Telco Customer Churn Prediction Report

Author: Thattaphol Puttawithee

Tools: Python (Pandas, Scikit-learn, XGBoost), Power BI, SQL Server

Dataset: Telco Customer Churn (Kaggle)

Date: October 2025

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Import data to Jupyter Notebook

Query data from SQL Server

```
import pandas as pd
from sqlalchemy import create_engine

pd.set_option('display.max_columns', None)

engine = create_engine(
    r"mssql+pyodbc://LAPTOP-QC1AHOCH\SQLEXPRESS/telco_db"
    r"?driver=ODBC+Driver+17+for+SQL+Server&trusted_connection=yes"
)

df = pd.read_sql("SELECT * FROM stg_Churn;", engine)
df
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingT
0	0002-ORFBO	Female	0	Yes	Yes	9	Yes	No	DSL	No	Yes	No	Yes	Y
1	0003-MKNFE	Male	0	No	No	9	Yes	Yes	DSL	No	No	No	No	N
2	0004-TLHLJ	Male	0	No	No	4	Yes	No	Fiber optic	No	No	Yes	No	N
3	0011-IGKFF	Male	1	Yes	No	13	Yes	No	Fiber optic	No	Yes	Yes	No	Y
4	0013-EXCHZ	Female	1	Yes	No	3	Yes	No	Fiber optic	No	No	No	Yes	Y
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	Female	0	No	No	13	Yes	No	DSL	Yes	No	No	Yes	N
7039	9992-RRAMN	Male	0	Yes	No	22	Yes	Yes	Fiber optic	No	No	No	No	N
7040	9992-UJOEL	Male	0	No	No	2	Yes	No	DSL	No	Yes	No	No	N
7041	9993-LHIEB	Male	0	Yes	Yes	67	Yes	No	DSL	Yes	No	Yes	Yes	N
7042	9995-HOTOH	Male	0	Yes	Yes	63	No	No phone service	DSL	Yes	Yes	Yes	No	Y

7043 rows × 21 columns

```
df["ChargeRatio"] = df["TotalCharges"] / (df["tenure"] + 1)
df
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingT
0	0002-ORFBO	Female	0	Yes	Yes	9	Yes	No	DSL	No	Yes	No	Yes	Y
1	0003-MKNFE	Male	0	No	No	9	Yes	Yes	DSL	No	No	No	No	N
2	0004-TLHLJ	Male	0	No	No	4	Yes	No	Fiber optic	No	No	Yes	No	N
3	0011-IGKFF	Male	1	Yes	No	13	Yes	No	Fiber optic	No	Yes	Yes	No	Y
4	0013-EXCHZ	Female	1	Yes	No	3	Yes	No	Fiber optic	No	No	No	Yes	Y
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	Female	0	No	No	13	Yes	No	DSL	Yes	No	No	Yes	N
7039	9992-RRAMN	Male	0	Yes	No	22	Yes	Yes	Fiber optic	No	No	No	No	N
7040	9992-UJOEL	Male	0	No	No	2	Yes	No	DSL	No	Yes	No	No	N
7041	9993-LHIEB	Male	0	Yes	Yes	67	Yes	No	DSL	Yes	No	Yes	Yes	N
7042	9995-HOTOH	Male	0	Yes	Yes	63	No	No phone service	DSL	Yes	Yes	Yes	No	Y

7043 rows × 22 columns

```
df["PaymentMethod"].unique()
```

```
array(['Mailed check', 'Electronic check', 'Credit card (automatic)',
       'Bank transfer (automatic)'], dtype=object)
```

```
df["PaymentAutomatic"] = df["PaymentMethod"].apply(lambda x: 1 if "automatic" in x.lower() else 0)
```

```
for m in [12, 24, 36, 48, 60]:
    df[f"tenure_ge_{m}m"] = (df["tenure"] >= m).astype(int)
```

```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 28 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   object 
 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      7032 non-null   float64
 20  Churn             7043 non-null   object 
 21  ChargeRatio       7032 non-null   float64
 22  PaymentAutomatic  7043 non-null   int64  
 23  tenure_ge_12m     7043 non-null   int64  
 24  tenure_ge_24m     7043 non-null   int64  
 25  tenure_ge_36m     7043 non-null   int64  
 26  tenure_ge_48m     7043 non-null   int64  
 27  tenure_ge_60m     7043 non-null   int64  
dtypes: float64(3), int64(7), object(18)
memory usage: 1.5+ MB
```

