customer_churn_analysis

March 21, 2025

1 1. Framing the Business Problem

Customer churn refers to when customers stop using a company's products or services. For telecom companies, predicting which customers are likely to churn is crucial for several reasons:

Revenue Retention: It costs 5-25x more to acquire new customers than to retain existing ones Targeted Interventions: Identifying at-risk customers allows for proactive retention efforts Understanding Pain Points: Churn analysis reveals product/service weaknesses

Machine Learning Problem Statement: We will build a classification model that predicts whether a customer will churn in the near future based on their profile and usage patterns. This is a binary classification problem (churn: yes/no).

2 2. Defining Relevant Metrics

When dealing with churn prediction, we need to consider appropriate evaluation metrics:

Recall/Sensitivity: The percentage of actual churners correctly identified (higher priority as missing a potential churner is costly) Precision: The percentage of predicted churners who actually churn F1-Score: Harmonic mean of precision and recall AUC-ROC: Area Under the Receiver Operating Characteristic curve (measures model's ability to distinguish between classes) Business Impact Metrics: Cost savings from retention campaigns, ROI of predictive model

For business teams, we should set expectations about:

Trade-offs between different metrics (e.g., higher recall often means lower precision) Realistic performance benchmarks based on industry standards Implementation timeline and resource requirements

3 3. Data Understanding and Exploratory Data Analysis

[ ]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Suppress warnings
import warnings
```

```python
warnings.filterwarnings('ignore')

# Set style for plots
plt.style.use('fivethirtyeight')
sns.set_theme(style='whitegrid')

# Load data
df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')

# First look at the data
print(f"Dataset shape: {df.shape}")
df.head()
```

```
Dataset shape: (7043, 21)
```

[ ]:

```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  … DeviceProtection  \
0  No phone service             DSL             No  …               No
1                No             DSL            Yes  …              Yes
2                No             DSL            Yes  …               No
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

               PaymentMethod MonthlyCharges  TotalCharges Churn
0           Electronic check          29.85         29.85    No
1               Mailed check          56.95        1889.5    No
2               Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

3.1 3.1 Data Overview

[ ]:
```python
# Check column information
df.info()

# Summary statistics
df.describe().T

# Check for missing values
print("Missing values per column:")
print(df.isnull().sum())

# Check target variable distribution
print("\nTarget variable distribution:")
print(df['Churn'].value_counts(normalize=True) * 100)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
Missing values per column:
customerID          0
gender              0
SeniorCitizen       0
```

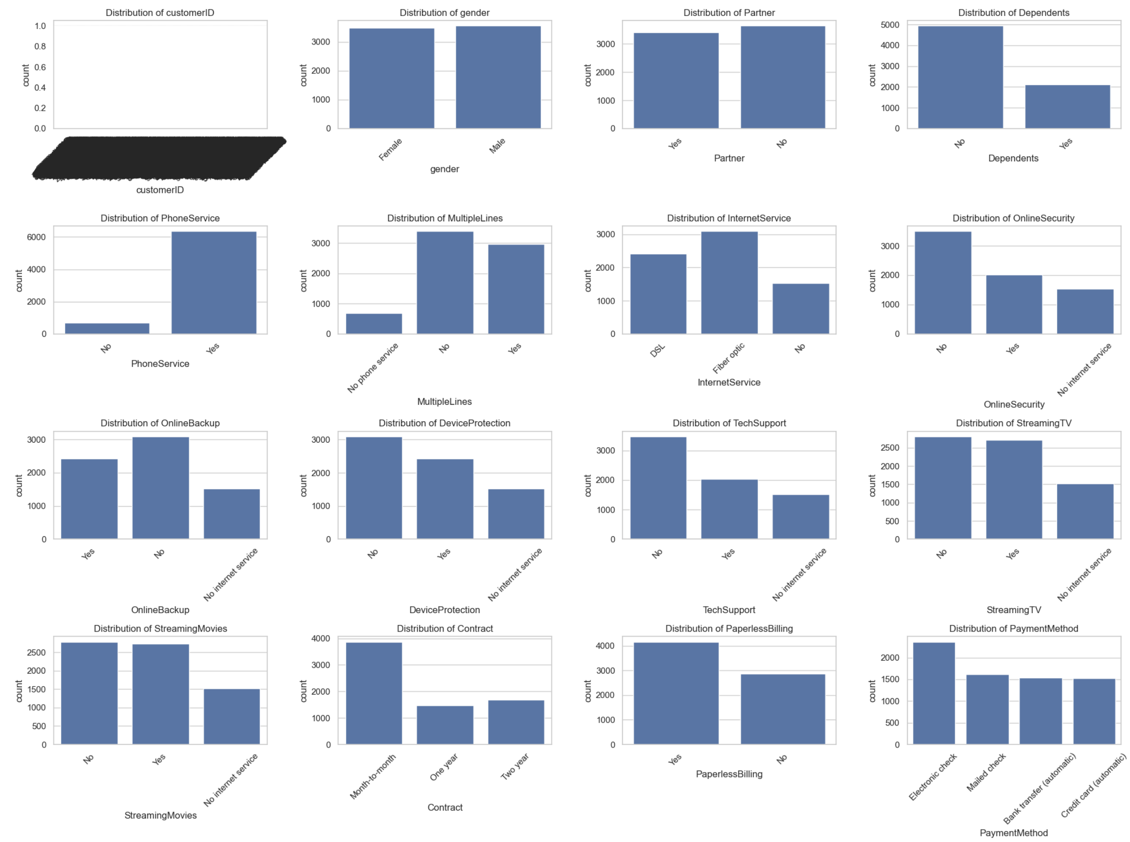
```
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64

Target variable distribution:
Churn
No     73.463013
Yes    26.536987
Name: proportion, dtype: float64
```

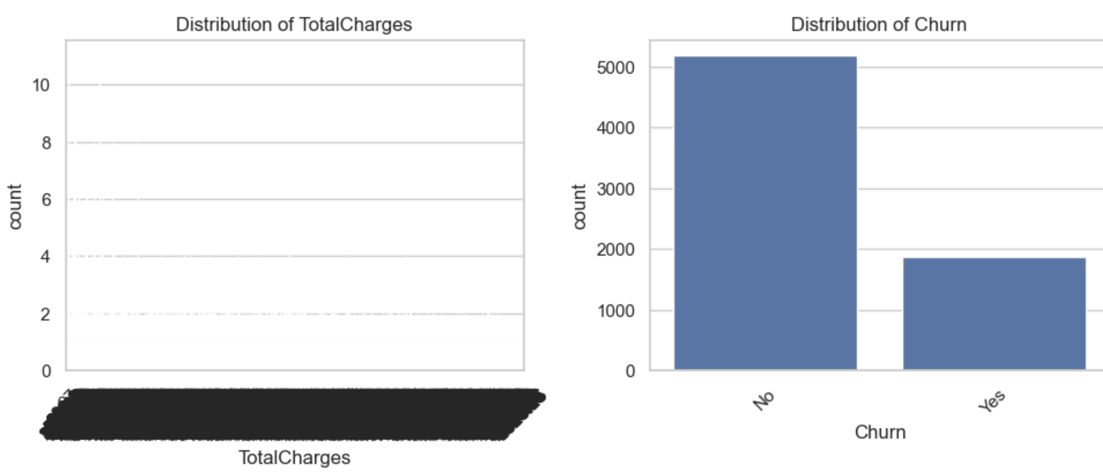
3.2 3.2 Univariate Analysis

Let's analyze the distribution of key variables:

[ ]:
```
# Split into multiple figures with 16 plots max per figure
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()
max_plots_per_figure = 16  # 4x4 grid
num_figures = (len(categorical_cols) + max_plots_per_figure - 1) //
 ↪max_plots_per_figure

for fig_num in range(num_figures):
    plt.figure(figsize=(20, 15))

    start_idx = fig_num * max_plots_per_figure
    end_idx = min((fig_num + 1) * max_plots_per_figure, len(categorical_cols))

    for i, col_idx in enumerate(range(start_idx, end_idx), 1):
        col = categorical_cols[col_idx]
        plt.subplot(4, 4, i)
        sns.countplot(x=col, data=df)
        plt.title(f'Distribution of {col}')
        plt.xticks(rotation=45)
```

```
plt.tight_layout()
plt.show()
```

