📘 Customer Churn Analysis – Telecom Industry

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Tools Used: Python (pandas, seaborn, scikit-learn), Power BI

🔍 Objective

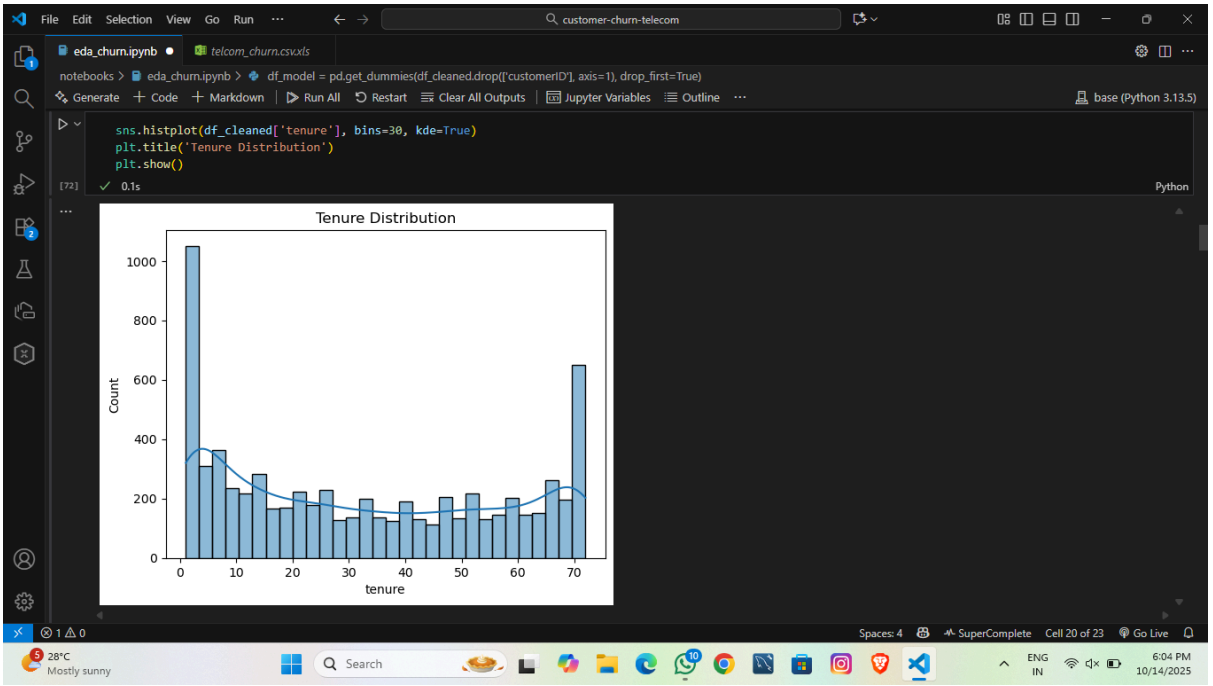
This project aims to identify key drivers of customer churn in the telecom industry and provide actionable insights to improve customer retention. By analyzing customer behavior and service usage patterns, we uncover trends that help reduce churn and enhance long-term engagement.

📊 Dataset Overview

• Source: AdventureWorks Telecom Dataset
• Records: 7,043 customers
• Features:• Demographics: Gender, SeniorCitizen, Partner, Dependents
• Services: InternetService, OnlineSecurity, StreamingTV, TechSupport
• Account Info: Tenure, Contract, PaymentMethod, MonthlyCharges, TotalCharges
• Target: Churn (Yes/No)