	tenure	MonthlyCharges	TotalCharges	ChargeRatio	PaymentAutomatic	tenure_ge_12m	tenure_ge_24m	tenure_ge_36m	tenure_ge_48m	tenure_ge_60m
count	7043.000000	7043.000000	7032.000000	7032.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000
mean	32.371149	64.761692	2283.300441	59.083067	0.435326	0.706233	0.557575	0.433196	0.326991	0.210564
std	24.559481	30.090047	2266.771363	30.514438	0.495835	0.455519	0.496709	0.495552	0.469147	0.407738
min	0.000000	18.250000	18.799999	9.183333	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	9.000000	35.500000	401.449997	26.225944	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	29.000000	70.349998	1397.475037	61.070387	0.000000	1.000000	1.000000	0.000000	0.000000	0.000000
75%	55.000000	89.849998	3794.737488	84.877538	1.000000	1.000000	1.000000	1.000000	1.000000	0.000000
max	72.000000	118.750000	8684.799805	118.969860	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

Check NULL

Check null value in the data

```
df.isna().sum()
```

```
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
ChargeRatio        11
PaymentAutomatic    0
tenure_ge_12m       0
tenure_ge_24m       0
tenure_ge_36m       0
tenure_ge_48m       0
tenure_ge_60m       0
dtype: int64
```

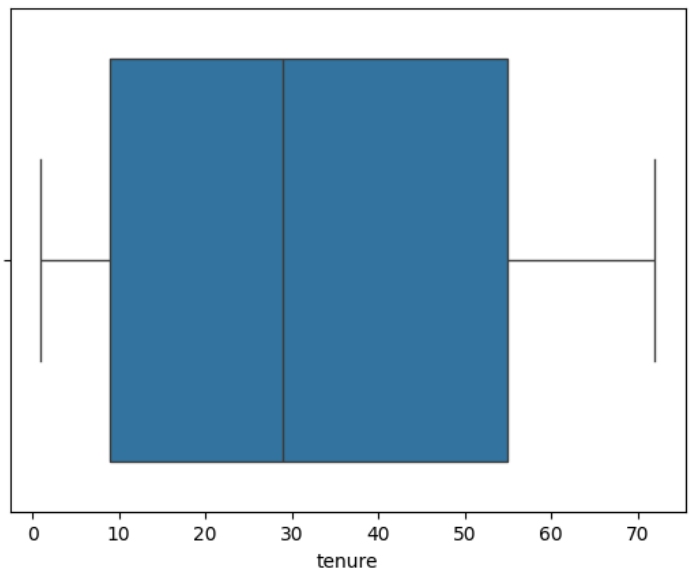
Remove null

```
df = df.dropna()
```

Check Outliers

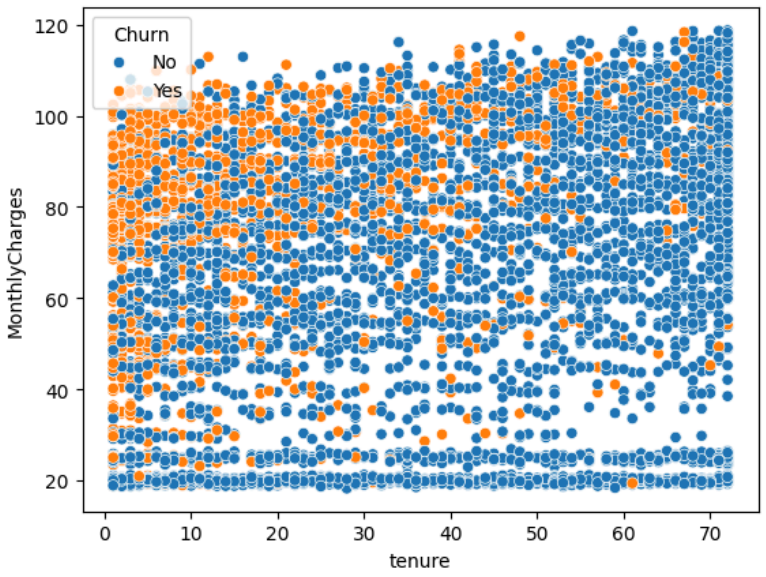
```
sns.boxplot(x=df['tenure'])
```

<Axes: xlabel='tenure'>



sns.scatterplot(x='tenure', y='MonthlyCharges', hue='Churn', data=df)

