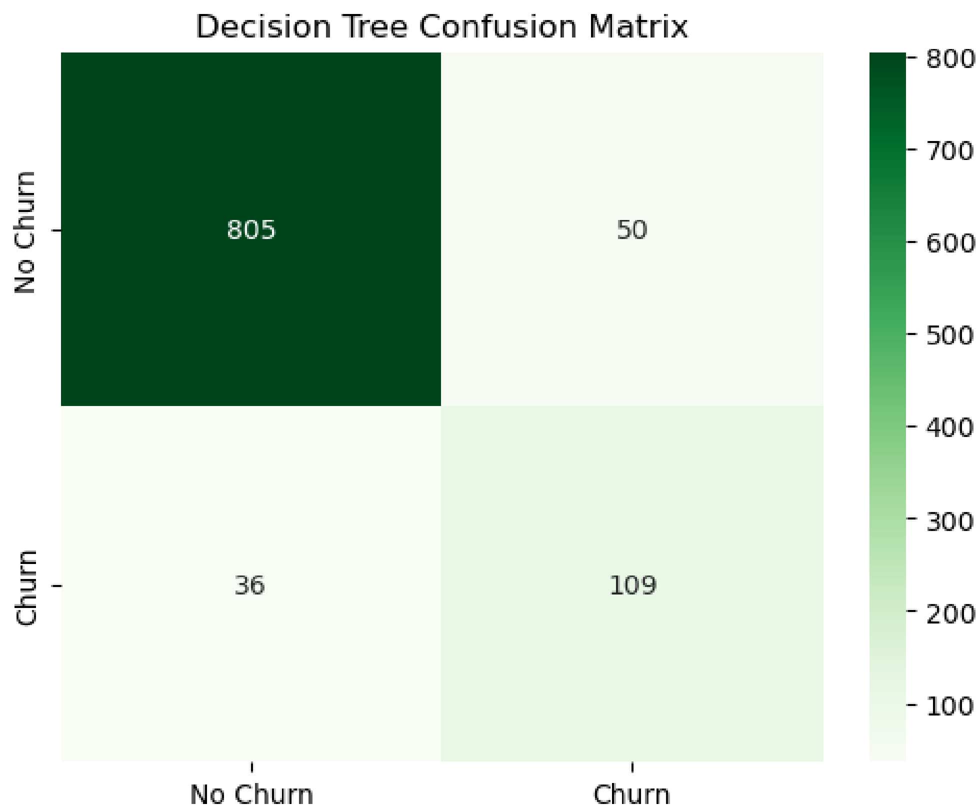
## 5.1 Model Implementation

The Decision Tree classifier was implemented to model nonlinear relationships and improve interpretability compared to Logistic Regression. The "balanced" class weight was used to mitigate class imbalance and ensure equal consideration of churn and non-churn customers.

[19]:
```
dt = DecisionTreeClassifier(
    criterion="gini",
    max_depth=5,
    class_weight="balanced",
    random_state=42
)
dt.fit(X_train, y_train)

# Predictions
```

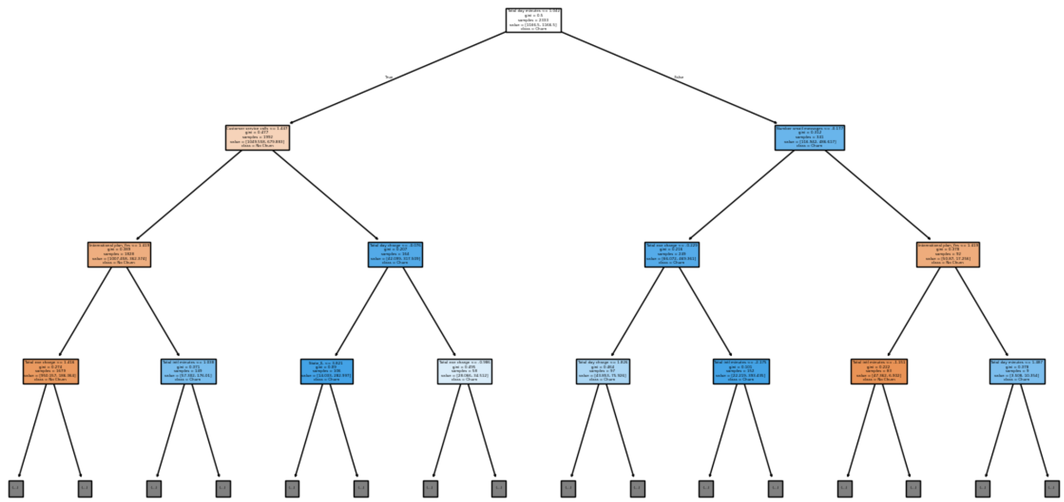
```python
y_pred_dt = dt.predict(X_test)
y_prob_dt = dt.predict_proba(X_test)[:,1]

# Evaluation
print("Decision Tree Report:\n", classification_report(y_test, y_pred_dt))
print("ROC-AUC:", roc_auc_score(y_test, y_prob_dt))

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_dt)
sns.heatmap(cm, annot=True, fmt='d', cmap="Greens",
            xticklabels=["No Churn", "Churn"],
            yticklabels=["No Churn", "Churn"])
plt.title("Decision Tree Confusion Matrix")
plt.show()
```

```
Decision Tree Report:
               precision    recall  f1-score   support

           0       0.96      0.94      0.95       855
           1       0.69      0.75      0.72       145

    accuracy                           0.91      1000
   macro avg       0.82      0.85      0.83      1000
weighted avg       0.92      0.91      0.92      1000

ROC-AUC: 0.8576245210727969
```




