Telco Customer Churn Analysis

January 4, 2026

1 Telco Customer Churn Analysis — End-to-End Case Study

1.1 Project Objective

This project analyzes customer churn for a telecommunications company.

Churn Definition A customer is considered churned if:

- `Churn = "Yes"` → Customer has left the company
- `Churn = "No"` → Customer is still active

Churn is a critical metric because:

- Retaining customers costs less than acquiring new ones
- Churn reduces recurring revenue & lifetime value
- High churn signals dissatisfaction & competition pressure

1.2 Project Goals

This project aims to:

1. Understand churn behaviour and key drivers
2. Compare churn vs non-churn customer groups
3. Engineer behavioural & lifecycle features
4. Train churn prediction models
5. Evaluate model performance
6. Provide actionable business recommendations

1.3 Dataset Description

Each row represents a customer record.

Key attributes include:

- Demographics

- Account information

- Subscription plans

- Billing details

- Service usage
- Churn outcome

The dataset is ideal for an **end-to-end churn analytics case study**.

1.3.1 Data Cleaning & Preparation

Import Libraries & Load Data

[1]:
```
import pandas as pd
import numpy as np

df = pd.read_csv("WA_Fn-UseC_-Telco-Customer-Churn 2 -␣
↪WA_Fn-UseC_-Telco-Customer-Churn 2.csv")

df.head()
```

[1]:
```
   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       1889.50     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]
```

Dataset Structure & Summary

Inspect column types, shape, and completeness.

[3]:
```
df.shape, df.info()
```

```
<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      7032 non-null   float64
 20  Churn             7043 non-null   object
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

[3]:
```
((7043, 21), None)
```

To check for missing values and ensure data consistency.

[5]:
```
df.isna().sum()
```

[5]:
```
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
```

[7]:
```
df['TotalCharges'] = df['TotalCharges'].fillna(0)
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
```

Numeric churn flag

[9]:
```
df['Churn_flag'] = (df['Churn'] == 'Yes').astype(int)
```

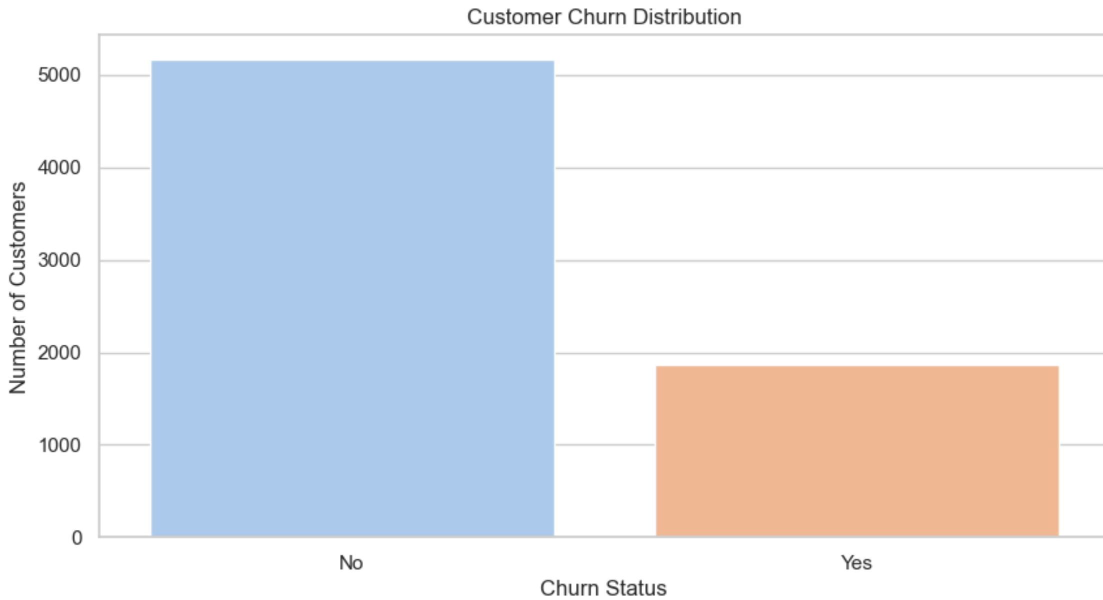
[11]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (10,5)
```

1.3.2 Churn Distribution

To compute the churn ratio to understand the dataset balance.