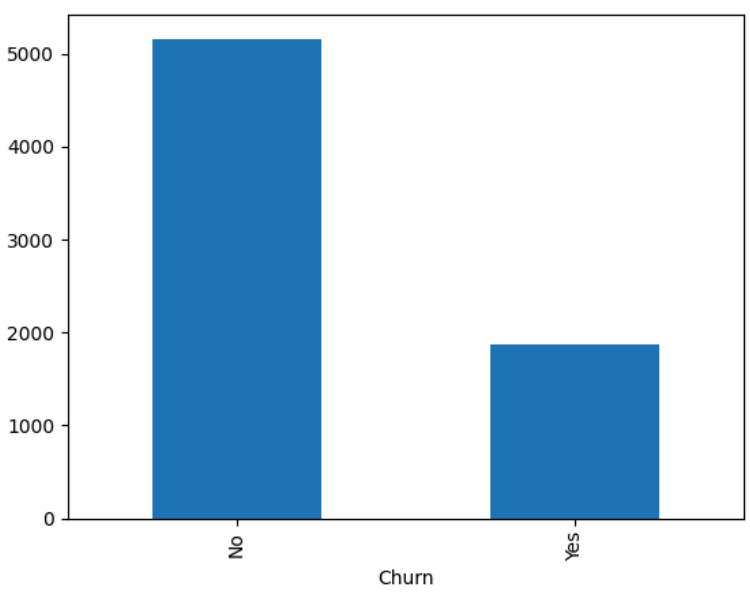
<Axes: xlabel='tenure', ylabel='MonthlyCharges'>



Check data balance

df['Churn'].value_counts().plot(kind='bar')

<Axes: xlabel='Churn'>



df

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingT
0	0002-ORFBO	Female	0	Yes	Yes	9	Yes	No	DSL	No	Yes	No	Yes	Y
1	0003-MKNFE	Male	0	No	No	9	Yes	Yes	DSL	No	No	No	No	N
2	0004-TLHLJ	Male	0	No	No	4	Yes	No	Fiber optic	No	No	Yes	No	N
3	0011-IGKFF	Male	1	Yes	No	13	Yes	No	Fiber optic	No	Yes	Yes	No	Y
4	0013-EXCHZ	Female	1	Yes	No	3	Yes	No	Fiber optic	No	No	No	Yes	Y
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	Female	0	No	No	13	Yes	No	DSL	Yes	No	No	Yes	N
7039	9992-RRAMN	Male	0	Yes	No	22	Yes	Yes	Fiber optic	No	No	No	No	N
7040	9992-UJOEL	Male	0	No	No	2	Yes	No	DSL	No	Yes	No	No	N
7041	9993-LHIEB	Male	0	Yes	Yes	67	Yes	No	DSL	Yes	No	Yes	Yes	N
7042	9995-HOTOH	Male	0	Yes	Yes	63	No	No phone service	DSL	Yes	Yes	Yes	No	Y

7032 rows × 28 columns

Recall From Rule-based (baseline) after EDA

with tenure < 12 and Monthly charges > 70

```
countBaseline = ((df["tenure"] < 12) & (df["MonthlyCharges"] > 70)).sum()
countBaselineChurn = ((df["tenure"] < 12) & (df["MonthlyCharges"] > 70) & (df["Churn"] == 'Yes')).sum()
recallOfBaseline = countBaselineChurn / countBaseline
print("Count of customers with tenure < 12 months and MonthlyCharges > $70:", countBaseline)
print("Count of churned customers in this group:", countBaselineChurn)
print("Recall of baseline model:", recallOfBaseline)
```

```
Count of customers with tenure < 12 months and MonthlyCharges > $70: 824
Count of churned customers in this group: 567
Recall of baseline model: 0.6881067961165048
```

Feature Engineering

```
binary_cols = ['Partner', 'Dependents', 'PhoneService', 'MultipleLines',
               'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
               'TechSupport', 'StreamingTV', 'StreamingMovies',
               'PaperlessBilling', 'Churn']

df[binary_cols] = df[binary_cols].replace({'Yes': 1, 'No': 0})
df['gender'] = df['gender'].replace({'Male': 1, 'Female': 0})
df['MultipleLines'] = df['MultipleLines'].replace({'No phone service': -1})
df
```

```
C:\Temp\ipykernel_1696\2260154420.py:6: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To op
  df[binary_cols] = df[binary_cols].replace({'Yes': 1, 'No': 0})
C:\Temp\ipykernel_1696\2260154420.py:7: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To op
  df['gender'] = df['gender'].replace({'Male': 1, 'Female': 0})
C:\Temp\ipykernel_1696\2260154420.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[binary_cols] = df[binary_cols].replace({'Yes': 1, 'No': 0})
C:\Temp\ipykernel_1696\2260154420.py:8: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To op
  df['MultipleLines'] = df['MultipleLines'].replace({'No phone service': -1})
C:\Temp\ipykernel_1696\2260154420.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['MultipleLines'] = df['MultipleLines'].replace({'No phone service': -1})
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingT
0	0002-ORFBO	0	0	1	1	9	1	0	DSL	0	1	0	1	
1	0003-MKNFE	1	0	0	0	9	1	1	DSL	0	0	0	0	
2	0004-TLHLJ	1	0	0	0	4	1	0	Fiber optic	0	0	1	0	
3	0011-IGKFF	1	1	1	0	13	1	0	Fiber optic	0	1	1	0	
4	0013-EXCHZ	0	1	1	0	3	1	0	Fiber optic	0	0	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	0	0	0	0	13	1	0	DSL	1	0	0	1	
7039	9992-RRAMN	1	0	1	0	22	1	1	Fiber optic	0	0	0	0	
7040	9992-UJOEL	1	0	0	0	2	1	0	DSL	0	1	0	0	
7041	9993-LHIEB	1	0	1	1	67	1	0	DSL	1	0	1	1	
7042	9995-HOTOH	1	0	1	1	63	0	-1	DSL	1	1	1	0	

7032 rows × 28 columns