[20]:

```
plt.figure(figsize=(15,8))
plot_tree(dt, feature_names=X.columns, class_names=["No Churn","Churn"],␣
  ↪filled=True, max_depth=3)
plt.show()
```



### 5.2 Optimisation

[21]:
```
param_grid_dt = {
    "max_depth": [3, 5, 7, 9, 11, None],
    "min_samples_split": [2, 5, 10, 15, 20],
    "min_samples_leaf": [1, 2, 4, 6, 8, 10],
    "criterion": ["gini", "entropy"]
}
dt = DecisionTreeClassifier(
    class_weight="balanced",
    random_state=42
)


grid_dt = GridSearchCV(
    estimator=dt,
    param_grid=param_grid_dt,
    cv=5,
    scoring="recall",        # optimize for recall
    n_jobs=-1,
    error_score="raise"
)

grid_dt.fit(X_train, y_train)


print("Best Parameters (Decision Tree):", grid_dt.best_params_)
```

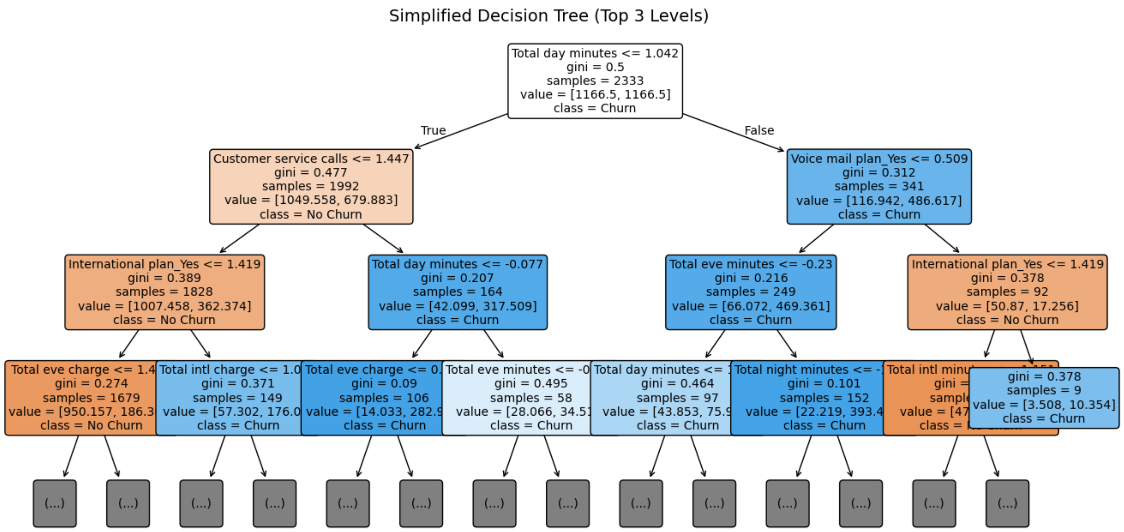
```
print(f"Best Recall: {grid_dt.best_score_:.3f}")
```

```
Best Parameters (Decision Tree): {'criterion': 'gini', 'max_depth': 7,
'min_samples_leaf': 6, 'min_samples_split': 20}
Best Recall: 0.814
```