[13]:
```
churn_counts = df['Churn'].value_counts()

sns.barplot(x=churn_counts.index, y=churn_counts.values, palette="pastel")
plt.title("Customer Churn Distribution")
plt.ylabel("Number of Customers")
plt.xlabel("Churn Status")
plt.show()
```

```
C:\Users\mildr\AppData\Local\Temp\ipykernel_6848\1081618862.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=churn_counts.index, y=churn_counts.values, palette="pastel")
```



1.4 Exploratory Data Analysis (EDA)

Goal: - Compare churn vs non-churn groups - Identify high-risk churn segments - Support feature engineering & modeling

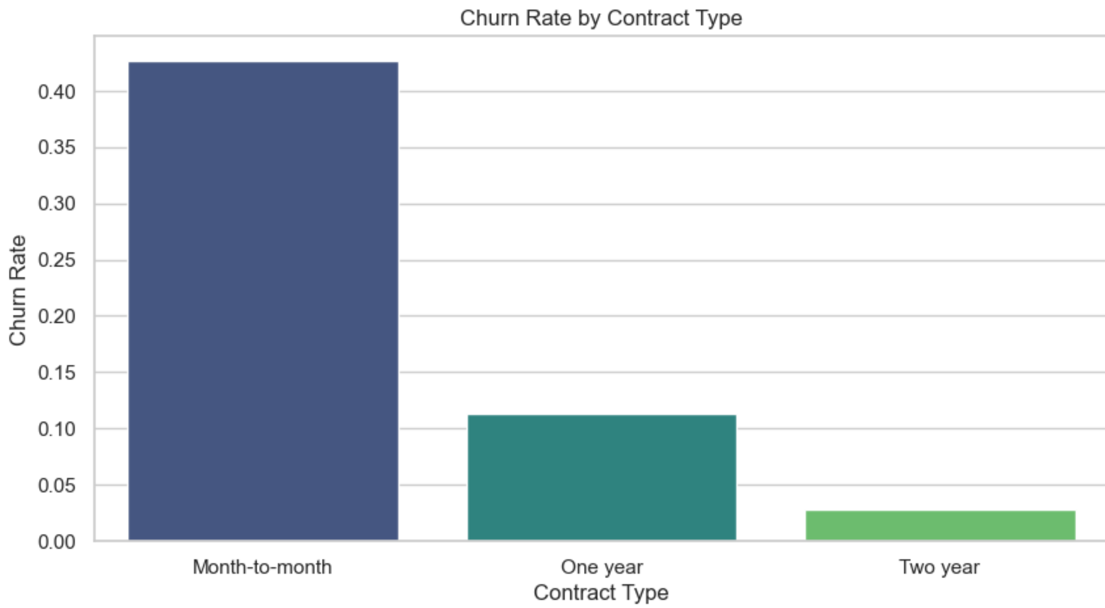
1.4.1 Churn vs Contract Type

[15]:

```
contract_churn = (
    df.groupby('Contract')['Churn_flag'].mean().reset_index()
)

sns.barplot(
    data=contract_churn,
    x='Contract',
    y='Churn_flag',
    palette="viridis"
)

plt.title("Churn Rate by Contract Type")
plt.ylabel("Churn Rate")
plt.xlabel("Contract Type")
plt.show()
```

```
C:\Users\mildr\AppData\Local\Temp\ipykernel_6848\1435280597.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.
```

```
sns.barplot(
```