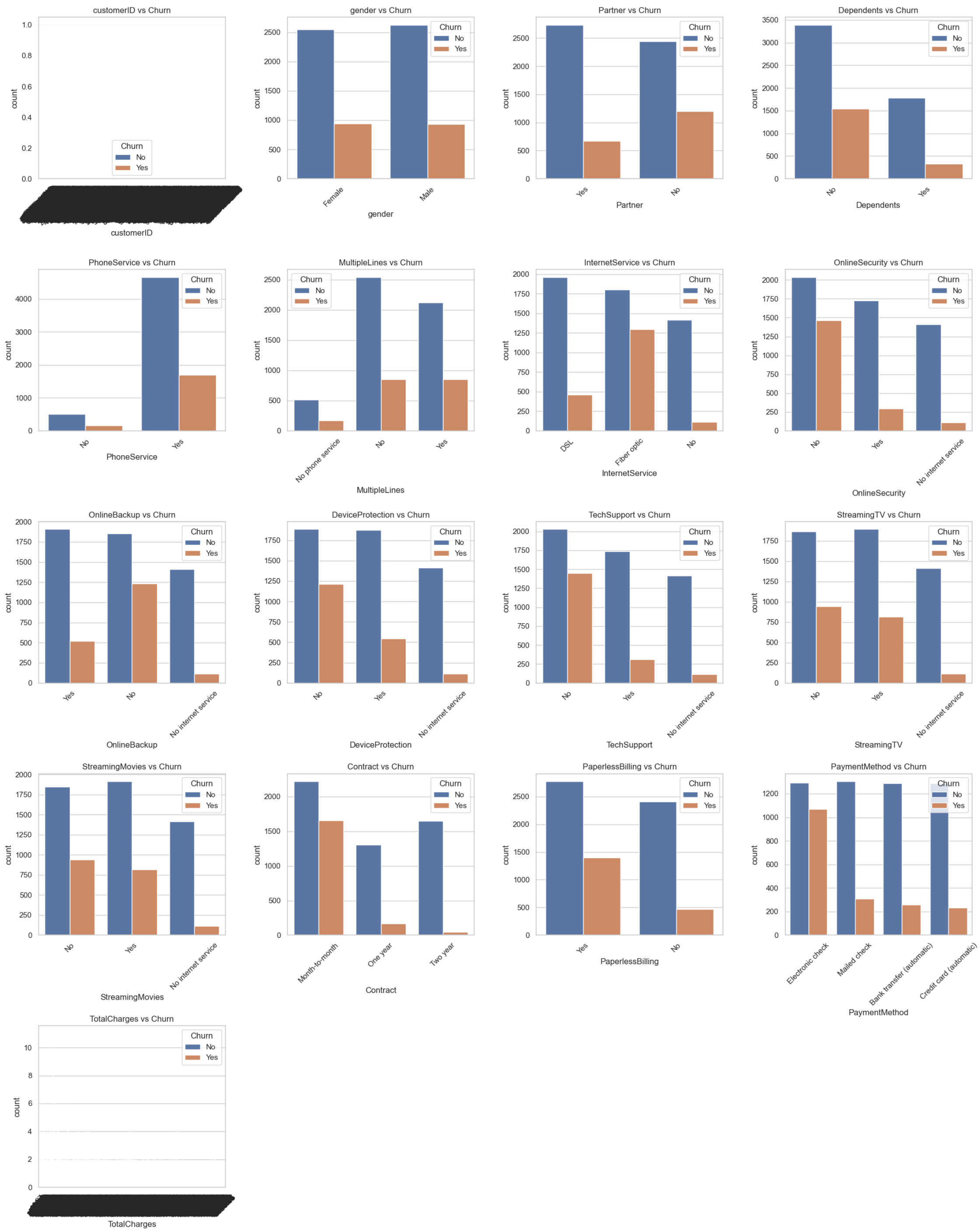




3.3 3.3 Bivariate Analysis

Let's analyze the relationship between features and the target variable:

[ ]:
```
# Create a copy of the DataFrame for visualization purposes
viz_df = df.copy()

# For categorical features vs Churn
# First, get categorical columns excluding Churn
cat_cols_no_churn = [col for col in categorical_cols if col != 'Churn']
num_cols = len(cat_cols_no_churn)
rows = (num_cols + 3) // 4  # Calculate needed rows (ceiling division)

plt.figure(figsize=(20, 5*rows))
for i, col in enumerate(cat_cols_no_churn, 1):
    plt.subplot(rows, 4, i)
    sns.countplot(x=col, hue='Churn', data=viz_df)
    plt.title(f'{col} vs Churn')
    plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```


customerID vs Churn
Churn
No
Yes
count
customerID
gender vs Churn
Female
Male
gender
Partner vs Churn
Yes
No
Partner
Dependents vs Churn
No
Yes
Dependents
PhoneService vs Churn
No
Yes
PhoneService
MultipleLines vs Churn
No phone service
No
Yes
MultipleLines
InternetService vs Churn
DSL
Fiber optic
No
InternetService
OnlineSecurity vs Churn
No
Yes
No internet service
OnlineSecurity
OnlineBackup vs Churn
Yes
No
No internet service
OnlineBackup
DeviceProtection vs Churn
No
Yes
No internet service
DeviceProtection
TechSupport vs Churn
No
Yes
No internet service
TechSupport
StreamingTV vs Churn
No
Yes
No internet service
StreamingTV
StreamingMovies vs Churn
No
Yes
No internet service
StreamingMovies
Contract vs Churn
Month-to-month
One year
Two year
Contract
PaperlessBilling vs Churn
Yes
No
PaperlessBilling
PaymentMethod vs Churn
Electronic check
Mailed check
Bank transfer (automatic)
Credit card (automatic)
PaymentMethod
TotalCharges vs Churn
TotalCharges

4 4. Data Preprocessing

4.1 4.1 Missing Value Treatment

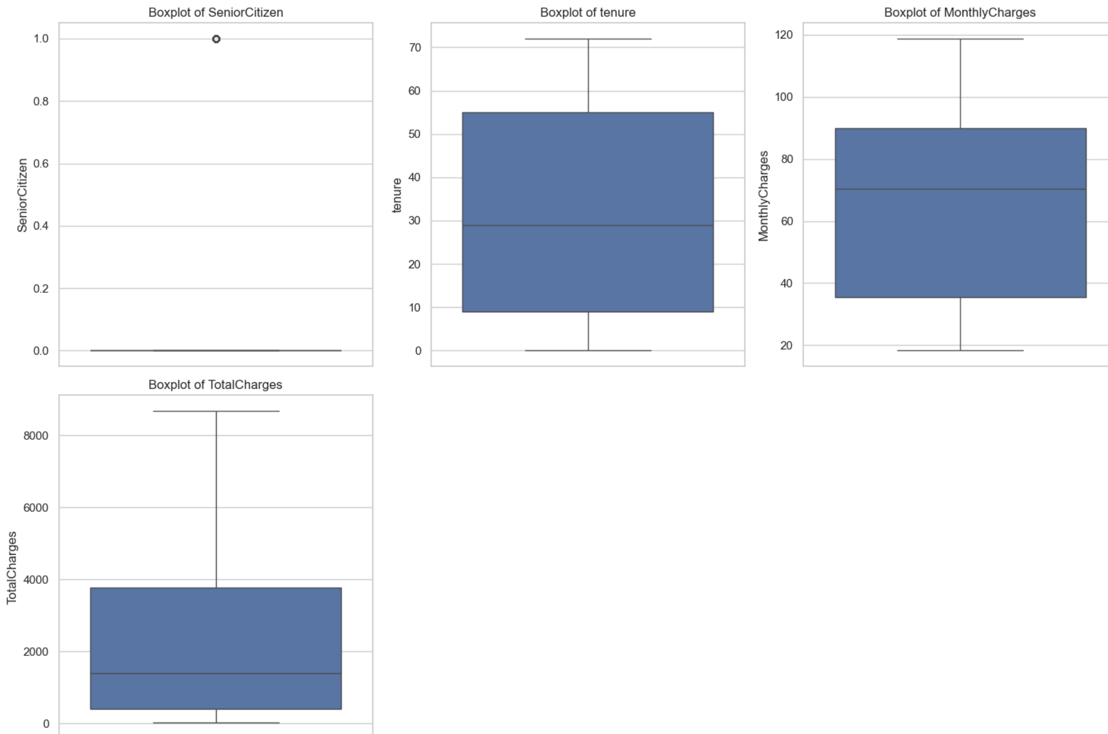
[ ]:
```
# Convert TotalCharges to numeric (it might be stored as object due to spaces)
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

# Check for missing values again
print("Missing values per column:")
print(df.isnull().sum())

# Handle missing values in TotalCharges
# Option 1: Impute with median
df['TotalCharges'].fillna(df['TotalCharges'].median(), inplace=True)

# Option 2: For customers with 0 tenure, we could set TotalCharges to 0
# df.loc[df['tenure'] == 0, 'TotalCharges'] = 0
```

```
Missing values per column:
customerID           0
gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines        0
InternetService      0
OnlineSecurity       0
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

4.2 4.2 Outlier Treatment

[ ]:
```
# Function to detect and visualize outliers using boxplots
def detect_outliers(df, numeric_cols):
    plt.figure(figsize=(15, 10))
    for i, col in enumerate(numeric_cols, 1):
```

```
        plt.subplot(2, 3, i)
        sns.boxplot(y=df[col])
        plt.title(f'Boxplot of {col}')

    plt.tight_layout()
    plt.show()

# First define numerical_cols by selecting numerical data types
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()

# Then filter out customerID
numeric_cols = [col for col in numerical_cols if col not in ['customerID']]
detect_outliers(df, numeric_cols)

# We can use IQR method to cap outliers if necessary
# Example for one column:
def cap_outliers(df, col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    df[col] = np.where(df[col] > upper_bound, upper_bound,
                       np.where(df[col] < lower_bound, lower_bound, df[col]))
    return df

# Apply to numeric columns if needed
# for col in numeric_cols:
#     df = cap_outliers(df, col)
```



5 5. Feature Engineering and Encoding

5.1 5.1 Feature Engineering

[ ]:
```
# Create new features that might be useful for prediction
# 1. Average monthly charges
df['AvgMonthlyCharges'] = df['TotalCharges'] / (df['tenure'] + 1)  # Adding 1 to avoid division by zero

# 2. Total services subscribed
services = ['PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
            'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies']

df['TotalServices'] = 0
for service in services:
    # For binary yes/no columns
    if set(df[service].unique()) == {'Yes', 'No'} or set(df[service].unique()) == {'Yes', 'No', 'No internet service'}:
        df['TotalServices'] += np.where(df[service] == 'Yes', 1, 0)
    # For internet service which has 'DSL', 'Fiber optic', 'No'
```

```
    elif service == 'InternetService':
        df['TotalServices'] += np.where(df[service] != 'No', 1, 0)

# 3. Contract category (group by contract length)
df['ContractCategory'] = df['Contract'].map({'Month-to-month': 0, 'One year':␣
↪1, 'Two year': 2})

# 4. Senior citizen family indicator
df['SeniorFamily'] = np.where((df['SeniorCitizen'] == 1) & (df['Partner'] ==␣
↪'Yes'), 1, 0)

# 5. Value customer indicator (high monthly charges, long tenure)
df['ValueCustomer'] = np.where((df['tenure'] > df['tenure'].median()) &
                               (df['MonthlyCharges'] > df['MonthlyCharges'].
↪median()), 1, 0)
```

5.2 5.2 Label Encoding / One-Hot Encoding

[ ]:
```
# Drop customerID as it's not useful for modeling
df.drop('customerID', axis=1, inplace=True)

# Identify categorical columns (excluding target variable)
categorical_features = [col for col in df.select_dtypes(include=['object']).
↪columns if col != 'Churn']

# One-hot encode categorical features
df_encoded = pd.get_dummies(df, columns=categorical_features, drop_first=True)

# Handle the target variable
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df_encoded['Churn'] = le.fit_transform(df['Churn'])

# Map the encoded values to original labels for reference
churn_mapping = dict(zip(le.classes_, le.transform(le.classes_)))
print("Churn Mapping:", churn_mapping)
```

```
Churn Mapping: {'No': 0, 'Yes': 1}
```