[22]:
```
best_dt = grid_dt.best_estimator_

from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer, accuracy_score, precision_score,
 ↪recall_score, f1_score, roc_auc_score

scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': make_scorer(roc_auc_score)
}

cv_results = cross_validate(best_dt, X, y, cv=5, scoring=scoring)

for metric in scoring.keys():
    print(f"{metric.capitalize()}: {cv_results['test_' + metric].mean():.3f}")
```

```
Accuracy: 0.902
Precision: 0.632
Recall: 0.791
F1: 0.701
Roc_auc: 0.856
```

[23]:
```
plt.figure(figsize=(16,8))
plot_tree(
    best_dt,
    feature_names=X.columns,
    class_names=["No Churn", "Churn"],
    filled=True,
    rounded=True,
    fontsize=10,
    max_depth=3
)
plt.title("Simplified Decision Tree (Top 3 Levels)", fontsize=14)
plt.show()
```




# 6 3. Random Forest

The Random Forest classifier was implemented to improve generalization and reduce overfitting compared to the single Decision Tree. By combining multiple trees through bagging (bootstrap aggregation), it aims to achieve higher predictive performance and stability.

[24]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

param_grid_rf = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 15, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2'],
    'criterion': ['gini', 'entropy']
}


rf = RandomForestClassifier( class_weight='balanced',random_state=42,n_jobs=-1)


grid_rf = GridSearchCV(estimator=rf,
    param_grid=param_grid_rf,
    cv=5,
    scoring='recall',
    n_jobs=-1,
    verbose=0
```

```
)

grid_rf.fit(X_train, y_train)

print("Best Parameters (Random Forest):", grid_rf.best_params_)
print(f"Best Recall: {grid_rf.best_score_:.3f}")
```

```
Best Parameters (Random Forest): {'criterion': 'gini', 'max_depth': 5,
'max_features': 'sqrt', 'min_samples_leaf': 2, 'min_samples_split': 2,
'n_estimators': 300}
Best Recall: 0.769
```

[25]:

```
from sklearn.model_selection import cross_validate
from sklearn.metrics import make_scorer, accuracy_score, precision_score,␣
↪recall_score, f1_score, roc_auc_score
import numpy as np

# --- Retrieve the best Random Forest model from GridSearchCV ---
best_rf = grid_rf.best_estimator_

# --- Define scoring metrics ---
scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': make_scorer(roc_auc_score)
}

# --- Perform 5-fold cross-validation ---
cv_results_rf = cross_validate(best_rf, X, y, cv=5, scoring=scoring, n_jobs=-1)

# --- Print formatted results ---
print("=== Random Forest Cross-Validation Results (Optimized Model) ===")
for metric in scoring.keys():
    mean_score = np.mean(cv_results_rf[f'test_{metric}'])
    std_score = np.std(cv_results_rf[f'test_{metric}'])
    print(f"{metric.capitalize():<10}: {mean_score:.3f} ± {std_score:.3f}")
```

```
=== Random Forest Cross-Validation Results (Optimized Model) ===
Accuracy  : 0.904 ± 0.005
Precision : 0.634 ± 0.018
Recall    : 0.799 ± 0.020
F1        : 0.706 ± 0.012
Roc_auc   : 0.860 ± 0.009
```

---

# 7 4. Neural Network

The Neural Network (Multi-Layer Perceptron, MLP) was implemented to capture complex, nonlinear relationships among churn predictors that simpler models may overlook. Neural networks can approximate intricate decision boundaries, offering the potential to detect subtle churn patterns beyond those identifiable by tree-based or linear models.

[26]:
```
mlp = MLPClassifier(
    hidden_layer_sizes=(64, 32),
    activation='relu',
    solver='adam',
    max_iter=500,
    random_state=42
)

scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': make_scorer(roc_auc_score)
}

cv_results = cross_validate(mlp, X, y, cv=5, scoring=scoring)

print("=== Neural Network (MLP) Cross-Validation Results ===")
for metric in scoring.keys():
    print(f"{metric.capitalize()}: {cv_results['test_' + metric].mean():.4f}")
print(f"ROC-AUC Std: {cv_results['test_roc_auc'].std():.4f}")
```