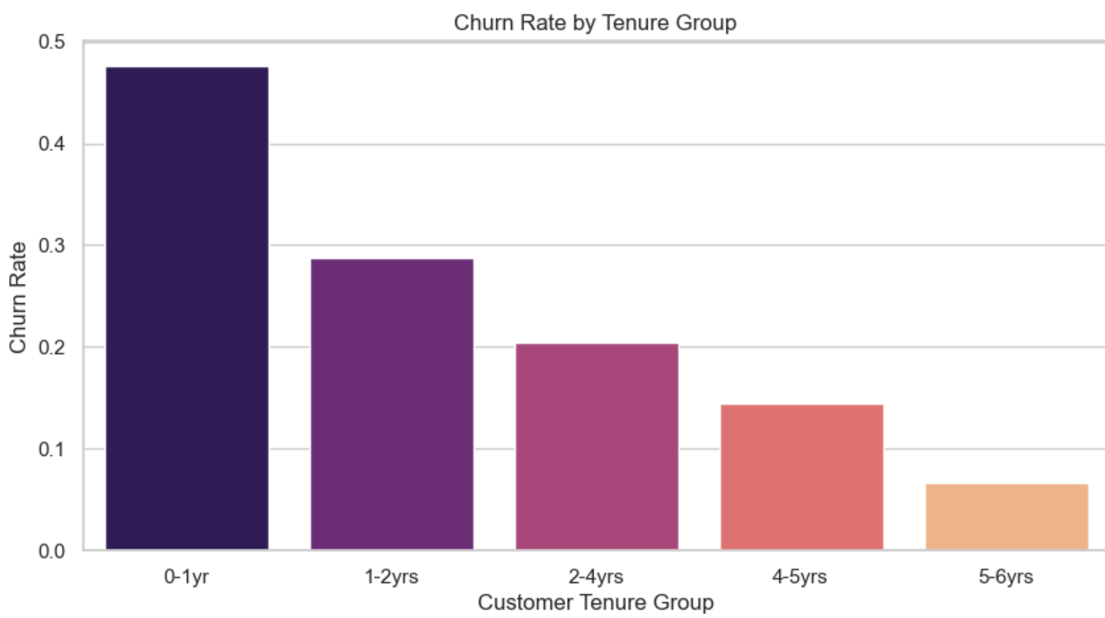


Short-term contracts = **highest churn risk**

1.4.2 Churn vs Tenure Groups

[17]:
```python
bins = [0,12,24,48,60,72]
labels = ['0-1yr','1-2yrs','2-4yrs','4-5yrs','5-6yrs']

df['tenure_group'] = pd.cut(df['tenure'], bins=bins, labels=labels)

tenure_churn = (
    df.groupby('tenure_group')['Churn_flag'].mean().reset_index()
)

sns.barplot(
    data=tenure_churn,
    x='tenure_group',
    y='Churn_flag',
    palette="magma"
)

plt.title("Churn Rate by Tenure Group")
plt.ylabel("Churn Rate")
plt.xlabel("Customer Tenure Group")
plt.show()
```

```
C:\Users\mildr\AppData\Local\Temp\ipykernel_6848\1005993199.py:7: FutureWarning:
The default of observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current behavior or
observed=True to adopt the future default and silence this warning.
  df.groupby('tenure_group')['Churn_flag'].mean().reset_index()
C:\Users\mildr\AppData\Local\Temp\ipykernel_6848\1005993199.py:10:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(
```