5.3 5.3 Handling New Categorical Levels

For production systems, you need to handle potential new categories that weren't present in training:

[ ]:
```
from sklearn.preprocessing import OneHotEncoder

# Create a more robust encoding process using sklearn's OneHotEncoder
def encode_categorical_features(train_df, test_df, categorical_cols):
```

```python
    # Initialize the encoder
    encoder = OneHotEncoder(sparse=False, handle_unknown='ignore')

    # Fit on training data
    encoder.fit(train_df[categorical_cols])

    # Transform both training and test data
    train_encoded = encoder.transform(train_df[categorical_cols])
    test_encoded = encoder.transform(test_df[categorical_cols])

    # Get feature names
    feature_names = [f"{col}_{cat}" for i, col in enumerate(categorical_cols)
                     for cat in encoder.categories_[i]]

    # Convert to DataFrame
    train_encoded_df = pd.DataFrame(train_encoded, columns=feature_names,␣
↪index=train_df.index)
    test_encoded_df = pd.DataFrame(test_encoded, columns=feature_names,␣
↪index=test_df.index)

    # Drop original categorical columns and concat encoded features
    train_df = train_df.drop(categorical_cols, axis=1)
    test_df = test_df.drop(categorical_cols, axis=1)

    train_df = pd.concat([train_df, train_encoded_df], axis=1)
    test_df = pd.concat([test_df, test_encoded_df], axis=1)

    return train_df, test_df, encoder

# This function would be used with train/test splits
# Example usage:
# train_encoded, test_encoded, encoder = encode_categorical_features(train,␣
↪test, categorical_features)
```

6 6. Target Encoding and Avoiding Data Leakage

Target encoding is a technique where you replace a categorical value with the mean of the target variable for that value. It's effective but can lead to data leakage if not implemented correctly.

[ ]:
```python
from sklearn.model_selection import KFold

def target_encode_kfold(df, column, target, n_folds=5):
    """
    Apply target encoding using k-fold to prevent data leakage
    """
    # Create a copy of the dataframe
    df_copy = df.copy()
```

```
    # Create a new column for the encoded feature
    encoded_column = f"{column}_target_encoded"
    df_copy[encoded_column] = np.nan

    # Set up KFold
    kfold = KFold(n_splits=n_folds, shuffle=True, random_state=42)

    # For each fold
    for train_idx, test_idx in kfold.split(df_copy):
        # Get the means from the training fold
        means = df_copy.iloc[train_idx].groupby(column)[target].mean()

        # Map the means to the test fold
        df_copy.loc[test_idx, encoded_column] = df_copy.iloc[test_idx][column].
 ↪map(means)

    # Handle missing values (categories that didn't appear in a particular fold)
    global_mean = df_copy[target].mean()
    df_copy[encoded_column].fillna(global_mean, inplace=True)

    return df_copy, encoded_column

# Example application for a categorical column
# df_encoded, new_col = target_encode_kfold(df, 'Contract', 'Churn')
```

7 7. Feature Transforms and Feature Selection

7.1 7.1 Feature Scaling

[ ]:
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Identify numerical columns for scaling
numeric_features = [col for col in df_encoded.select_dtypes(include=['int64',␣
 ↪'float64']).columns
                    if col != 'Churn']  # Exclude target

# StandardScaler (Z-score normalization)
scaler = StandardScaler()
df_encoded[numeric_features] = scaler.
 ↪fit_transform(df_encoded[numeric_features])

# Alternative: MinMaxScaler (scales to range [0,1])
# minmax_scaler = MinMaxScaler()
# df_encoded[numeric_features] = minmax_scaler.
 ↪fit_transform(df_encoded[numeric_features])
```

7.2 7.2 Feature Selection using RFE

[ ]:
```
from sklearn.feature_selection import RFE
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

# Split the data
X = df_encoded.drop('Churn', axis=1)
y = df_encoded['Churn']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42, stratify=y)

# Initialize the model
base_model = RandomForestClassifier(random_state=42)

# Initialize RFE with the desired number of features
n_features_to_select = 15  # Example: select top 15 features
rfe = RFE(estimator=base_model, n_features_to_select=n_features_to_select)

# Fit RFE
rfe.fit(X_train, y_train)

# Get selected features
selected_features = [feature for feature, selected in zip(X.columns, rfe.
↪support_) if selected]
print(f"Selected features ({len(selected_features)}):")
for i, feature in enumerate(selected_features, 1):
    print(f"{i}. {feature}")

# Create a dataframe with only selected features
X_train_selected = X_train[selected_features]
X_test_selected = X_test[selected_features]
```

```
Selected features (15):
1. SeniorCitizen
2. tenure
3. MonthlyCharges
4. TotalCharges
5. AvgMonthlyCharges
6. TotalServices
7. ContractCategory
8. gender_Male
9. Partner_Yes
10. Dependents_Yes
11. InternetService_Fiber optic
12. OnlineSecurity_Yes
13. OnlineBackup_Yes
14. PaperlessBilling_Yes
```

15. PaymentMethod_Electronic check

8 8. Solving Class Imbalance

Churn data is often imbalanced. Here are techniques to address this: ## 8.1 Resampling Techniques

[ ]:
```
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from imblearn.combine import SMOTEENN, SMOTETomek

# Check class distribution
print("Original class distribution:")
print(y_train.value_counts(normalize=True) * 100)

# 1. Oversampling with SMOTE
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train_selected, y_train)
print("\nSMOTE class distribution:")
print(pd.Series(y_train_smote).value_counts(normalize=True) * 100)

# 2. Undersampling
rus = RandomUnderSampler(random_state=42)
X_train_rus, y_train_rus = rus.fit_resample(X_train_selected, y_train)
print("\nUndersampling class distribution:")
print(pd.Series(y_train_rus).value_counts(normalize=True) * 100)

# 3. Combined approach: SMOTE + ENN
smote_enn = SMOTEENN(random_state=42)
X_train_smoteenn, y_train_smoteenn = smote_enn.fit_resample(X_train_selected,␣
↪y_train)
print("\nSMOTEENN class distribution:")
print(pd.Series(y_train_smoteenn).value_counts(normalize=True) * 100)
```

```
Original class distribution:
Churn
0    73.464679
1    26.535321
Name: proportion, dtype: float64

SMOTE class distribution:
Churn
0    50.0
1    50.0
Name: proportion, dtype: float64

Undersampling class distribution:
Churn
```

```
0    50.0
1    50.0
Name: proportion, dtype: float64

SMOTEENN class distribution:
Churn
1    53.218302
0    46.781698
Name: proportion, dtype: float64
```

8.1 8.2 Class Weights

[ ]:
```
# Instead of resampling, we can use class_weight parameter in many sklearn␣
↪models
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

# Use 'balanced' for automatic weight calculation based on class frequencies
rf_balanced = RandomForestClassifier(random_state=42, class_weight='balanced')
rf_balanced.fit(X_train_selected, y_train)

# Predict and evaluate
y_pred_balanced = rf_balanced.predict(X_test_selected)
print("Classification report with balanced class weights:")
print(classification_report(y_test, y_pred_balanced))
```

```
Classification report with balanced class weights:
              precision    recall  f1-score   support

           0       0.82      0.90      0.86      1035
           1       0.63      0.46      0.53       374

    accuracy                           0.78      1409
   macro avg       0.72      0.68      0.70      1409
weighted avg       0.77      0.78      0.77      1409
```

9 9. Model Training and Evaluation

Let's implement and evaluate several models:

[ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score
from sklearn.metrics import confusion_matrix, classification_report, roc_curve,␣
↪precision_recall_curve
```

```python
import time

# Function to evaluate models
def evaluate_model(model, X_train, X_test, y_train, y_test, model_name):
    # Start time
    start_time = time.time()

    # Train the model
    model.fit(X_train, y_train)

    # End time
    train_time = time.time() - start_time

    # Make predictions (both class labels and probabilities)
    y_pred = model.predict(X_test)
    y_pred_proba = model.predict_proba(X_test)[:, 1]  # Probabilities for␣
 ↪positive class

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred_proba)

    # Create confusion matrix
    cm = confusion_matrix(y_test, y_pred)

    # Compile results
    results = {
        'model_name': model_name,
        'model': model,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1_score': f1,
        'roc_auc': roc_auc,
        'confusion_matrix': cm,
        'train_time': train_time,
        'y_pred': y_pred,
        'y_pred_proba': y_pred_proba
    }

    return results

# Initialize models
models = {
```