```
=== Neural Network (MLP) Cross-Validation Results ===
Accuracy: 0.8758
Precision: 0.6999
Recall: 0.3064
F1: 0.4133
Roc_auc: 0.6393
ROC-AUC Std: 0.0209
```

[27]:
```
# Define a deeper architecture
deep_mlp = MLPClassifier(
    hidden_layer_sizes=(128, 64, 32, 16),
    activation='relu',
    solver='adam',
    alpha=0.0005,
    learning_rate='adaptive',
    max_iter=1000,
    random_state=42
)
```

```python
# Scoring metrics
scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': make_scorer(roc_auc_score)
}

# 5-fold cross-validation
cv_results = cross_validate(deep_mlp, X, y, cv=5, scoring=scoring)

# Display results
print("=== Deep Neural Network (4-Layer MLP) Cross-Validation Results ===")
for metric in scoring.keys():
    print(f"{metric.capitalize()}: {cv_results['test_' + metric].mean():.4f}")
print(f"ROC-AUC Std: {cv_results['test_roc_auc'].std():.4f}")
```

```
=== Deep Neural Network (4-Layer MLP) Cross-Validation Results ===
Accuracy: 0.8860
Precision: 0.6596
Recall: 0.4679
F1: 0.5429
Roc_auc: 0.7124
ROC-AUC Std: 0.0146
```

---

# 8 Gen AI Suggestions

This section documents how GenAI (ChatGPT 5.0) was used to support the model improvement process. The main goal was to refine the existing models (Decision Tree and Random Forest) to improve recall, reduce overfitting, and increase generalization while keeping interpretability when possible.

## 8.1 Forward Selection

GenAI suggested using forward feature selection to identify the most informative predictors for churn. This approach starts with no features and iteratively adds those that improve model performance until no significant gain is observed.

### 8.1.1 Decision Tree

[28]:
```python
X = df.drop(['Churn'], axis=1)
X = pd.get_dummies(X, drop_first=True)  # categorical → numeric

# dummy columns
```

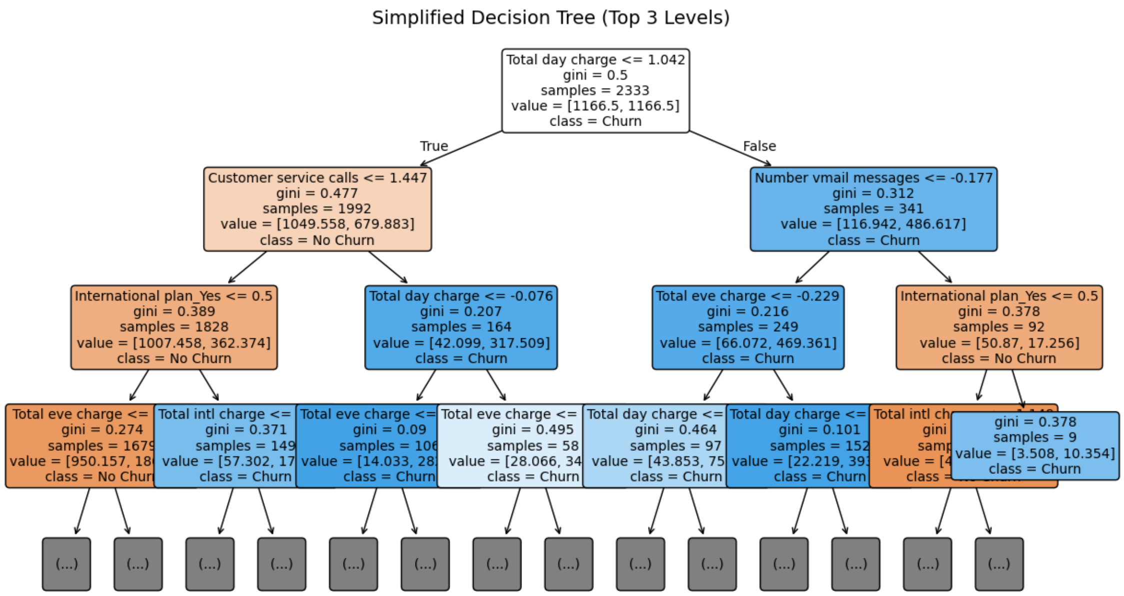
```python
X = X.loc[:, ~X.columns.str.startswith('State_')]