```
Services_cols = (['OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies'])
df[Services_cols] = df[Services_cols].replace({'No internet service': 0})
df.isin(['No internet service']).sum()
```

```
C:\Temp\ipykernel_1696\3187367540.py:2: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To op
  df[Services_cols] = df[Services_cols].replace({'No internet service': 0})
C:\Temp\ipykernel_1696\3187367540.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[Services_cols] = df[Services_cols].replace({'No internet service': 0})
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
ChargeRatio         0
PaymentAutomatic    0
tenure_ge_12m       0
tenure_ge_24m       0
```

```
tenure_ge_36m     0
tenure_ge_48m     0
tenure_ge_60m     0
dtype: int64
```

```
df['SeniorCitizen'] = df['SeniorCitizen'].astype(int)
```

```
C:\Temp\ipykernel_1696\2584085859.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['SeniorCitizen'] = df['SeniorCitizen'].astype(int)
```

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
numeric_cols = ['tenure', 'MonthlyCharges', 'TotalCharges', 'ChargeRatio']

df[numeric_cols] = scaler.fit_transform(df[numeric_cols])
df
```

```
C:\Temp\ipykernel_1696\3296849014.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df[numeric_cols] = scaler.fit_transform(df[numeric_cols])
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	Streamin
0	0002-ORFBO	0	0	1	1	-0.954296	1	0	DSL	0	1	0	1	
1	0003-MKNFE	1	0	0	0	-0.954296	1	1	DSL	0	0	0	0	
2	0004-TLHLJ	1	0	0	0	-1.158016	1	0	Fiber optic	0	0	1	0	
3	0011-IGKFF	1	1	1	0	-0.791321	1	0	Fiber optic	0	1	1	0	
4	0013-EXCHZ	0	1	1	0	-1.198760	1	0	Fiber optic	0	0	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	0	0	0	0	-0.791321	1	0	DSL	1	0	0	1	
7039	9992-RRAMN	1	0	1	0	-0.424625	1	1	Fiber optic	0	0	0	0	
7040	9992-UJOEL	1	0	0	0	-1.239504	1	0	DSL	0	1	0	0	
7041	9993-LHIEB	1	0	1	1	1.408853	1	0	DSL	1	0	1	1	
7042	9995-HOTOH	1	0	1	1	1.245878	0	-1	DSL	1	1	1	0	

7032 rows × 28 columns

```
categorical_cols = ['InternetService', 'Contract', 'PaymentMethod']

df = pd.get_dummies(df, columns=categorical_cols, drop_first=True, dtype=int)
df
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingM
0	0002-ORFBO	0	0	1	1	-0.954296	1	0	0	1	0	1	1	
1	0003-MKNFE	1	0	0	0	-0.954296	1	1	0	0	0	0	0	
2	0004-TLHLJ	1	0	0	0	-1.158016	1	0	0	0	1	0	0	
3	0011-IGKFF	1	1	1	0	-0.791321	1	0	0	1	1	0	1	
4	0013-EXCHZ	0	1	1	0	-1.198760	1	0	0	0	0	1	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	0	0	0	0	-0.791321	1	0	1	0	0	1	0	
7039	9992-RRAMN	1	0	1	0	-0.424625	1	1	0	0	0	0	0	
7040	9992-UJOEL	1	0	0	0	-1.239504	1	0	0	1	0	0	0	
7041	9993-LHIEB	1	0	1	1	1.408853	1	0	1	0	1	1	0	
7042	9995-HOTOH	1	0	1	1	1.245878	0	-1	1	1	1	0	1	