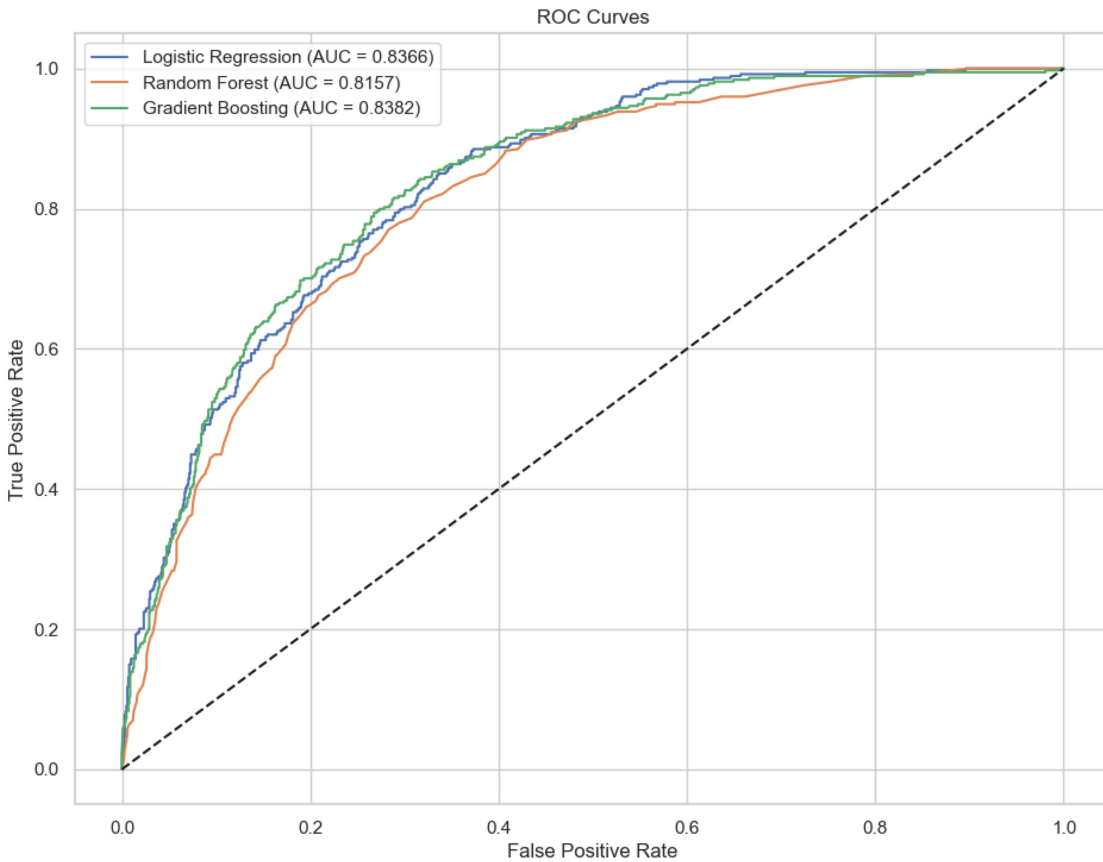
```
    'Logistic Regression': LogisticRegression(random_state=42, max_iter=1000,␣
 ↪class_weight='balanced'),
    'Random Forest': RandomForestClassifier(random_state=42,␣
 ↪class_weight='balanced'),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42)
}

# Evaluate all models
results = {}
for name, model in models.items():
    results[name] = evaluate_model(model, X_train_smote, X_test_selected,␣
 ↪y_train_smote, y_test, name)

    # Print results
    print(f"\n{name} Results:")
    print(f"Accuracy: {results[name]['accuracy']:.4f}")
    print(f"Precision: {results[name]['precision']:.4f}")
    print(f"Recall: {results[name]['recall']:.4f}")
    print(f"F1-Score: {results[name]['f1_score']:.4f}")
    print(f"ROC-AUC: {results[name]['roc_auc']:.4f}")
    print(f"Training Time: {results[name]['train_time']:.2f} seconds")
    print("\nConfusion Matrix:")
    print(results[name]['confusion_matrix'])
    print("\nClassification Report:")
    print(classification_report(y_test, results[name]['y_pred']))
```

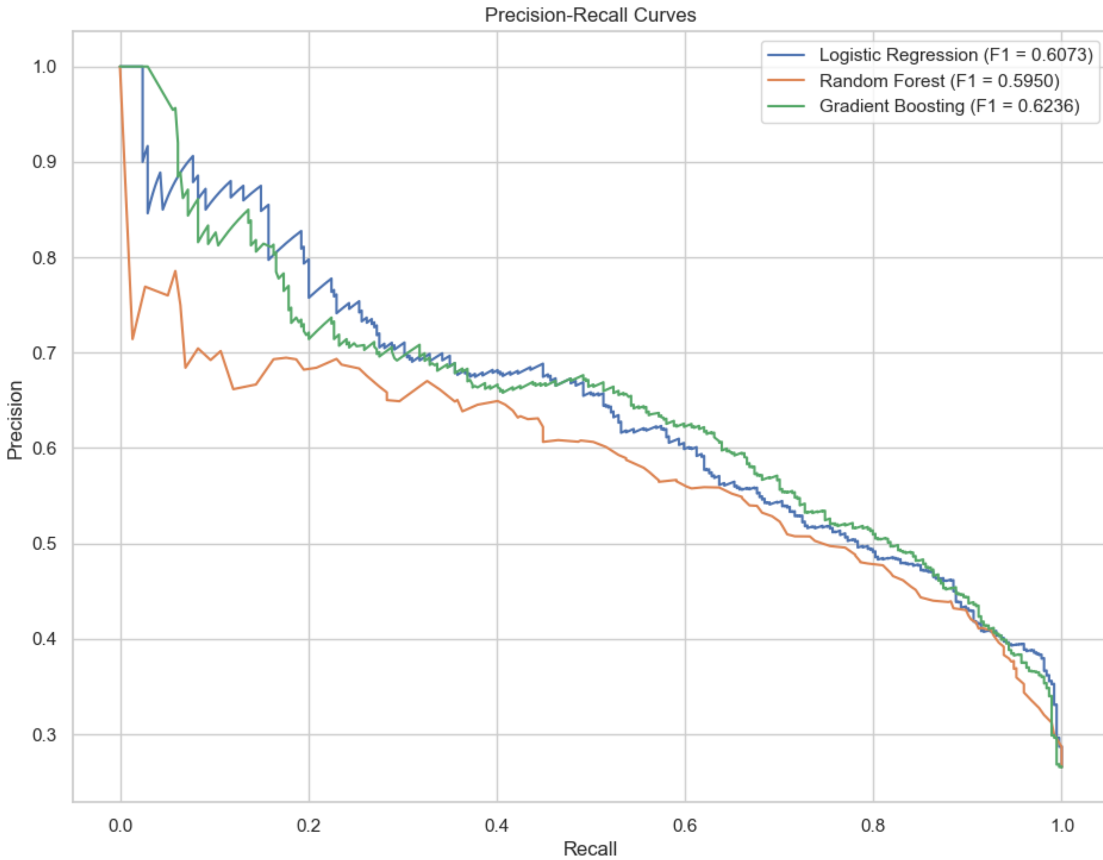
```
Logistic Regression Results:
Accuracy: 0.7310
Precision: 0.4958
Recall: 0.7834
F1-Score: 0.6073
ROC-AUC: 0.8366
Training Time: 0.06 seconds

Confusion Matrix:
[[737 298]
 [ 81 293]]

Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.71      0.80      1035
           1       0.50      0.78      0.61       374

    accuracy                           0.73      1409
   macro avg       0.70      0.75      0.70      1409
```

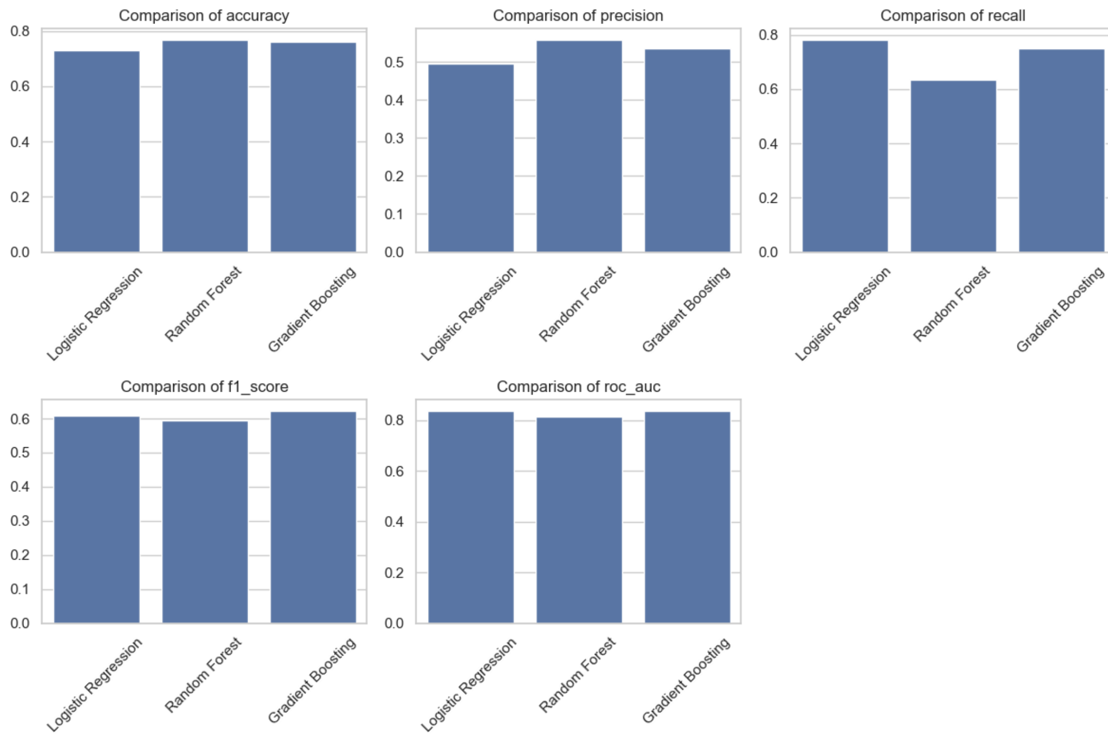
```
weighted avg       0.79      0.73      0.75      1409


Random Forest Results:
Accuracy: 0.7700
Precision: 0.5587
Recall: 0.6364
F1-Score: 0.5950
ROC-AUC: 0.8157
Training Time: 0.66 seconds

Confusion Matrix:
[[847 188]
 [136 238]]

Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.82      0.84      1035
           1       0.56      0.64      0.59       374

    accuracy                           0.77      1409
   macro avg       0.71      0.73      0.72      1409
weighted avg       0.78      0.77      0.77      1409


Gradient Boosting Results:
Accuracy: 0.7601
Precision: 0.5344
Recall: 0.7487
F1-Score: 0.6236
ROC-AUC: 0.8382
Training Time: 1.00 seconds

Confusion Matrix:
[[791 244]
 [ 94 280]]

Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.76      0.82      1035
           1       0.53      0.75      0.62       374

    accuracy                           0.76      1409
   macro avg       0.71      0.76      0.72      1409
weighted avg       0.80      0.76      0.77      1409
```