# Target variable
y = df['Churn'].astype(int)

# Train-test split with stratification
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.3,
    random_state=42,
    stratify=y
)

scaler = StandardScaler()
X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()


num_cols = X_train.select_dtypes(include=['float64', 'int64']).columns
X_train_scaled[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test_scaled[num_cols] = scaler.transform(X_test[num_cols])


from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.tree import DecisionTreeClassifier

dt_model = DecisionTreeClassifier(random_state=42, class_weight='balanced')

sfs_forward = SequentialFeatureSelector(
    dt_model,
    n_features_to_select=10,
    direction='forward',
    scoring='recall',
    cv=5,
    n_jobs=-1
)

sfs_forward.fit(X_train_scaled, y_train)
forward_features = X_train_scaled.columns[sfs_forward.get_support()]
print("Forward Selection Features:\n", forward_features)
```

```
Forward Selection Features:
 Index(['Area code', 'Number vmail messages', 'Total day charge',
       'Total eve charge', 'Total intl minutes', 'Total intl calls',
       'Total intl charge', 'Customer service calls', 'International plan_Yes',
       'Voice mail plan_Yes'],
      dtype='object')
```

[29]:
```python
X_train_fs = X_train_scaled[forward_features]
X_test_fs  = X_test_scaled[forward_features]

dt = DecisionTreeClassifier(random_state=42, class_weight='balanced')

param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 5, 7, 10, None],
    'min_samples_split': [2, 5, 10, 20],
    'min_samples_leaf': [1, 3, 5, 10]
}

grid_dt = GridSearchCV(
    dt,
    param_grid,
    scoring='recall',
    cv=5,
    n_jobs=-1
)
grid_dt.fit(X_train_fs, y_train)

print(" Best Parameters (Decision Tree):", grid_dt.best_params_)
print(" Best CV Recall:", grid_dt.best_score_)

#  Evaluate on test data
best_dt = grid_dt.best_estimator_
y_pred_test = best_dt.predict(X_test_fs)
y_prob_test = best_dt.predict_proba(X_test_fs)[:, 1]

print(" Test Classification Report:")
print(classification_report(y_test, y_pred_test))

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_test))
print("ROC-AUC (Test):", roc_auc_score(y_test, y_prob_test))

#  Cross-validation evaluation for multiple metrics
scoring = {
    'accuracy': 'accuracy',
    'precision': 'precision',
    'recall': 'recall',
    'f1': 'f1',
    'roc_auc': 'roc_auc'
}

cv_results = cross_validate(best_dt, X_train_fs, y_train, cv=5, scoring=scoring)

for metric in scoring.keys():
```

```python
    print(f"{metric.capitalize()}: {np.mean(cv_results['test_' + metric]):.4f}")

plt.figure(figsize=(14, 8))
plot_tree(
    best_dt,
    feature_names=forward_features,
    class_names=["No Churn", "Churn"],
    filled=True,
    rounded=True,
    max_depth=3,
    fontsize=10
)
plt.title("Simplified Decision Tree (Top 3 Levels)", fontsize=14)
plt.show()
```

```
 Best Parameters (Decision Tree): {'criterion': 'gini', 'max_depth': None,
'min_samples_leaf': 5, 'min_samples_split': 20}
 Best CV Recall: 0.8344161545215101
 Test Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.87      0.91       855
           1       0.51      0.77      0.61       145

    accuracy                           0.86      1000
   macro avg       0.73      0.82      0.76      1000
weighted avg       0.89      0.86      0.87      1000

Confusion Matrix:
 [[746 109]
 [ 33 112]]
ROC-AUC (Test): 0.8628231498285944
Accuracy: 0.8628
Precision: 0.5168
Recall: 0.8344
F1: 0.6379
Roc_auc: 0.8957
```




### 8.1.2 Random Forest

```python
[30]: selected_features = forward_features

X_train_fs = X_train_scaled[selected_features]
X_test_fs  = X_test_scaled[selected_features]

rf = RandomForestClassifier(
    random_state=42,
    class_weight='balanced',
    n_jobs=-1
)

param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 15, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 3, 5],
    'max_features': ['sqrt', 'log2']
}

#  Grid Search with recall-focused optimization
grid_rf = GridSearchCV(
    rf,
    param_grid,
    scoring='recall',
```

```
    cv=5,
    n_jobs=-1,
    verbose=1
)

grid_rf.fit(X_train_fs, y_train)

print(" Best Parameters (Random Forest):", grid_rf.best_params_)
print(" Best CV Recall:", grid_rf.best_score_)