7032 rows × 32 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7032 entries, 0 to 7042
Data columns (total 32 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   customerID            7032 non-null   object
 1   gender                7032 non-null   int64
 2   SeniorCitizen         7032 non-null   int64
 3   Partner               7032 non-null   int64
 4   Dependents            7032 non-null   int64
 5   tenure                7032 non-null   float64
 6   PhoneService          7032 non-null   int64
 7   MultipleLines         7032 non-null   int64
 8   OnlineSecurity        7032 non-null   int64
 9   OnlineBackup          7032 non-null   int64
 10  DeviceProtection      7032 non-null   int64
 11  TechSupport           7032 non-null   int64
 12  StreamingTV           7032 non-null   int64
 13  StreamingMovies       7032 non-null   int64
 14  PaperlessBilling      7032 non-null   int64
 15  MonthlyCharges        7032 non-null   float64
 16  TotalCharges          7032 non-null   float64
 17  Churn                 7032 non-null   int64
 18  ChargeRatio           7032 non-null   float64
 19  PaymentAutomatic      7032 non-null   int64
 20  tenure_ge_12m         7032 non-null   int64
 21  tenure_ge_24m         7032 non-null   int64
 22  tenure_ge_36m         7032 non-null   int64
 23  tenure_ge_48m         7032 non-null   int64
```

```
 24  tenure_ge_60m                          7032 non-null   int64
 25  InternetService_Fiber optic            7032 non-null   int64
 26  InternetService_No                     7032 non-null   int64
 27  Contract_One year                      7032 non-null   int64
 28  Contract_Two year                      7032 non-null   int64
 29  PaymentMethod_Credit card (automatic)  7032 non-null   int64
 30  PaymentMethod_Electronic check         7032 non-null   int64
 31  PaymentMethod_Mailed check             7032 non-null   int64
dtypes: float64(4), int64(27), object(1)
memory usage: 1.8+ MB
```

Train Test split

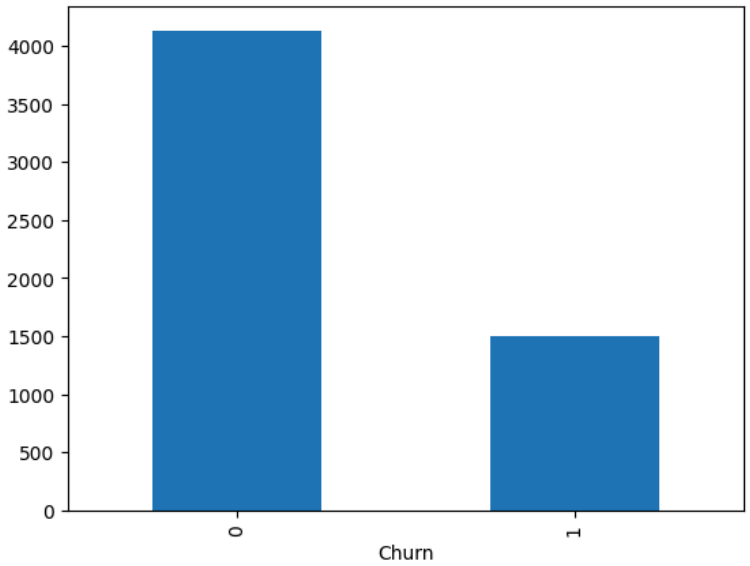
```
from sklearn.model_selection import train_test_split
X = df.drop(['Churn', 'customerID','TotalCharges','gender'], axis=1)
y = df['Churn']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((5625, 28), (1407, 28), (5625,), (1407,))
```

Class imbalance

```
y_train.value_counts().plot(kind='bar')
```

```
<Axes: xlabel='Churn'>
```



Prepare SMOTE

```
import pandas as pd
from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=42)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)

y_train_series = pd.Series(y_train)
y_train_res_series = pd.Series(y_train_res)

print("Before SMOTE:", y_train_series.value_counts().to_dict())
print("After SMOTE :", y_train_res_series.value_counts().to_dict())
```

```
Before SMOTE: {0: 4130, 1: 1495}
After SMOTE : {0: 4130, 1: 4130}
```

Logistic Regression

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

model_lr = LogisticRegression(class_weight='balanced', max_iter=1000) # balanced for imbalanced data
model_lr.fit(X_train, y_train)
y_pred_lr = model_lr.predict(X_test)

print(classification_report(y_test, y_pred_lr))
print("ROC AUC:", roc_auc_score(y_test, model_lr.predict_proba(X_test)[:,1]))
```

```
              precision    recall  f1-score   support

           0       0.90      0.74      0.82      1033
           1       0.53      0.78      0.63       374

    accuracy                           0.75      1407
   macro avg       0.71      0.76      0.72      1407
weighted avg       0.80      0.75      0.77      1407

ROC AUC: 0.8509261224510926
```

