Telco Customer Churn Prediction Report

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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	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCh
0	0002-ORFBO	Female	0	Yes	Yes	9	Yes	No	DSL	No	Yes	No	Yes	Yes	No	One year	Yes	Mailed check	65.599998	593.2
1	0003-MKNFE	Male	0	No	No	9	Yes	Yes	DSL	No	No	No	No	No	Yes	Month-to-month	No	Mailed check	59.900002	542.4
2	0004-TLHLJ	Male	0	No	No	4	Yes	No	Fiber optic	No	No	Yes	No	No	No	Month-to-month	Yes	Electronic check	73.900002	280.8
3	0011-IGKFF	Male	1	Yes	No	13	Yes	No	Fiber optic	No	Yes	Yes	No	Yes	Yes	Month-to-month	Yes	Electronic check	98.000000	1237.8
4	0013-EXCHZ	Female	1	Yes	No	3	Yes	No	Fiber optic	No	No	No	Yes	Yes	No	Month-to-month	Yes	Mailed check	83.900002	267.3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	Female	0	No	No	13	Yes	No	DSL	Yes	No	No	Yes	No	No	One year	No	Mailed check	55.150002	742.9
7039	9992-RRAMN	Male	0	Yes	No	22	Yes	Yes	Fiber optic	No	No	No	No	No	Yes	Month-to-month	Yes	Electronic check	85.099998	1873.6
7040	9992-UJOEL	Male	0	No	No	2	Yes	No	DSL	No	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	50.299999	92.7
7041	9993-LHIEB	Male	0	Yes	Yes	67	Yes	No	DSL	Yes	No	Yes	Yes	No	Yes	Two year	No	Mailed check	67.849998	4627.6
7042	9995-HOTOH	Male	0	Yes	Yes	63	No	No phone service	DSL	Yes	Yes	Yes	No	Yes	Yes	Two year	No	Electronic check	59.000000	3707.6

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	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCh
0	0002-ORFBO	Female	0	Yes	Yes	9	Yes	No	DSL	No	Yes	No	Yes	Yes	No	One year	Yes	Mailed check	65.599998	593.2
1	0003-MKNFE	Male	0	No	No	9	Yes	Yes	DSL	No	No	No	No	No	Yes	Month-to-month	No	Mailed check	59.900002	542.4
2	0004-TLHLJ	Male	0	No	No	4	Yes	No	Fiber optic	No	No	Yes	No	No	No	Month-to-month	Yes	Electronic check	73.900002	280.8
3	0011-IGKFF	Male	1	Yes	No	13	Yes	No	Fiber optic	No	Yes	Yes	No	Yes	Yes	Month-to-month	Yes	Electronic check	98.000000	1237.8
4	0013-EXCHZ	Female	1	Yes	No	3	Yes	No	Fiber optic	No	No	No	Yes	Yes	No	Month-to-month	Yes	Mailed check	83.900002	267.3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	Female	0	No	No	13	Yes	No	DSL	Yes	No	No	Yes	No	No	One year	No	Mailed check	55.150002	742.9
7039	9992-RRAMN	Male	0	Yes	No	22	Yes	Yes	Fiber optic	No	No	No	No	No	Yes	Month-to-month	Yes	Electronic check	85.099998	1873.6
7040	9992-UJOEL	Male	0	No	No	2	Yes	No	DSL	No	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	50.299999	92.7
7041	9993-LHIEB	Male	0	Yes	Yes	67	Yes	No	DSL	Yes	No	Yes	Yes	No	Yes	Two year	No	Mailed check	67.849998	4627.6
7042	9995-HOTOH	Male	0	Yes	Yes	63	No	No phone service	DSL	Yes	Yes	Yes	No	Yes	Yes	Two year	No	Electronic check	59.000000	3707.6