9.1 9.1 Visualization of Model Performance

[ ]:
```
# Visualize ROC curves
plt.figure(figsize=(10, 8))
for name, result in results.items():
    fpr, tpr, _ = roc_curve(y_test, result['y_pred_proba'])
    plt.plot(fpr, tpr, label=f"{name} (AUC = {result['roc_auc']:.4f})")

plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves')
plt.legend()
plt.show()

# Visualize Precision-Recall curves
plt.figure(figsize=(10, 8))
for name, result in results.items():
    precision, recall, _ = precision_recall_curve(y_test,␣
 ↪result['y_pred_proba'])
    plt.plot(recall, precision, label=f"{name} (F1 = {result['f1_score']:.4f})")

plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curves')
plt.legend()
plt.show()

# Compare metrics across models
metrics = ['accuracy', 'precision', 'recall', 'f1_score', 'roc_auc']
model_names = list(results.keys())

plt.figure(figsize=(12, 8))
for i, metric in enumerate(metrics, 1):
    plt.subplot(2, 3, i)
    # Use the actual metric name instead of 'metric_value'
    values = [results[model][metric] for model in model_names]
    sns.barplot(x=model_names, y=values)
    plt.title(f'Comparison of {metric}')
    plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```


ROC Curves
Logistic Regression (AUC = 0.8366)
Random Forest (AUC = 0.8157)
Gradient Boosting (AUC = 0.8382)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0

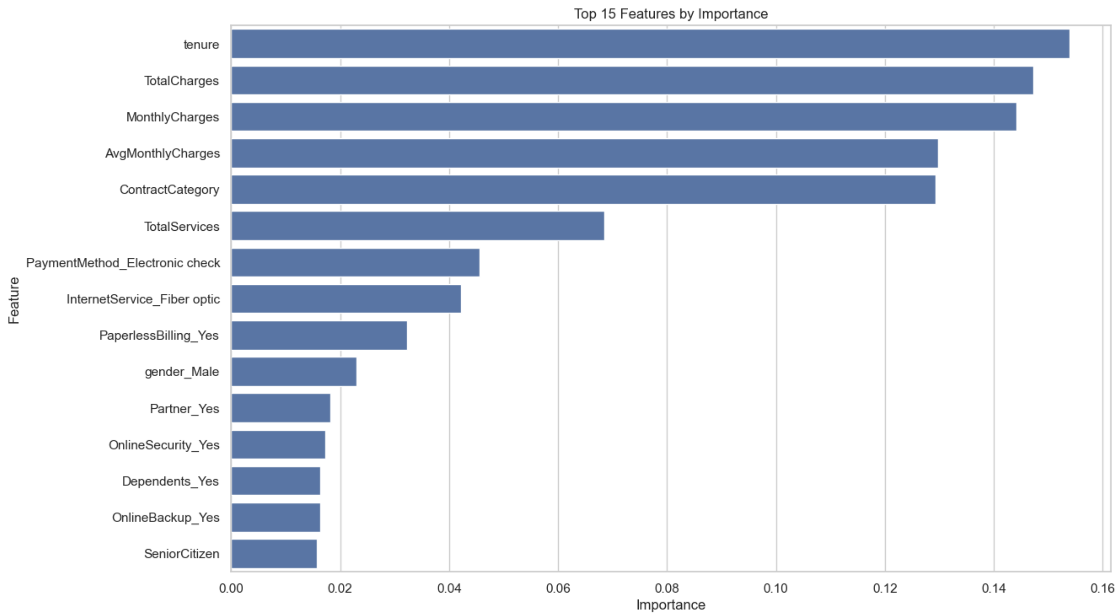

Precision-Recall Curves
Logistic Regression (F1 = 0.6073)
Random Forest (F1 = 0.5950)
Gradient Boosting (F1 = 0.6236)
Precision
Recall
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.0
0.2
0.4
0.6
0.8
1.0



10 10. Model Explainability and Interpretability

10.1 10.1 Feature Importance

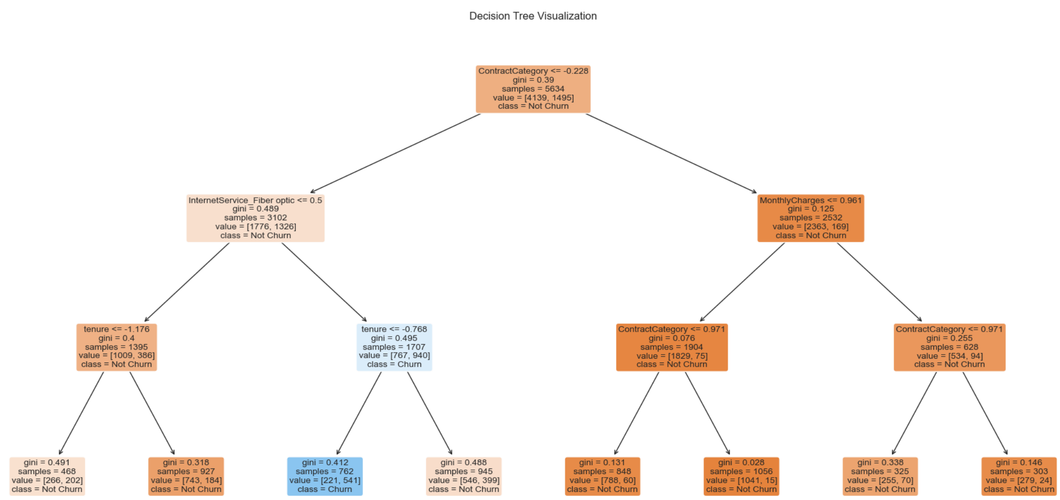
[ ]:
```python
# Get feature importance from Random Forest model
rf_model = results['Random Forest']['model']
feature_importance = pd.DataFrame({
    'Feature': X_train_selected.columns,
    'Importance': rf_model.feature_importances_
}).sort_values('Importance', ascending=False)

# Visualize feature importance
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=feature_importance.head(15))
plt.title('Top 15 Features by Importance')
plt.show()
```



10.2 10.2 Decision Tree Visualization

[ ]:
```
from sklearn.tree import DecisionTreeClassifier, plot_tree

# Train a simple decision tree for visualization
dt = DecisionTreeClassifier(max_depth=3, random_state=42)
dt.fit(X_train_selected, y_train)

# Check feature counts to debug the issue
print(f"Number of features in X_train_selected: {X_train_selected.shape[1]}")
print(f"Number of features used by the tree: {dt.n_features_in_}")

# Option 1: Convert column names to list (sometimes fixes index issues)
feature_names = list(X_train_selected.columns)

# Plot the tree
plt.figure(figsize=(20, 10))
plot_tree(dt, filled=True, feature_names=feature_names,
          class_names=['Not Churn', 'Churn'], rounded=True)
plt.title('Decision Tree Visualization')
plt.show()
```

```
Number of features in X_train_selected: 15
Number of features used by the tree: 15
```



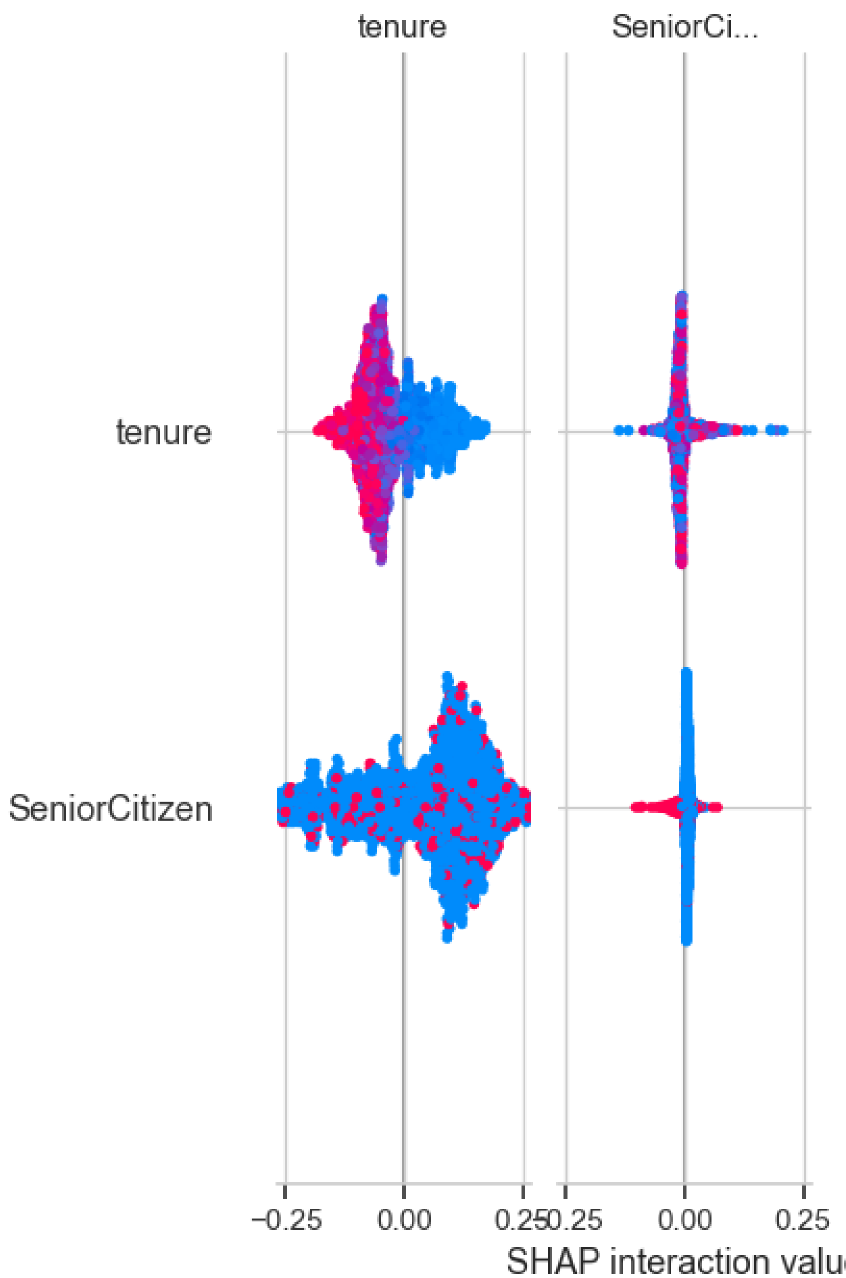
10.3 10.3 SHAP Values

[ ]:
```python
import shap