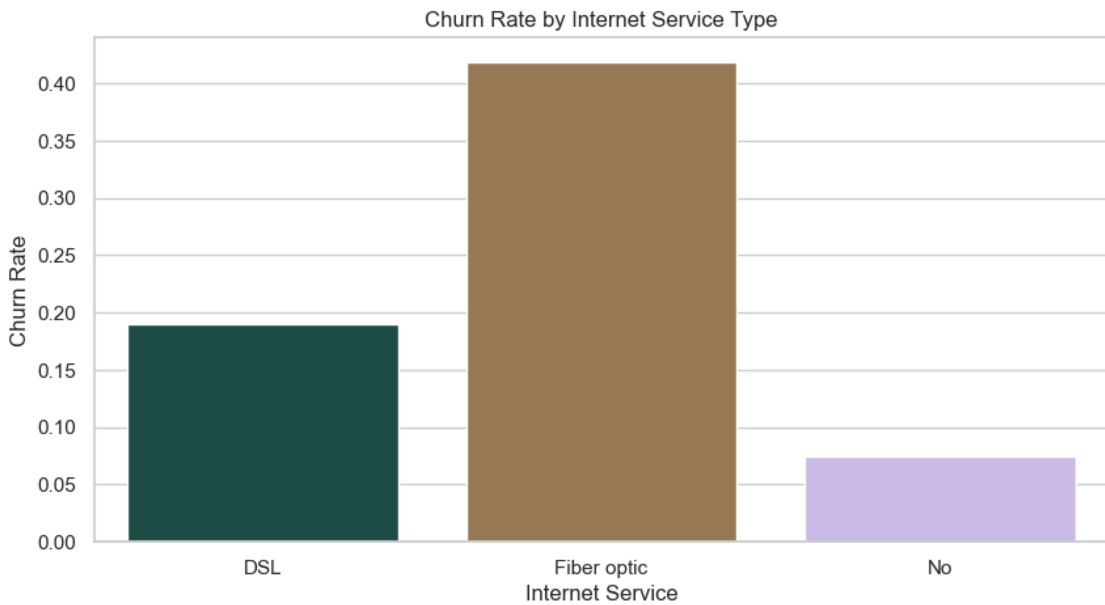
Retention is most critical during first 12 months

1.4.3 Churn vs Internet Service

[19]:
```
internet_churn = (
    df.groupby('InternetService')['Churn_flag'].mean().reset_index()
)

sns.barplot(
    data=internet_churn,
    x='InternetService',
    y='Churn_flag',
    palette="cubehelix"
```

```
)

plt.title("Churn Rate by Internet Service Type")
plt.ylabel("Churn Rate")
plt.xlabel("Internet Service")
plt.show()
```

```
C:\Users\mildr\AppData\Local\Temp\ipykernel_6848\1479068448.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(
```



Fiber users may be:

. more price-sensitive

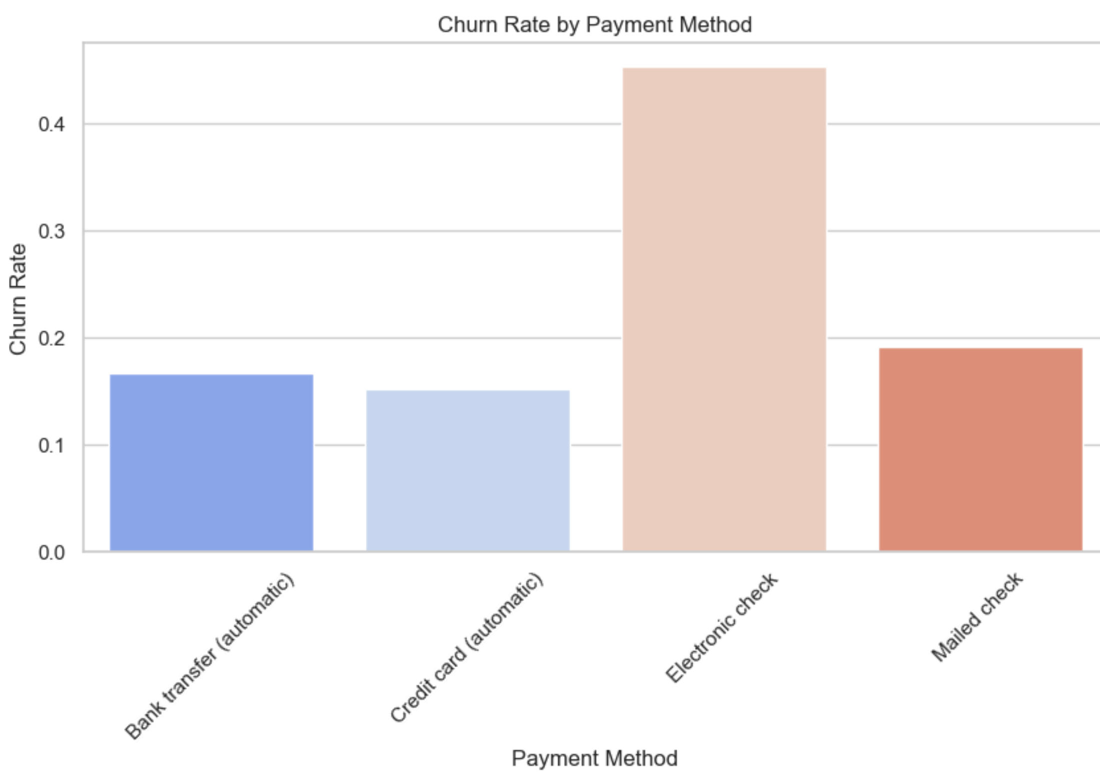
. higher performance expectations

1.4.4 Churn vs Payment Method

[21]:
```
payment_churn = (
    df.groupby('PaymentMethod')['Churn_flag'].mean().reset_index()
)

sns.barplot(
```

```
    data=payment_churn,
    x='PaymentMethod',
    y='Churn_flag',
    palette="coolwarm"
)

plt.title("Churn Rate by Payment Method")
plt.ylabel("Churn Rate")
plt.xlabel("Payment Method")
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\mildr\AppData\Local\Temp\ipykernel_6848\413570720.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(
```



Auto-pay customers show higher retention stability

1.5 Feature Engineering

To create behavioural and lifecycle features.

Number of subscribed services

[23]:
```
service_cols = [
    'PhoneService','MultipleLines','OnlineSecurity','OnlineBackup',
    'DeviceProtection','TechSupport','StreamingTV','StreamingMovies'
]

df['num_services'] = df[service_cols].apply(lambda x: (x == 'Yes').sum(),␣
 ↪axis=1)
```

Tenure lifecycle bins

[25]:
```
df['tenure_group'] = pd.cut(df['tenure'], bins=bins, labels=labels)
```

Final feature matrix

[27]:
```
X = df.drop(columns=['customerID','Churn','Churn_flag'])
y = df['Churn_flag']
```

1.6 Train-Test Split & Preprocessing

Model Training Pipeline

Includes preprocessing + encoding + scaling.

[29]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

cat_cols = X.select_dtypes(include=['object']).columns.tolist()
num_cols = X.select_dtypes(include=['int64','float64']).columns.tolist()

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

preprocess = ColumnTransformer([
    ('cat', OneHotEncoder(drop='first', handle_unknown='ignore'), cat_cols),
    ('num', StandardScaler(), num_cols)
])
```

Logic Regression Model

[31]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪roc_auc_score
```

```python
log_model = Pipeline(steps=[
    ('prep', preprocess),
    ('clf', LogisticRegression(max_iter=1000))
])

log_model.fit(X_train, y_train)

y_pred_lr = log_model.predict(X_test)
y_prob_lr = log_model.predict_proba(X_test)[:,1]

print(confusion_matrix(y_test, y_pred_lr))
print(classification_report(y_test, y_pred_lr))
print("ROC-AUC:", roc_auc_score(y_test, y_prob_lr))
```

```
[[926 109]
 [165 209]]
              precision    recall  f1-score   support

           0       0.85      0.89      0.87      1035
           1       0.66      0.56      0.60       374

    accuracy                           0.81      1409
   macro avg       0.75      0.73      0.74      1409
weighted avg       0.80      0.81      0.80      1409

ROC-AUC: 0.8422666563331527
```

Random Forest Model

[33]:
```python
from sklearn.ensemble import RandomForestClassifier

rf_model = Pipeline(steps=[
    ('prep', preprocess),
    ('clf', RandomForestClassifier(
        n_estimators=300,
        random_state=42,
        min_samples_split=5,
        min_samples_leaf=2,
        class_weight='balanced'
    ))
])

rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)
y_prob_rf = rf_model.predict_proba(X_test)[:,1]
```

```python
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
print("ROC-AUC:", roc_auc_score(y_test, y_prob_rf))
```

```
[[856 179]
 [133 241]]
              precision    recall  f1-score   support

           0       0.87      0.83      0.85      1035
           1       0.57      0.64      0.61       374

    accuracy                           0.78      1409
   macro avg       0.72      0.74      0.73      1409
weighted avg       0.79      0.78      0.78      1409

ROC-AUC: 0.8366374744891368
```

Feature Importance (Random Forest)