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
```

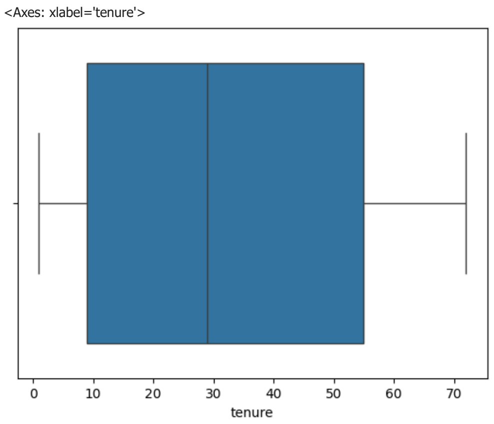
Remove null

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

Check Outliers

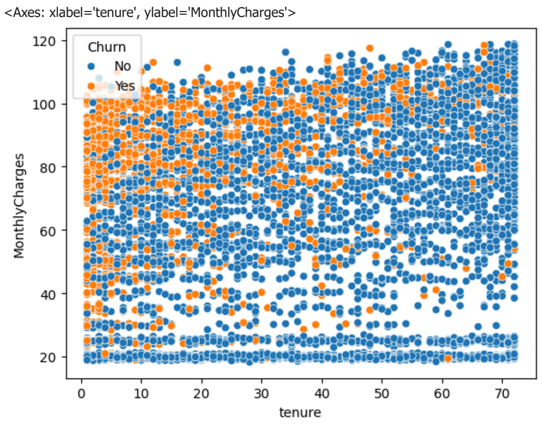
```
sns.boxplot(x=df['tenure'])
```

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




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

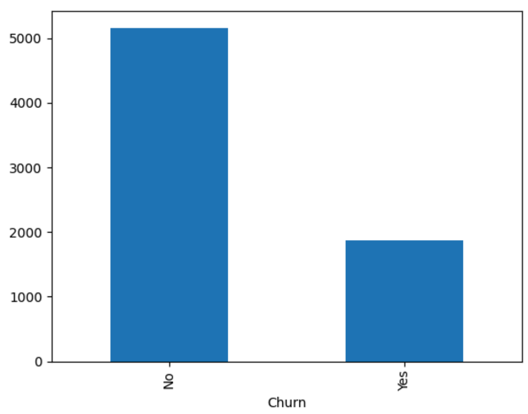
```
<Axes: xlabel='tenure', ylabel='MonthlyCharges'>
```



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	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCh
0	0002-ORFBO	Female	0	Yes	Yes	9	Yes	No	DSL	No	Yes	No	Yes	Yes	No	One year	Yes	Mailed check	65.599998	593.2
1	0003-MKNFE	Male	0	No	No	9	Yes	Yes	DSL	No	No	No	No	No	Yes	Month-to-month	No	Mailed check	59.900002	542.4
2	0004-TLHLJ	Male	0	No	No	4	Yes	No	Fiber optic	No	No	Yes	No	No	No	Month-to-month	Yes	Electronic check	73.900002	280.8
3	0011-IGKFF	Male	1	Yes	No	13	Yes	No	Fiber optic	No	Yes	Yes	No	Yes	Yes	Month-to-month	Yes	Electronic check	98.000000	1237.8
4	0013-EXCHZ	Female	1	Yes	No	3	Yes	No	Fiber optic	No	No	No	Yes	Yes	No	Month-to-month	Yes	Mailed check	83.900002	267.3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	Female	0	No	No	13	Yes	No	DSL	Yes	No	No	Yes	No	No	One year	No	Mailed check	55.150002	742.9
7039	9992-RRAMN	Male	0	Yes	No	22	Yes	Yes	Fiber optic	No	No	No	No	No	Yes	Month-to-month	Yes	Electronic check	85.099998	1873.6
7040	9992-UJOEL	Male	0	No	No	2	Yes	No	DSL	No	Yes	No	No	No	No	Month-to-month	Yes	Mailed check	50.299999	92.7
7041	9993-LHIEB	Male	0	Yes	Yes	67	Yes	No	DSL	Yes	No	Yes	Yes	No	Yes	Two year	No	Mailed check	67.849998	4627.6
7042	9995-HOTOH	Male	0	Yes	Yes	63	No	No phone service	DSL	Yes	Yes	Yes	No	Yes	Yes	Two year	No	Electronic check	59.000000	3707.6

7032 rows × 28 columns