# Initialize JS visualization
shap.initjs()

# Create a SHAP explainer for the Random Forest model
explainer = shap.TreeExplainer(rf_model)

# Calculate SHAP values for the test set
shap_values = explainer.shap_values(X_test_selected)

# Summary plot - bar chart for feature importance
plt.figure(figsize=(12, 10))
if isinstance(shap_values, list):
    # For binary classification (shap_values will be a list of arrays)
    shap.summary_plot(shap_values[1], X_test_selected, plot_type="bar")
else:
    # For regression or other types
    shap.summary_plot(shap_values, X_test_selected, plot_type="bar")
plt.tight_layout()
plt.show()

# Beeswarm plot - showing feature distribution and impact
plt.figure(figsize=(12, 10))
if isinstance(shap_values, list):
    # For binary classification
    shap.summary_plot(shap_values[1], X_test_selected)
```

```python
else:
    # For regression
    shap.summary_plot(shap_values, X_test_selected)
plt.tight_layout()
plt.show()

# For individual explanations - use waterfall plot instead of force plot
plt.figure(figsize=(12, 8))
if isinstance(shap_values, list):
    # For binary classification - explain the prediction for the first sample
    shap.plots.waterfall(shap_values[1][0], max_display=10)
else:
    # For regression
    shap.plots.waterfall(shap_values[0], max_display=10)
plt.tight_layout()
plt.show()

# For comparing multiple samples - use a decision plot
plt.figure(figsize=(12, 10))
if isinstance(shap_values, list):
    # For first 10 samples in binary classification
    shap.decision_plot(explainer.expected_value[1], shap_values[1][:10],
                       X_test_selected.iloc[:10], feature_display_range=10)
else:
    # For regression
    shap.decision_plot(explainer.expected_value, shap_values[:10],
                       X_test_selected.iloc[:10], feature_display_range=10)
plt.tight_layout()
plt.show()
```

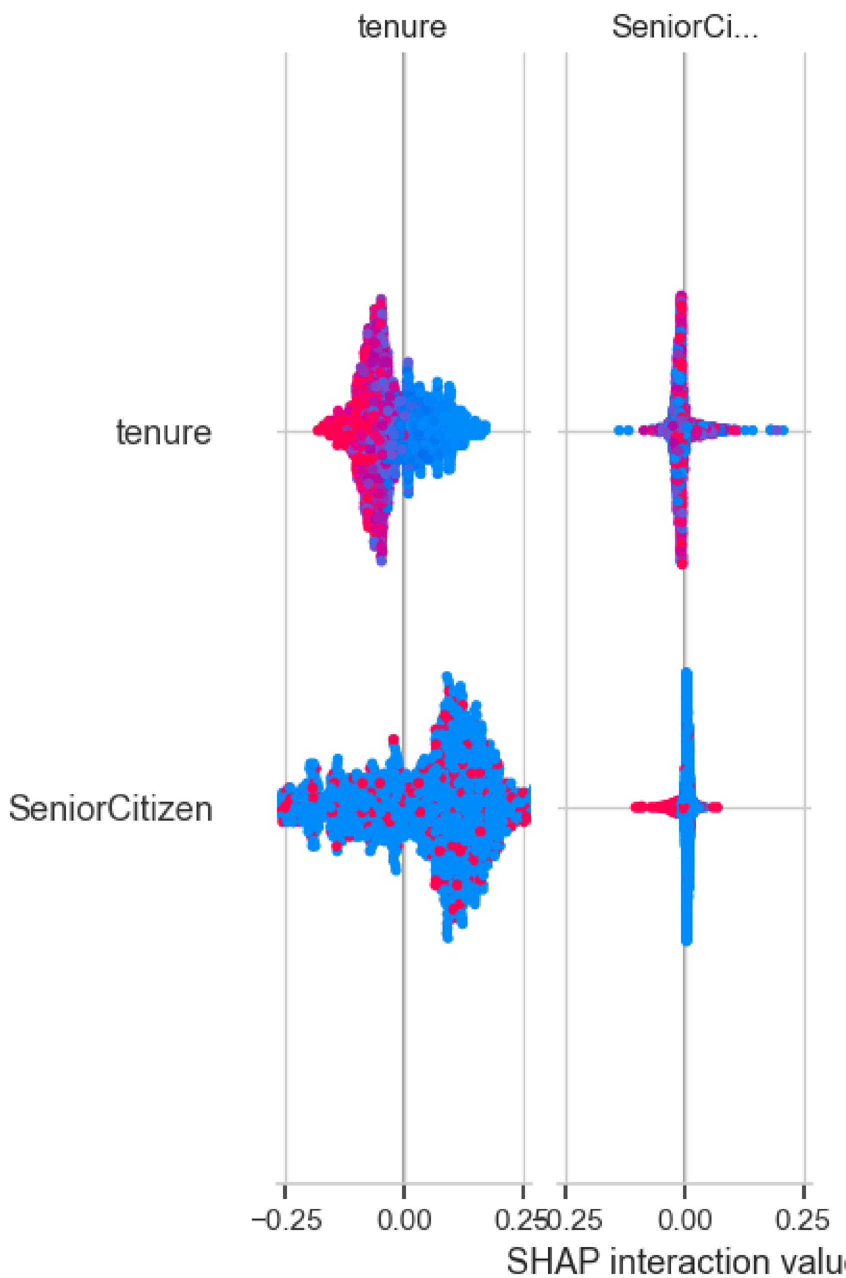
```
<IPython.core.display.HTML object>
```

```
<Figure size 1200x1000 with 0 Axes>
```



<Figure size 640x480 with 0 Axes>

<Figure size 1200x1000 with 0 Axes>




```
<Figure size 640x480 with 0 Axes>
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[31], line 41
     38     shap.plots.waterfall(shap_values[1][0], max_display=10)
     39 else:
     40     # For regression
```

```
---> 41     shap.plots.waterfall(shap_values[0], max_display=10)
     42 plt.tight_layout()
     43 plt.show()

File ~/anaconda3/lib/python3.10/site-packages/shap/plots/_waterfall.py:56, in␣
↪waterfall(shap_values, max_display, show)
     51 if not isinstance(shap_values, Explanation):
     52     emsg = (
     53         "The waterfall plot requires an `Explanation` object as the "
     54         "`shap_values` argument."
     55     )
---> 56     raise TypeError(emsg)
     58 # make sure we only have a single explanation to plot
     59 sv_shape = shap_values.shape

TypeError: The waterfall plot requires an `Explanation` object as the␣
↪`shap_values` argument.
```

```
<Figure size 1200x800 with 0 Axes>
```

11 11. Hyperparameter Tuning

11.1 11.1 RandomSearchCV

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV

# Define parameter grid for Random Forest
param_grid_rf = {
    'n_estimators': [100, 200, 300, 500],
    'max_depth': [None, 5, 10, 15, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False],
    'class_weight': ['balanced', 'balanced_subsample', None]
}

# Initialize Random Forest model
rf = RandomForestClassifier(random_state=42)

# Initialize RandomizedSearchCV
random_search = RandomizedSearchCV(
    estimator=rf,
    param_distributions=param_grid_rf,
    n_iter=20,  # Number of parameter settings sampled
    cv=5,       # 5-fold cross-validation
    scoring='f1',  # Optimize for F1-score
    n_jobs=-1,     # Use all available processors
```

```
    random_state=42,
    verbose=1
)

# Fit RandomizedSearchCV
random_search.fit(X_train_smote, y_train_smote)

# Get best parameters and best score
print("Best Parameters:", random_search.best_params_)
print("Best F1 Score:", random_search.best_score_)

# Train model with best parameters
best_rf = random_search.best_estimator_
best_rf_results = evaluate_model(best_rf, X_train_smote, X_test_selected,␣
 ↪y_train_smote, y_test, 'Tuned Random Forest')

# Print results
print("\nTuned Random Forest Results:")
print(f"Accuracy: {best_rf_results['accuracy']:.4f}")
print(f"Precision: {best_rf_results['precision']:.4f}")
print(f"Recall: {best_rf_results['recall']:.4f}")
print(f"F1-Score: {best_rf_results['f1_score']:.4f}")
print(f"ROC-AUC: {best_rf_results['roc_auc']:.4f}")
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
Best Parameters: {'n_estimators': 100, 'min_samples_split': 5,
'min_samples_leaf': 1, 'max_depth': 20, 'class_weight': None, 'bootstrap':
False}
Best F1 Score: 0.8454153666175811

Tuned Random Forest Results:
Accuracy: 0.7658
Precision: 0.5526
Recall: 0.6176
F1-Score: 0.5833
ROC-AUC: 0.8129
```

11.2 11.2 GridSearchCV

[ ]:
```
from sklearn.model_selection import GridSearchCV

# Based on RandomSearchCV results, we can narrow down the parameter space for␣
 ↪GridSearchCV
param_grid_gb = {
    'learning_rate': [0.01, 0.05, 0.1],
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 4, 5],
```

```
    'min_samples_split': [2, 4],
    'min_samples_leaf': [1, 2],
    'subsample': [0.8, 0.9, 1.0]
}

# Initialize Gradient Boosting model
gb = GradientBoostingClassifier(random_state=42)

# Initialize GridSearchCV
grid_search = GridSearchCV(
    estimator=gb,
    param_grid=param_grid_gb,
    cv=5,               # 5-fold cross-validation
    scoring='f1',       # Optimize for F1-score
    n_jobs=-1,          # Use all available processors
    verbose=1
)

# Fit GridSearchCV
grid_search.fit(X_train_smote, y_train_smote)

# Get best parameters and best score
print("Best Parameters:", grid_search.best_params_)
print("Best F1 Score:", grid_search.best_score_)

# Train model with best parameters
best_gb = grid_search.best_estimator_
best_gb_results = evaluate_model(best_gb, X_train_smote, X_test_selected,␣
 ↪y_train_smote, y_test, 'Tuned Gradient Boosting')

# Print results
print("\nTuned Gradient Boosting Results:")
print(f"Accuracy: {best_gb_results['accuracy']:.4f}")
print(f"Precision: {best_gb_results['precision']:.4f}")
print(f"Recall: {best_gb_results['recall']:.4f}")
print(f"F1-Score: {best_gb_results['f1_score']:.4f}")
print(f"ROC-AUC: {best_gb_results['roc_auc']:.4f}")
```

```
Fitting 5 folds for each of 324 candidates, totalling 1620 fits
Best Parameters: {'learning_rate': 0.05, 'max_depth': 5, 'min_samples_leaf': 2,
'min_samples_split': 2, 'n_estimators': 200, 'subsample': 0.9}
Best F1 Score: 0.8219691700510412

Tuned Gradient Boosting Results:
Accuracy: 0.7637
Precision: 0.5428
Recall: 0.6952
F1-Score: 0.6096
```