RandomForest

```
from sklearn.ensemble import RandomForestClassifier

model_rf = RandomForestClassifier(
    n_estimators=300,
    class_weight='balanced_subsample', # balanced_subsample for imbalanced data
    max_depth=10,
    random_state=42
)
model_rf.fit(X_train, y_train)
rf_pred = model_rf.predict(X_test)
```

```
print("ROC AUC:", roc_auc_score(y_test, model_rf.predict_proba(X_test)[:,1]))
print(classification_report(y_test, rf_pred))
```

```
ROC AUC: 0.8445405883905969
              precision    recall  f1-score   support

           0       0.89      0.79      0.84      1033
           1       0.56      0.72      0.63       374

    accuracy                           0.78      1407
   macro avg       0.72      0.76      0.74      1407
weighted avg       0.80      0.78      0.78      1407
```

XGB

```
from xgboost import XGBClassifier

xgb = XGBClassifier(
    scale_pos_weight=(len(y_train[y_train==0]) / len(y_train[y_train==1])),
    learning_rate=0.05,
    n_estimators=500,
    max_depth=4,
    subsample=0.8,
    colsample_bytree=0.8,
    random_state=42
)
xgb.fit(X_train, y_train)
xgb_pred = xgb.predict(X_test)

print("ROC AUC:", roc_auc_score(y_test, xgb.predict_proba(X_test)[:,1]))
print("\nClassification Report:\n", classification_report(y_test, xgb_pred))
```

```
ROC AUC: 0.8408806187264134
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.76      0.82      1033
           1       0.53      0.75      0.62       374

    accuracy                           0.76      1407
   macro avg       0.71      0.76      0.72      1407
weighted avg       0.80      0.76      0.77      1407
```

Hyperparameter Tuning

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import RandomizedSearchCV, StratifiedKFold
from scipy.stats import loguniform

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

lr = LogisticRegression(class_weight='balanced', solver='liblinear', max_iter=5000)

lr_param = {
    "C": loguniform(1e-3, 1e2),   # 0.001..100
    "penalty": ["l1", "l2"],
}

lr_rs = RandomizedSearchCV(
    lr, lr_param, n_iter=40, scoring="roc_auc", cv=cv,
    n_jobs=-1, random_state=42, error_score="raise"
)
lr_rs.fit(X_train, y_train)
print("Best parameters:", lr_rs.best_params_)
```

```
Best parameters: {'C': np.float64(0.5414413211338525), 'penalty': 'l2'}
```

```
import numpy as np
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, classification_report

best_lr = lr_rs.best_estimator_
y_proba = best_lr.predict_proba(X_test)[:, 1]

for t in [0.3, 0.4, 0.5, 0.6, 0.7]:
    y_pred_t = (y_proba >= t).astype(int)
    precision = precision_score(y_test, y_pred_t)
    recall = recall_score(y_test, y_pred_t)
    f1 = f1_score(y_test, y_pred_t)
    print(f"Threshold = {t:.1f} | Precision = {precision:.3f} | Recall = {recall:.3f} | F1 = {f1:.3f}")
```

```
Threshold = 0.3 | Precision = 0.429 | Recall = 0.922 | F1 = 0.586
Threshold = 0.4 | Precision = 0.478 | Recall = 0.869 | F1 = 0.617
Threshold = 0.5 | Precision = 0.524 | Recall = 0.783 | F1 = 0.628
Threshold = 0.6 | Precision = 0.575 | Recall = 0.690 | F1 = 0.627
Threshold = 0.7 | Precision = 0.650 | Recall = 0.545 | F1 = 0.593
```

XMG

```
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV, StratifiedKFold
from scipy.stats import randint, uniform, loguniform
from sklearn.metrics import roc_auc_score

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# For XGBoost class imbalance
scale = len(y_train[y_train==0]) / len(y_train[y_train==1] * 0.8)

xgb = XGBClassifier(
    objective='binary:logistic',
    eval_metric='auc',
    scale_pos_weight=scale,
    random_state=42
```

```
)

xgb_param = {
    "n_estimators": randint(300, 800),
    "learning_rate": uniform(0.01, 0.2),
    "max_depth": randint(3, 7),
    "min_child_weight": randint(1, 8),
    "subsample": uniform(0.6, 0.4),
    "colsample_bytree": uniform(0.6, 0.4),
    "gamma": uniform(0, 0.5),
    "reg_lambda": loguniform(1e-2, 1e2),
    "reg_alpha": loguniform(1e-3, 1e1),
}

xgb_rs = RandomizedSearchCV(
    estimator=xgb,
    param_distributions=xgb_param,
    n_iter=50,
    scoring='roc_auc',
    cv=cv,
    n_jobs=-1,
    random_state=42,
    verbose=1
)

xgb_rs.fit(X_train, y_train)