#  Evaluate on test data
best_rf = grid_rf.best_estimator_
y_pred_test = best_rf.predict(X_test_fs)
y_prob_test = best_rf.predict_proba(X_test_fs)[:, 1]

print(" Test Classification Report:")
print(classification_report(y_test, y_pred_test))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_test))
print("ROC-AUC (Test):", roc_auc_score(y_test, y_prob_test))

# Cross-validation metrics
scoring = {
    'accuracy': 'accuracy',
    'precision': 'precision',
    'recall': 'recall',
    'f1': 'f1',
    'roc_auc': 'roc_auc'
}

cv_results_rf = cross_validate(best_rf, X_train_fs, y_train, cv=5,␣
 ↪scoring=scoring)
for metric in scoring.keys():
    print(f"{metric.capitalize()}: {np.mean(cv_results_rf['test_' + metric]):.
 ↪4f}")
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits
 Best Parameters (Random Forest): {'max_depth': 5, 'max_features': 'sqrt',
'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 100}
 Best CV Recall: 0.8312115891132572
 Test Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.91      0.94       855
           1       0.60      0.81      0.69       145

    accuracy                           0.89      1000
   macro avg       0.78      0.86      0.81      1000
weighted avg       0.91      0.89      0.90      1000
```

```
Confusion Matrix:
 [[775  80]
 [ 27 118]]
ROC-AUC (Test): 0.895728977616455
Accuracy: 0.9156
Precision: 0.6714
Recall: 0.8312
F1: 0.7420
Roc_auc: 0.9085
```

### 8.2 Nested Cross Validation

To improve the reliability of model evaluation and reduce bias introduced during hyperparameter tuning. Nested cross-validation combines an inner loop (for hyperparameter optimization) and an outer loop (for unbiased performance estimation). This approach provides a more accurate measure of how the model generalizes to unseen data, especially when multiple tuning steps are applied.

[31]:
```
dt = DecisionTreeClassifier(class_weight='balanced', random_state=42)
rf = RandomForestClassifier(class_weight='balanced', random_state=42)

# Parameter grids
dt_param_grid = {
    'max_depth': [3, 5, 7, 9],
    'min_samples_split': [2, 5, 10],
    'criterion': ['gini', 'entropy']
}

rf_param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10]
}

# Nested CV setup
inner_cv = KFold(n_splits=5, shuffle=True, random_state=42)
outer_cv = KFold(n_splits=5, shuffle=True, random_state=42)

# Use the built-in 'roc_auc' string instead of custom scorer
scorer = 'recall'

# Decision Tree Nested CV
dt_grid = GridSearchCV(dt, dt_param_grid, cv=inner_cv, scoring=scorer,
 ↪n_jobs=-1)
dt_nested_scores = cross_val_score(dt_grid, X, y, cv=outer_cv, scoring=scorer,
 ↪n_jobs=-1)

# Random Forest Nested CV
```

```
rf_grid = GridSearchCV(rf, rf_param_grid, cv=inner_cv, scoring=scorer,␣
 ↪n_jobs=-1)
rf_nested_scores = cross_val_score(rf_grid, X, y, cv=outer_cv, scoring=scorer,␣
 ↪n_jobs=-1)

print(f"Decision Tree Nested CV Recall: {np.mean(dt_nested_scores):.4f} ± {np.
 ↪std(dt_nested_scores):.4f}")
print(f"Random Forest Nested CV Recall: {np.mean(rf_nested_scores):.4f} ± {np.
 ↪std(rf_nested_scores):.4f}")
```

```
Decision Tree Nested CV Recall: 0.7811 ± 0.0200
Random Forest Nested CV Recall: 0.7666 ± 0.0143
```

[32]:

```
# Define models
dt = DecisionTreeClassifier(class_weight='balanced', random_state=42)
rf = RandomForestClassifier(class_weight='balanced', random_state=42)

# Parameter grids
dt_param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 5, 7, 9, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 5, 10]
}

rf_param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 5]
}

# Cross-validation setup
inner_cv = KFold(n_splits=5, shuffle=True, random_state=42)
outer_cv = KFold(n_splits=5, shuffle=True, random_state=42)