```
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_3172\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 opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df[binary_cols] = df[binary_cols].replace({'Yes': 1, 'No': 0})
C:\Temp\ipykernel_3172\2260154420.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[binary_cols] = df[binary_cols].replace({'Yes': 1, 'No': 0})
C:\Temp\ipykernel_3172\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 opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df['gender'] = df['gender'].replace({'Male': 1, 'Female': 0})
C:\Temp\ipykernel_3172\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['gender'] = df['gender'].replace({'Male': 1, 'Female': 0})
C:\Temp\ipykernel_3172\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 opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df['MultipleLines'] = df['MultipleLines'].replace({'No phone service': -1})
C:\Temp\ipykernel_3172\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	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCh
0	0002-ORFBO	0	0	1	1	9	1	0	DSL	0	1	0	1	1	0	One year	1	Mailed check	65.599998	593.2
1	0003-MKNFE	1	0	0	0	9	1	1	DSL	0	0	0	0	0	1	Month-to-month	0	Mailed check	59.900002	542.4
2	0004-TLHLJ	1	0	0	0	4	1	0	Fiber optic	0	0	1	0	0	0	Month-to-month	1	Electronic check	73.900002	280.8
3	0011-IGKFF	1	1	1	0	13	1	0	Fiber optic	0	1	1	0	1	1	Month-to-month	1	Electronic check	98.000000	1237.8
4	0013-EXCHZ	0	1	1	0	3	1	0	Fiber optic	0	0	0	1	1	0	Month-to-month	1	Mailed check	83.900002	267.3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	0	0	0	0	13	1	0	DSL	1	0	0	1	0	0	One year	0	Mailed check	55.150002	742.9
7039	9992-RRAMN	1	0	1	0	22	1	1	Fiber optic	0	0	0	0	0	1	Month-to-month	1	Electronic check	85.099998	1873.6
7040	9992-UJOEL	1	0	0	0	2	1	0	DSL	0	1	0	0	0	0	Month-to-month	1	Mailed check	50.299999	92.7
7041	9993-LHIEB	1	0	1	1	67	1	0	DSL	1	0	1	1	0	1	Two year	0	Mailed check	67.849998	4627.6
7042	9995-HOTOH	1	0	1	1	63	0	-1	DSL	1	1	1	0	1	1	Two year	0	Electronic check	59.000000	3707.6

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_3172\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 opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df[Services_cols] = df[Services_cols].replace({'No internet service': 0})
C:\Temp\ipykernel_3172\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_3172\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_3172\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	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	Total
0	0002-ORFBO	0	0	1	1	-0.954296	1	0	DSL	0	1	0	1	1	0	One year	1	Mailed check	0.026652	-
1	0003-MKNFE	1	0	0	0	-0.954296	1	1	DSL	0	0	0	0	0	1	Month-to-month	0	Mailed check	-0.162819	-
2	0004-TLHLJ	1	0	0	0	-1.158016	1	0	Fiber optic	0	0	1	0	0	0	Month-to-month	1	Electronic check	0.302548	-
3	0011-IGKFF	1	1	1	0	-0.791321	1	0	Fiber optic	0	1	1	0	1	1	Month-to-month	1	Electronic check	1.103642	-
4	0013-EXCHZ	0	1	1	0	-1.198760	1	0	Fiber optic	0	0	0	1	1	0	Month-to-month	1	Mailed check	0.634952	-
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	0	0	0	0	-0.791321	1	0	DSL	1	0	0	1	0	0	One year	0	Mailed check	-0.320711	-
7039	9992-RRAMN	1	0	1	0	-0.424625	1	1	Fiber optic	0	0	0	0	0	1	Month-to-month	1	Electronic check	0.674841	-
7040	9992-UJOEL	1	0	0	0	-1.239504	1	0	DSL	0	1	0	0	0	0	Month-to-month	1	Mailed check	-0.481927	-
7041	9993-LHIEB	1	0	1	1	1.408853	1	0	DSL	1	0	1	1	0	1	Two year	0	Mailed check	0.101443	
7042	9995-HOTOH	1	0	1	1	1.245878	0	-1	DSL	1	1	1	0	1	1	Two year	0	Electronic check	-0.192735	

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	StreamingMovies	PaperlessBilling	MonthlyCharges	TotalCharges	Churn	ChargeRatio	PaymentAutor
0	0002-ORFBO	0	0	1	1	-0.954296	1	0	0	1	0	1	1	0	1	0.026652	-0.745607	0	0.008093	
1	0003-MKNFE	1	0	0	0	-0.954296	1	1	0	0	0	0	0	1	0	-0.162819	-0.768063	0	-0.158725	
2	0004-TLHLJ	1	0	0	0	-1.158016	1	0	0	0	1	0	0	0	1	0.302548	-0.883456	1	-0.095472	
3	0011-IGKFF	1	1	1	0	-0.791321	1	0	0	1	1	0	1	1	1	1.103642	-0.461240	1	0.961410	
4	0013-EXCHZ	0	1	1	0	-1.198760	1	0	0	0	0	1	1	0	1	0.634952	-0.889390	1	0.254551	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	9987-LUTYD	0	0	0	0	-0.791321	1	0	1	0	0	1	0	0	0	-0.320711	-0.679605	0	-0.197258	
7039	9992-RRAMN	1	0	1	0	-0.424625	1	1	0	0	0	0	0	1	1	0.674841	-0.180711	1	0.733546	
7040	9992-UJOEL	1	0	0	0	-1.239504	1	0	0	1	0	0	0	0	1	-0.481927	-0.966443	0	-0.923117	
7041	9993-LHIEB	1	0	1	1	1.408853	1	0	1	0	1	1	0	1	0	0.101443	1.034298	0	0.294000	
7042	9995-HOTOH	1	0	1	1	1.245878	0	-1	1	1	1	0	1	1	0	-0.192735	0.628383	0	-0.037749	