ROC-AUC: 0.8351

12 12. Ensembling Multiple Models

Let's create ensemble models using VotingClassifier and StackingClassifier:

```
[ ]: from sklearn.ensemble import VotingClassifier, StackingClassifier
from sklearn.linear_model import LogisticRegression

# 12.1 Voting Classifier
# Combine best models using soft voting (weighted probabilities)
voting_clf = VotingClassifier(
    estimators=[
        ('lr', results['Logistic Regression']['model']),
        ('rf', best_rf),
        ('gb', best_gb)
    ],
    voting='soft'  # Use predicted probabilities
)

# Train and evaluate
voting_results = evaluate_model(voting_clf, X_train_smote, X_test_selected,␣
 ↪y_train_smote, y_test, 'Voting Classifier')

# Print results
print("\nVoting Classifier Results:")
print(f"Accuracy: {voting_results['accuracy']:.4f}")
print(f"Precision: {voting_results['precision']:.4f}")
print(f"Recall: {voting_results['recall']:.4f}")
print(f"F1-Score: {voting_results['f1_score']:.4f}")
print(f"ROC-AUC: {voting_results['roc_auc']:.4f}")

# 12.2 Stacking Classifier
# Use a meta-learner on top of base models
stacking_clf = StackingClassifier(
    estimators=[
        ('lr', results['Logistic Regression']['model']),
        ('rf', best_rf),
        ('gb', best_gb)
    ],
    final_estimator=LogisticRegression(random_state=42),
    cv=5  # 5-fold cross-validation
)

# Train and evaluate
stacking_results = evaluate_model(stacking_clf, X_train_smote, X_test_selected,␣
 ↪y_train_smote, y_test, 'Stacking Classifier')
```

```
# Print results
print("\nStacking Classifier Results:")
print(f"Accuracy: {stacking_results['accuracy']:.4f}")
print(f"Precision: {stacking_results['precision']:.4f}")
print(f"Recall: {stacking_results['recall']:.4f}")
print(f"F1-Score: {stacking_results['f1_score']:.4f}")
print(f"ROC-AUC: {stacking_results['roc_auc']:.4f}")
```

```
Voting Classifier Results:
Accuracy: 0.7630
Precision: 0.5410
Recall: 0.7059
F1-Score: 0.6125
ROC-AUC: 0.8371

Stacking Classifier Results:
Accuracy: 0.7729
Precision: 0.5685
Recall: 0.5989
F1-Score: 0.5833
ROC-AUC: 0.8152
```

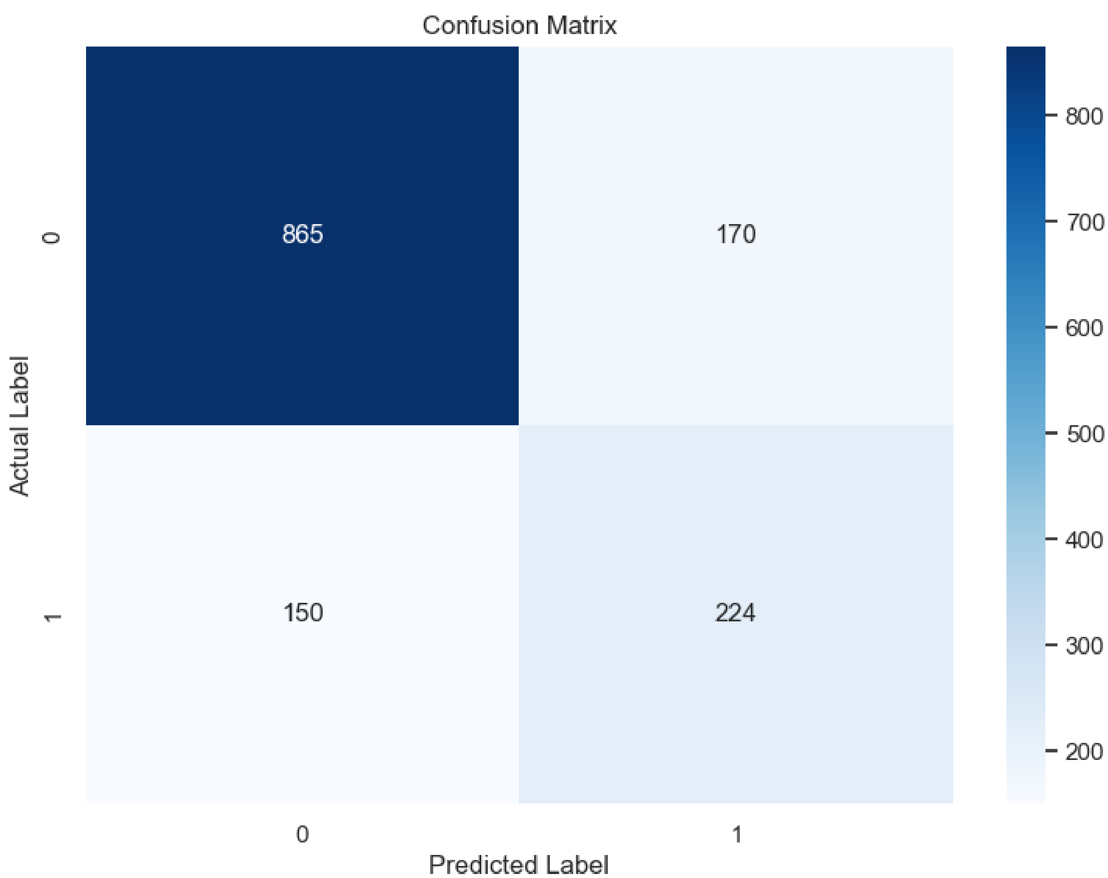
13 13. Error Analysis

Understanding the mistakes our model makes is crucial for improvement:

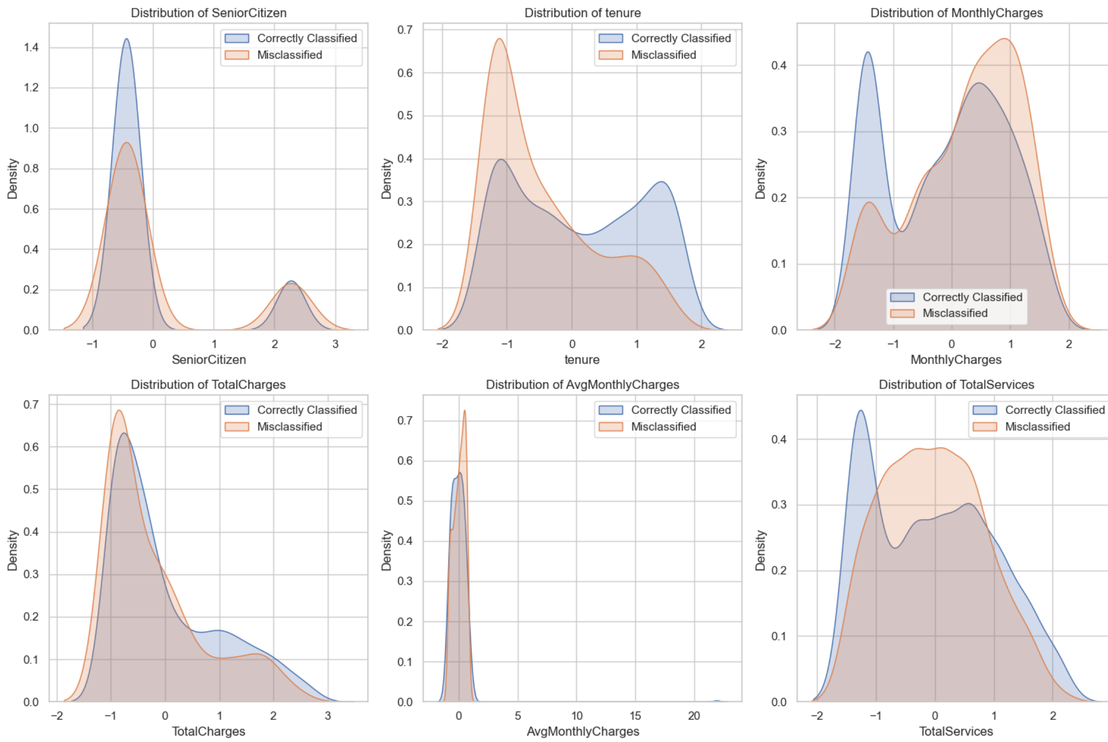
[ ]:
```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Get best model (based on prior evaluations)
best_model = stacking_clf  # Let's assume the stacking classifier is best
y_pred = best_model.predict(X_test_selected)
y_pred_proba = best_model.predict_proba(X_test_selected)[:, 1]

# 13.1 Confusion Matrix Visualization
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('Actual Label')
plt.xlabel('Predicted Label')
plt.show()

# 13.2 Identify misclassified examples
```