# Define metrics
scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': 'roc_auc'
}

# ---- DECISION TREE ----
```

```
dt_grid = GridSearchCV(dt, dt_param_grid, cv=inner_cv, scoring='roc_auc',␣
↪n_jobs=-1)
dt_cv_results = cross_validate(dt_grid, X, y, cv=outer_cv, scoring=scoring,␣
↪n_jobs=-1)

print("=== Decision Tree Nested Cross-Validation Results ===")
for metric in scoring.keys():
    print(f"{metric.capitalize()}: {np.mean(dt_cv_results['test_' + metric]):.
↪4f} ± {np.std(dt_cv_results['test_' + metric]):.4f}")

# ---- RANDOM FOREST ----
rf_grid = GridSearchCV(rf, rf_param_grid, cv=inner_cv, scoring='roc_auc',␣
↪n_jobs=-1)
rf_cv_results = cross_validate(rf_grid, X, y, cv=outer_cv, scoring=scoring,␣
↪n_jobs=-1)

print("\n=== Random Forest Nested Cross-Validation Results ===")
for metric in scoring.keys():
    print(f"{metric.capitalize()}: {np.mean(rf_cv_results['test_' + metric]):.
↪4f} ± {np.std(rf_cv_results['test_' + metric]):.4f}")
```

```
=== Decision Tree Nested Cross-Validation Results ===
Accuracy: 0.8983 ± 0.0236
Precision: 0.6257 ± 0.0729
Recall: 0.7981 ± 0.0397
F1: 0.6981 ± 0.0429
Roc_auc: 0.8894 ± 0.0117

=== Random Forest Nested Cross-Validation Results ===
Accuracy: 0.9484 ± 0.0048
Precision: 0.9050 ± 0.0488
Recall: 0.7229 ± 0.0182
F1: 0.8026 ± 0.0108
Roc_auc: 0.9133 ± 0.0091
```

---

## 8.3 Regularisation through pruning

To reduce overfitting and improve interpretability in the Decision Tree model by applying cost-complexity pruning. Pruning simplifies the tree by removing branches that provide little predictive power, allowing the model to generalise better on unseen data.

[33]:
```
# Cross-validation setup
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
scoring = {
    'accuracy': make_scorer(accuracy_score),
    'precision': make_scorer(precision_score),
```

```
    'recall': make_scorer(recall_score),
    'f1': make_scorer(f1_score),
    'roc_auc': 'roc_auc'
}

# Baseline (unpruned) model
dt_unpruned = DecisionTreeClassifier(class_weight='balanced', random_state=42)
unpruned_results = cross_validate(dt_unpruned, X, y, cv=cv, scoring=scoring,␣
 ↪n_jobs=-1)
```

[34]:
```
# Fit initial tree to extract pruning path
path = dt_unpruned.cost_complexity_pruning_path(X, y)
ccp_alphas = path.ccp_alphas[:-1]  # remove the maximum value (prunes all␣
 ↪leaves)

# Test different pruning levels
alpha_results = []
for alpha in ccp_alphas:
    dt = DecisionTreeClassifier(class_weight='balanced', random_state=42,␣
 ↪ccp_alpha=alpha)
    scores = cross_validate(dt, X, y, cv=cv, scoring=scoring)
    alpha_results.append({
        'alpha': alpha,
        'recall': np.mean(scores['test_recall']),
        'f1': np.mean(scores['test_f1']),
        'roc_auc': np.mean(scores['test_roc_auc']),
        'accuracy': np.mean(scores['test_accuracy'])
    })

alpha_df = pd.DataFrame(alpha_results)
best_alpha = alpha_df.loc[alpha_df['recall'].idxmax(), 'alpha']
print(f"Best alpha (max recall): {best_alpha}")
```

```
Best alpha (max recall): 0.00207813713768726
```

[35]:
```
dt_pruned = DecisionTreeClassifier(class_weight='balanced', random_state=42,␣
 ↪ccp_alpha=best_alpha)
pruned_results = cross_validate(dt_pruned, X, y, cv=cv, scoring=scoring,␣
 ↪n_jobs=-1)

def summarise(name, results):
    print(f"\n=== {name} ===")
    for metric in scoring.keys():
        mean, std = np.mean(results[f'test_{metric}']), np.
 ↪std(results[f'test_{metric}'])
        print(f"{metric.capitalize()}: {mean:.4f} ± {std:.4f}")
```

```
summarise("Unpruned Decision Tree", unpruned_results)
summarise("Pruned Decision Tree", pruned_results)
```

```
=== Unpruned Decision Tree ===
Accuracy: 0.9142 ± 0.0078
Precision: 0.7048 ± 0.0417
Recall: 0.7103 ± 0.0527
F1: 0.7054 ± 0.0256
Roc_auc: 0.8296 ± 0.0234