[35]:
```python
ohe = rf_model.named_steps['prep'].named_transformers_['cat']
cat_features = ohe.get_feature_names_out(cat_cols)

feature_names = list(cat_features) + num_cols

importances = rf_model.named_steps['clf'].feature_importances_

fi = pd.Series(importances, index=feature_names).sort_values(ascending=False)
fi.head(15)
```

[35]:
```
tenure                              0.175337
TotalCharges                        0.152870
MonthlyCharges                      0.119737
Contract_Two year                   0.072586
InternetService_Fiber optic         0.060801
PaymentMethod_Electronic check      0.040468
num_services                        0.033757
Contract_One year                   0.033624
OnlineSecurity_Yes                  0.028361
TechSupport_Yes                     0.022761
PaperlessBilling_Yes                0.021337
gender_Male                         0.019548
OnlineBackup_Yes                    0.017432
Partner_Yes                         0.016767
Dependents_Yes                      0.015592
dtype: float64
```

1.7 Post-Dictive Churn Analysis

We compare actual vs predicted churn at the segment level.

[37]:
```python
test_df = X_test.copy()
test_df['actual'] = y_test.values
test_df['pred'] = y_pred_rf
test_df['prob'] = y_prob_rf

test_df.head()
```

[37]:
```
      gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
437     Male              0     Yes        Yes      72          Yes
2280  Female              1      No         No       8          Yes
2235  Female              0     Yes        Yes      41          Yes
4460    Male              0     Yes         No      18          Yes
3761  Female              0     Yes         No      72          Yes

     MultipleLines InternetService OnlineSecurity OnlineBackup  …  \
437            Yes     Fiber optic            Yes          Yes  …
2280           Yes     Fiber optic             No           No  …
2235           Yes             DSL            Yes          Yes  …
4460            No     Fiber optic             No           No  …
3761           Yes             DSL            Yes          Yes  …

            Contract PaperlessBilling            PaymentMethod MonthlyCharges  \
437         Two year              Yes  Credit card (automatic)         114.05
2280  Month-to-month              Yes  Credit card (automatic)         100.15
2235        One year              Yes  Credit card (automatic)          78.35
4460  Month-to-month               No         Electronic check          78.20
3761        Two year              Yes  Credit card (automatic)          82.65

     TotalCharges tenure_group num_services  actual  pred      prob
437       8468.20       5-6yrs            8       0     0  0.010978
2280       908.55        0-1yr            5       0     1  0.850672
2235      3211.20       2-4yrs            6       0     0  0.132907
4460      1468.75       1-2yrs            3       0     0  0.402107
3761      5919.35       5-6yrs            7       0     0  0.019593

[5 rows x 24 columns]
```

Identify high-risk segment

[39]:
```python
segment = test_df[
    (test_df['Contract'] == 'Month-to-month') &
    (test_df['InternetService'] == 'Fiber optic') &
    (test_df['tenure'] <= 12)
]

segment[['actual','pred']].mean()
```

[39]:
```
actual    0.661290
pred      0.978495
dtype: float64
```

2 Business Recommendations

2.0.1 High-Risk Churn Segments

- Month-to-month customers
- Tenure below 12 months
- Fiber-optic users
- Electronic-check payment users

2.1 Recommended Retention Actions

2.1.1 1. Convert monthly contracts → 1-year plans

- loyalty rewards
- contract upgrade discounts

2.1.2 2. First-year onboarding program

- welcome support calls
- quarterly check-ins
- service education touchpoints

2.1.3 3. Fiber-customer experience improvement

- performance investigation
- premium support tier
- bundled feature offers

2.1.4 4. Move customers to auto-payment

- incentive for bank transfer/card autopay

2.1.5 5. Promote value-added services

Customers with: - TechSupport - OnlineSecurity

show **lower churn probability**

2.2 Final Conclusion

The analysis shows that churn is driven by:

- contract flexibility
- early-lifecycle risk
- billing method
- internet plan type
- service value perception

The Random Forest model provides:

- strong recall for churners
- reliable churn risk segmentation

This supports **data-driven retention strategy design**.

```
[ ]:
```