print("Best parameters:", xgb_rs.best_params_)
```

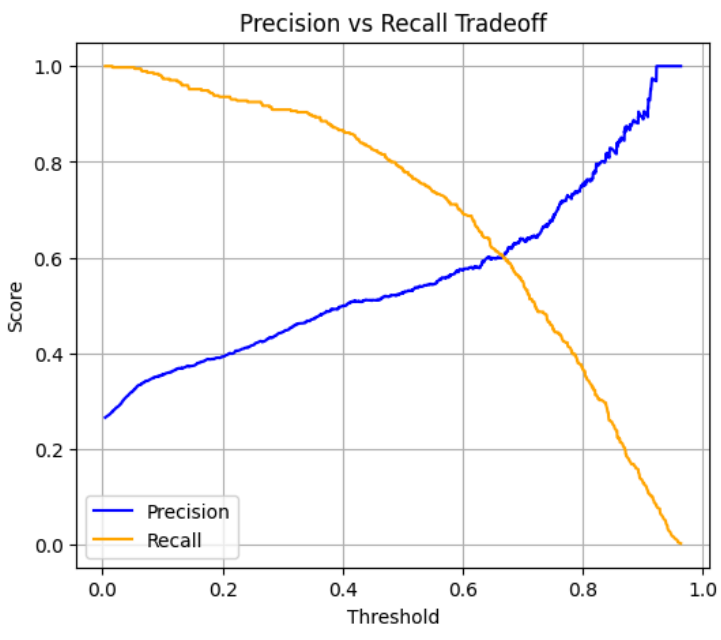
```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
Best parameters: {'colsample_bytree': np.float64(0.8232408008069365), 'gamma': np.float64(0.2019180855290204), 'learning_rate': np.float64(0.02297844942179631), 'max_depth': 4, 'min_child_weight': 4, 'n_estimators': 567, 'reg
```

```
import numpy as np
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score, classification_report

best_xgb = xgb_rs.best_estimator_
y_proba = best_xgb.predict_proba(X_test)[:, 1]

for t in [0.3, 0.4, 0.5, 0.6, 0.7]:
    y_pred_t = (y_proba >= t).astype(int)
    precision = precision_score(y_test, y_pred_t)
    recall = recall_score(y_test, y_pred_t)
    f1 = f1_score(y_test, y_pred_t)
    auc = roc_auc_score(y_test, y_proba)
    print(f"Threshold = {t:.1f} | Precision = {precision:.3f} | Recall = {recall:.3f} | F1 = {f1:.3f} | {auc:<10.3f}")
```

```
Threshold = 0.3 | Precision = 0.445 | Recall = 0.909 | F1 = 0.598 | 0.848
Threshold = 0.4 | Precision = 0.499 | Recall = 0.866 | F1 = 0.633 | 0.848
Threshold = 0.5 | Precision = 0.527 | Recall = 0.786 | F1 = 0.631 | 0.848
Threshold = 0.6 | Precision = 0.573 | Recall = 0.693 | F1 = 0.627 | 0.848
Threshold = 0.7 | Precision = 0.640 | Recall = 0.551 | F1 = 0.592 | 0.848
```

CrossValidation (threshold = 0.4)

```
import matplotlib.pyplot as plt
from sklearn.metrics import precision_recall_curve

precision, recall, thresholds = precision_recall_curve(y_test, y_proba)

plt.figure(figsize=(6,5))
plt.plot(thresholds, precision[:-1], label='Precision', color='blue')
plt.plot(thresholds, recall[:-1], label='Recall', color='orange')
plt.xlabel('Threshold')
plt.ylabel('Score')
plt.title('Precision vs Recall Tradeoff')
plt.legend()
plt.grid(True)
plt.show()
```




```
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score
import numpy as np

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

precisions, recalls, f1s, aucs = [], [], [], []

for train_idx, val_idx in cv.split(X_train, y_train):
    X_tr, X_val = X_train.iloc[train_idx], X_train.iloc[val_idx]
    y_tr, y_val = y_train.iloc[train_idx], y_train.iloc[val_idx]