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

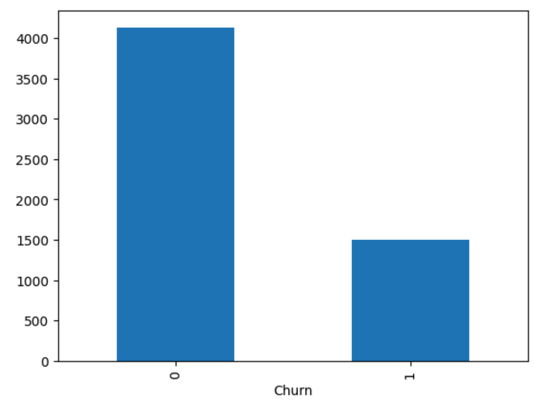
```
from sklearn.model_selection import train_test_split
X = df.drop(['Churn', 'customerID','TotalCharges','gender'], axis=1)
y = df['Churn']

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_)
```

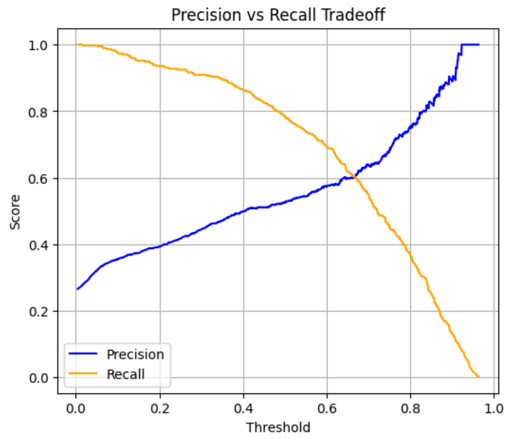
```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
Best parameters: {'colsample_bytree': np.float64(0.8232408008069365), 'gamma': np.float64(0.2019180855290204), 'learning_rate': np.float64(0.02297844942179631), 'max_depth': 4, 'min_child_weight': 4, 'n_estimators': 567, 'reg_alpha': np.float64(0.010165510266418737), 'reg_lambda': np.float64(0.9749762207436125), 'subsample':
```

```
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()
```



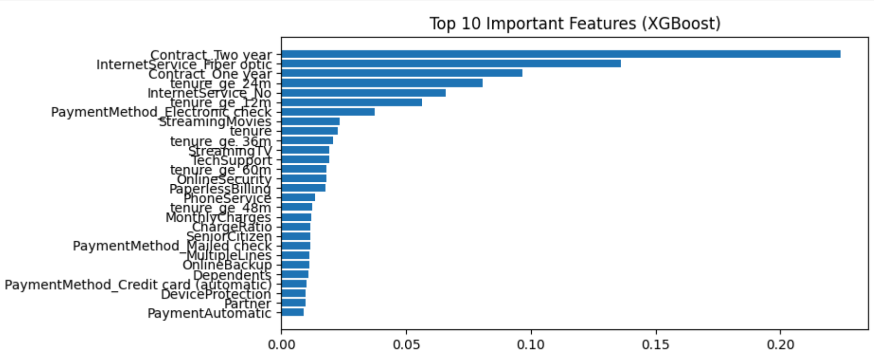

```
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score
import numpy as np

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 a customer churn prediction model using XGBoost, achieving 0.84 ROC-AUC. At threshold = 0.4, the model achieves 0.50 Precision, 0.86 Recall, and 0.63 F1-score. Insights show that contract type, tenure, and monthly charges are the strongest predictors of churn."

Key Insights

- Long-term contracts → drastically reduce churn
- Fiber optic customers → high churn risk
- Low tenure + high monthly charges → most likely to churn

Recommended Business Actions

- Offer loyalty discounts or incentives to short-tenure customers to reduce early churn.
- Improve satisfaction for fiber-optic customers through proactive service monitoring and feedback collection.
- Retarget paperless billing users with higher satisfaction campaigns