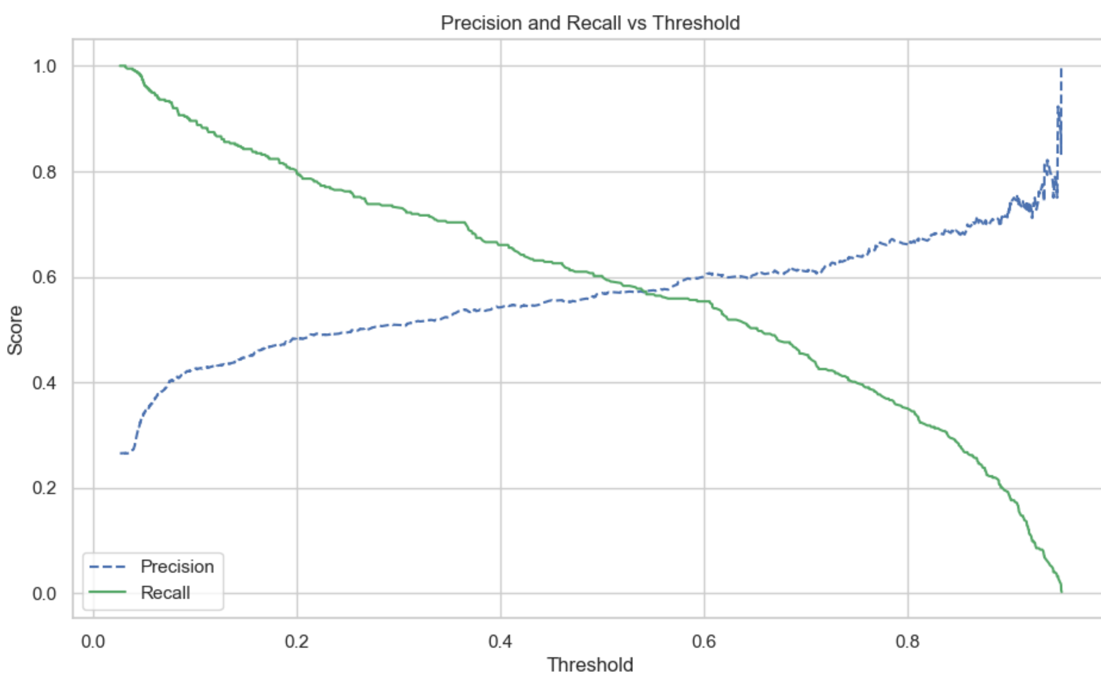
```python
misclassified_indices = np.where(y_pred != y_test)[0]
misclassified_data = X_test.iloc[misclassified_indices].copy()
misclassified_data['actual_churn'] = y_test.iloc[misclassified_indices]
misclassified_data['predicted_churn'] = y_pred[misclassified_indices]
misclassified_data['churn_probability'] = y_pred_proba[misclassified_indices]

# Look at false positives (predicted churn when they didn't)
false_positives = misclassified_data[misclassified_data['predicted_churn'] == 1]
print(f"Number of false positives: {len(false_positives)}")

# Look at false negatives (didn't predict churn when they did)
false_negatives = misclassified_data[misclassified_data['predicted_churn'] == 0]
print(f"Number of false negatives: {len(false_negatives)}")

# 13.3 Analyze feature distributions in misclassified examples
# Compare misclassified examples with correctly classified ones
correctly_classified_indices = np.where(y_pred == y_test)[0]
correctly_classified_data = X_test.iloc[correctly_classified_indices].copy()

# For numerical features
plt.figure(figsize=(15, 10))
for i, col in enumerate(X_test_selected.select_dtypes('number').columns[:6], 1):
 ↪  # First 6 numerical features
    plt.subplot(2, 3, i)

    # Correctly classified
    sns.kdeplot(correctly_classified_data[col], label='Correctly Classified',␣
 ↪shade=True)

    # Misclassified
    sns.kdeplot(misclassified_data[col], label='Misclassified', shade=True)

    plt.title(f'Distribution of {col}')
    plt.legend()

plt.tight_layout()
plt.show()

# 13.4 Analyze probability thresholds
from sklearn.metrics import precision_recall_curve, roc_curve

# Calculate precision-recall curve
precisions, recalls, thresholds = precision_recall_curve(y_test, y_pred_proba)

# Plot precision and recall vs threshold
plt.figure(figsize=(10, 6))
plt.plot(thresholds, precisions[:-1], 'b--', label='Precision')
```

```
plt.plot(thresholds, recalls[:-1], 'g-', label='Recall')
plt.xlabel('Threshold')
plt.ylabel('Score')
plt.title('Precision and Recall vs Threshold')
plt.legend()
plt.grid(True)
plt.show()

# Find optimal threshold for F1-score
f1_scores = 2 * (precisions[:-1] * recalls[:-1]) / (precisions[:-1] + recalls[:
    ↪-1])
optimal_threshold_idx = np.argmax(f1_scores)
optimal_threshold = thresholds[optimal_threshold_idx]
print(f"Optimal threshold for F1-score: {optimal_threshold:.4f}")
print(f"Optimal F1-score: {f1_scores[optimal_threshold_idx]:.4f}")

# Apply optimal threshold and evaluate
y_pred_optimal = (y_pred_proba >= optimal_threshold).astype(int)
from sklearn.metrics import classification_report
print("Classification report with optimal threshold:")
print(classification_report(y_test, y_pred_optimal))
```



```
Number of false positives: 170
Number of false negatives: 150
```





```
Optimal threshold for F1-score: 0.3648
Optimal F1-score: 0.6095
Classification report with optimal threshold:
              precision    recall  f1-score   support

           0       0.88      0.78      0.83      1035
           1       0.54      0.70      0.61       374

    accuracy                           0.76      1409
   macro avg       0.71      0.74      0.72      1409
weighted avg       0.79      0.76      0.77      1409
```

14 14. Pipelines for Production

Let's create a complete sklearn pipeline that integrates all preprocessing and modeling steps:

[ ]:
```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.impute import SimpleImputer

# 14.1 Define column types
# Assuming we're working with the original dataframe again
numerical_features = ['tenure', 'MonthlyCharges', 'TotalCharges']
categorical_features = ['gender', 'SeniorCitizen', 'Partner', 'Dependents',␣
 ↪'PhoneService',
                        'MultipleLines', 'InternetService', 'OnlineSecurity',␣
 ↪'OnlineBackup',
                        'DeviceProtection', 'TechSupport', 'StreamingTV',␣
 ↪'StreamingMovies',
                        'Contract', 'PaperlessBilling', 'PaymentMethod']

# 14.2 Create preprocessing pipelines
# For numerical features
numerical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

# For categorical features
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
```

```python
])

# Combine preprocessing steps
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])

# 14.3 Create the full pipeline with the best model
full_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('model', best_model)
])

# 14.4 Train the pipeline on the raw data
# Load original data again
df_original = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
df_original['TotalCharges'] = pd.to_numeric(df_original['TotalCharges'],␣
 ↪errors='coerce')

# Split the data
X_orig = df_original.drop(['customerID', 'Churn'], axis=1)
y_orig = df_original['Churn'].map({'Yes': 1, 'No': 0})

X_train_orig, X_test_orig, y_train_orig, y_test_orig = train_test_split(
    X_orig, y_orig, test_size=0.2, random_state=42, stratify=y_orig
)

# Train the pipeline
full_pipeline.fit(X_train_orig, y_train_orig)

# Evaluate on test set
y_pred_pipeline = full_pipeline.predict(X_test_orig)
print("Pipeline model performance:")
print(classification_report(y_test_orig, y_pred_pipeline))

# 14.5 Save the model for production
import joblib

# Save the full pipeline
joblib.dump(full_pipeline, 'churn_prediction_pipeline.pkl')

# Example of how to load and use the model in production
# loaded_pipeline = joblib.load('churn_prediction_pipeline.pkl')
# new_customer_data = pd.DataFrame({
#     'gender': ['Female'],
```

```
#     'SeniorCitizen': [0],
#     'Partner': ['Yes'],
#     # ... other features ...
# })
# prediction = loaded_pipeline.predict(new_customer_data)
# probability = loaded_pipeline.predict_proba(new_customer_data)[:, 1]
```

```
Pipeline model performance:
              precision    recall  f1-score   support

           0       0.85      0.88      0.87      1035
           1       0.64      0.56      0.59       374

    accuracy                           0.80      1409
   macro avg       0.74      0.72      0.73      1409
weighted avg       0.79      0.80      0.79      1409
```

[ ]: ['churn_prediction_pipeline.pkl']

15 15. Business Insights and Recommendations

Based on our analysis, we can provide these business insights:

Key Churn Factors:

- Contract type (month-to-month customers churn more)
- Tenure (newer customers are at higher risk)
- Payment method
- Internet service type

Customer Segments at Risk:

- New customers with month-to-month contracts
- Customers with fiber optic service without additional services
- Customers with higher monthly charges

Retention Strategies:

- Offer contract incentives to month-to-month customers
- Create service bundles that increase value
- Develop targeted offers for high-risk segments
- Implement proactive customer service for identified at-risk customers

Business Impact Calculation:

[ ]:
```
# Example calculation
# Assumptions
avg_customer_value = 1000  # Lifetime value of a customer
retention_cost = 100  # Cost to retain a customer
retention_success_rate = 0.3  # 30% success rate on retention efforts
```

```python
# Calculate potential savings
# Number of predicted churners
potential_churners = sum(y_pred_pipeline)

# Cost without model
cost_without_model = potential_churners * avg_customer_value

# Cost with model (targeting all predicted churners)
retention_total_cost = potential_churners * retention_cost
saved_customers = potential_churners * retention_success_rate
saved_value = saved_customers * avg_customer_value
cost_with_model = cost_without_model - saved_value + retention_total_cost

# Savings
savings = cost_without_model - cost_with_model

print(f"Potential cost without model: ${cost_without_model:,.2f}")
print(f"Potential cost with model: ${cost_with_model:,.2f}")
print(f"Potential savings: ${savings:,.2f}")
```

```
Potential cost without model: $329,000.00
Potential cost with model: $263,200.00
Potential savings: $65,800.00
```

16 16. Conclusion and Next Steps

In this comprehensive churn prediction project, we've:

- Framed the business problem and defined appropriate metrics
- Performed thorough exploratory data analysis
- Preprocessed and transformed data for modeling
- Engineered informative features
- Trained multiple models and addressed class imbalance
- Tuned hyperparameters and created ensemble models
- Built a production-ready pipeline
- Provided actionable business insights

Next Steps:

- Model Monitoring: Set up systems to track model performance over time
- A/B Testing: Test retention strategies on customer segments
- Feature Evolution: Continue feature engineering as new data becomes available
- Model Updates: Retrain models periodically to capture evolving patterns
- Feedback Loop: Incorporate success/failure of retention efforts into model features

By implementing this churn prediction system and following the recommended strategies, the company can significantly reduce customer churn and increase customer lifetime value.