    # Fit model
    model = best_xgb
    model.fit(X_tr, y_tr)
```

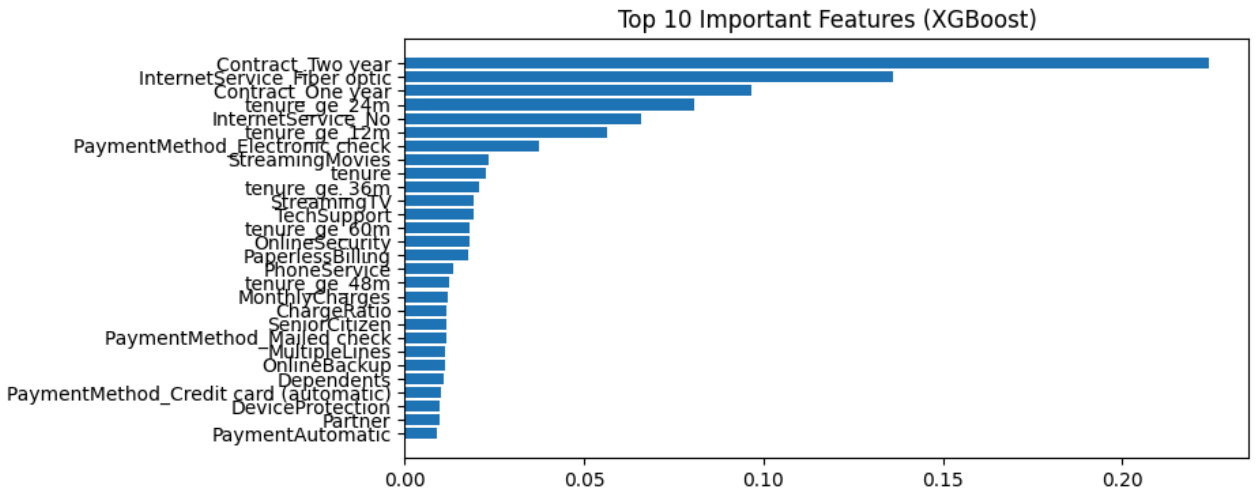
```
    # Predict probability
    y_proba = model.predict_proba(X_val)[:, 1]

    # Apply threshold = 0.4
    y_pred = (y_proba >= 0.4).astype(int)

    # Calculate metrics
    precisions.append(precision_score(y_val, y_pred))
    recalls.append(recall_score(y_val, y_pred))
    f1s.append(f1_score(y_val, y_pred))
    aucs.append(roc_auc_score(y_val, y_proba))

print("Threshold-based Cross Validation (t=0.4)")
print(f"ROC-AUC   : {np.mean(aucs):.3f} ± {np.std(aucs):.3f}")
print(f"Precision : {np.mean(precisions):.3f} ± {np.std(precisions):.3f}")
print(f"Recall    : {np.mean(recalls):.3f} ± {np.std(recalls):.3f}")
print(f"F1        : {np.mean(f1s):.3f} ± {np.std(f1s):.3f}")
```

```
Threshold-based Cross Validation (t=0.4)
ROC-AUC   : 0.842 ± 0.009
Precision : 0.487 ± 0.007
Recall    : 0.840 ± 0.022
F1        : 0.616 ± 0.008
```

```
# FINAL MODEL - XGBoost (threshold = 0.4)
import joblib
import numpy as np

final_xgb = xgb_rs.best_estimator_  # จาก RandomizedSearchCV
final_threshold = 0.4

# save model and threshold
joblib.dump(final_xgb, "final_xgb_model.joblib")
np.save("final_threshold.npy", np.array([final_threshold]))
print("Model and threshold saved.")
```

```
Model and threshold saved.
```

```
import pandas as pd
import matplotlib.pyplot as plt

importance = pd.DataFrame({
    "Feature": X_train.columns,
    "Importance": final_xgb.feature_importances_
}).sort_values("Importance", ascending=False)

plt.figure(figsize=(8,4))
plt.barh(importance["Feature"], importance["Importance"])
plt.gca().invert_yaxis()
plt.title("Top 10 Important Features (XGBoost)")
plt.show()
```



Executive Summary

Developed an end-to-end customer churn prediction system using XGBoost, achieving 0.84 ROC-AUC. At threshold = 0.4, the model delivers Precision = 0.50, Recall = 0.86, and F1-score = 0.63, optimized for retention-focused business decisions. Insights indicate that contract type, tenure, and monthly charges are the strongest churn predictors.

Compared with a rule-based baseline (Recall = 0.69), the model improves churn capture by +15%, enabling the business to retain more at-risk customers and improve campaign ROI through targeted retention strategies.

Key Insights

- Month-to-month customers churn significantly more than long-term contracts (1-year or 2-year).
- Fiber-optic customers show higher churn tendency compared to DSL users due to price and service satisfaction gaps.
- Customers with tenure below 12 months are at highest churn risk, especially those paying high monthly charges.

Recommended Business Actions

- Offer loyalty discounts or retention incentives for customers with tenure < 12 months to reduce early churn.
- Enhance fiber-optic customer experience via service quality monitoring, faster issue resolution, and satisfaction surveys.
- Retarget paperless billing users with personalized satisfaction campaigns to increase retention and reinforce digital convenience benefits.
- Integrate the churn model with the marketing CRM to prioritize high-risk, high-value customers for proactive outreach.