=== Pruned Decision Tree ===
Accuracy: 0.8992 ± 0.0130
Precision: 0.6184 ± 0.0397
Recall: 0.8076 ± 0.0337
F1: 0.6996 ± 0.0305
Roc_auc: 0.8826 ± 0.0161
```

---

### 8.4 SMOTE -Synthetic Minority Oversampling Technique)

To address the strong class imbalance in the dataset, where non-churn customers significantly outnumber churners (1995 vs. 338). This imbalance can bias models toward predicting the majority class, lowering recall for actual churners. To mitigate this, the Synthetic Minority Oversampling Technique (SMOTE) was applied to generate synthetic examples of the minority class (churners), creating a balanced dataset and improving model fairness.

[36]:
```
# Apply SMOTE only on training data
sm = SMOTE(random_state=42, sampling_strategy='auto')
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)

print("Before SMOTE:", np.bincount(y_train))
print("After SMOTE:", np.bincount(y_train_res))

dt_params = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [3, 5, 8, 10, None],
    'min_samples_split': [2, 5, 10, 20],
    'min_samples_leaf': [1, 2, 5, 10],
}

dt = DecisionTreeClassifier(class_weight='balanced', random_state=42)
dt_grid = GridSearchCV(dt, dt_params, cv=5, scoring='recall', n_jobs=-1)
dt_grid.fit(X_train_res, y_train_res)

best_dt = dt_grid.best_estimator_
y_pred_dt = best_dt.predict(X_test)
```

```python
y_proba_dt = best_dt.predict_proba(X_test)[:, 1]

print("\n=== Decision Tree (After SMOTE) ===")
print("Best Params:", dt_grid.best_params_)
print(classification_report(y_test, y_pred_dt))
print("ROC-AUC:", roc_auc_score(y_test, y_proba_dt))


rf_params = {
    'n_estimators': [100, 200],
    'max_depth': [5, 8, 10, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 5],
    'max_features': ['sqrt', 'log2']
}

rf = RandomForestClassifier(class_weight='balanced', random_state=42)
rf_grid = GridSearchCV(rf, rf_params, cv=5, scoring='recall', n_jobs=-1)
rf_grid.fit(X_train_res, y_train_res)

best_rf = rf_grid.best_estimator_
y_pred_rf = best_rf.predict(X_test)
y_proba_rf = best_rf.predict_proba(X_test)[:, 1]

print("\n=== Random Forest (After SMOTE) ===")
print("Best Params:", rf_grid.best_params_)
print(classification_report(y_test, y_pred_rf))
print("ROC-AUC:", roc_auc_score(y_test, y_proba_rf))


results = pd.DataFrame({
    'Model': ['Decision Tree', 'Random Forest'],
    'Best Params': [dt_grid.best_params_, rf_grid.best_params_],
    'AUC': [roc_auc_score(y_test, y_proba_dt), roc_auc_score(y_test,␣
 ↪y_proba_rf)],
})
print("\n=== Comparison Summary ===")
print(results)
```

```
Before SMOTE: [1995  338]
After SMOTE: [1995 1995]

=== Decision Tree (After SMOTE) ===
Best Params: {'criterion': 'entropy', 'max_depth': None, 'min_samples_leaf': 1,
'min_samples_split': 2}
              precision    recall  f1-score   support

           0       0.96      0.89      0.92       855
```

```
           1       0.55      0.77      0.64       145

    accuracy                           0.88      1000
   macro avg       0.76      0.83      0.78      1000
weighted avg       0.90      0.88      0.88      1000

ROC-AUC: 0.8329905222827183

=== Random Forest (After SMOTE) ===
Best Params: {'max_depth': None, 'max_features': 'sqrt', 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 200}
              precision    recall  f1-score   support

           0       0.96      0.95      0.96       855
           1       0.73      0.76      0.74       145

    accuracy                           0.92      1000
   macro avg       0.84      0.86      0.85      1000
weighted avg       0.93      0.92      0.92      1000

ROC-AUC: 0.8982375478927203

=== Comparison Summary ===
           Model                                       Best Params       AUC
0  Decision Tree  {'criterion': 'entropy', 'max_depth': None, 'm…  0.832991
1  Random Forest  {'max_depth': None, 'max_features': 'sqrt', 'm…  0.898238
```