📈 EDA Highlights

• Contract Type: Month-to-month contracts show the highest churn rate (6K churned vs 17K retained).
• Payment Method: Electronic check users have the highest churn (1.0M in TotalCharges churned).
• Tenure: Customers with tenure < 12 months are most likely to churn.
• Streaming Services & Tech Support: Customers without tech support or streaming services show higher churn percentages.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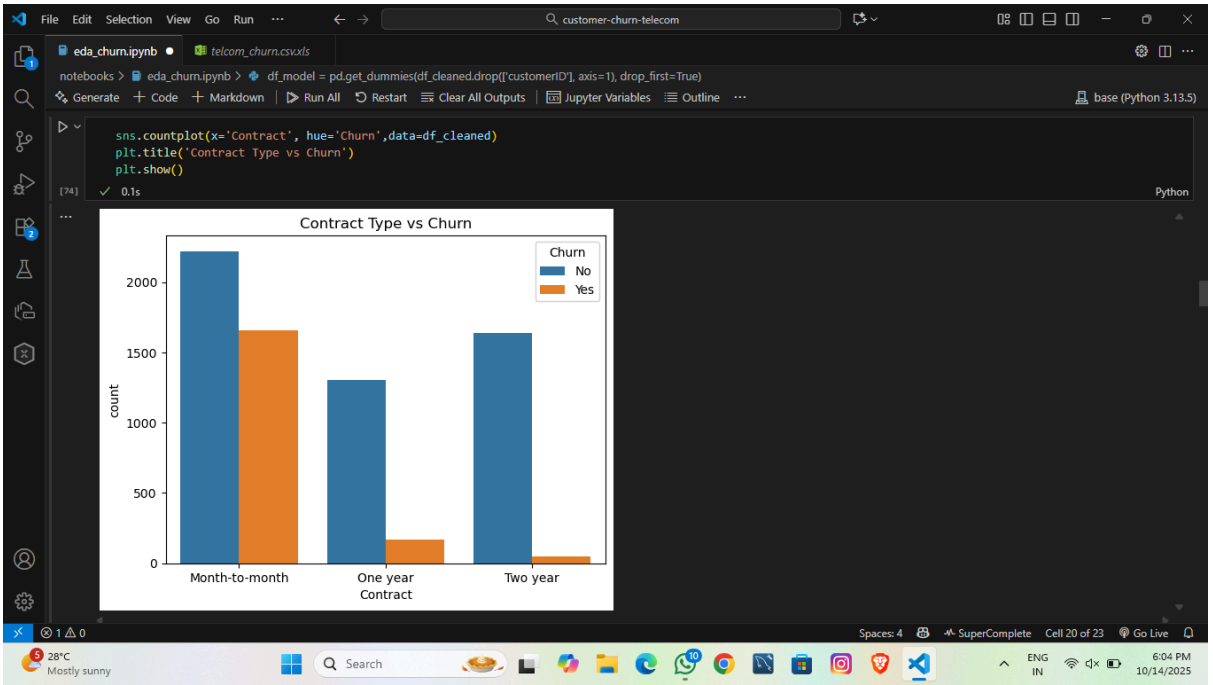
customer-churn-telecom
eda_churn.ipynb
telcom_churn.csv.xls
notebooks > eda_churn.ipynb > df_model = pd.get_dummies(df_cleaned.drop(['customerID'], axis=1), drop_first=True)
Generate Code Markdown Run All Restart Clear All Outputs Jupyter Variables Outline
base (Python 3.13.5)
sns.histplot(df_cleaned['tenure'], bins=30, kde=True)
plt.title('Tenure Distribution')
plt.show()
[72] 0.1s
Python
Tenure Distribution
Count
tenure
0
200
400
600
800
1000
0
10
20
30
40
50
60
70
Spaces: 4 SuperComplete Cell 20 of 23 Go Live
28°C
Mostly sunny
Search
ENG
IN
6:04 PM
10/14/2025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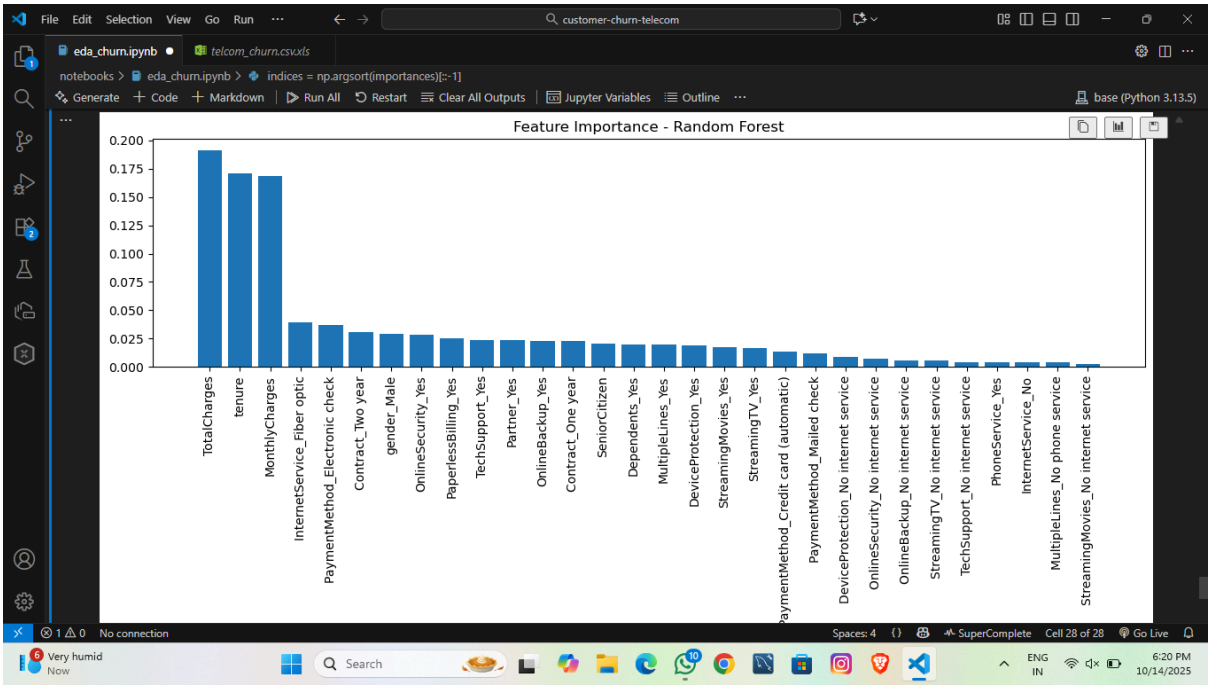
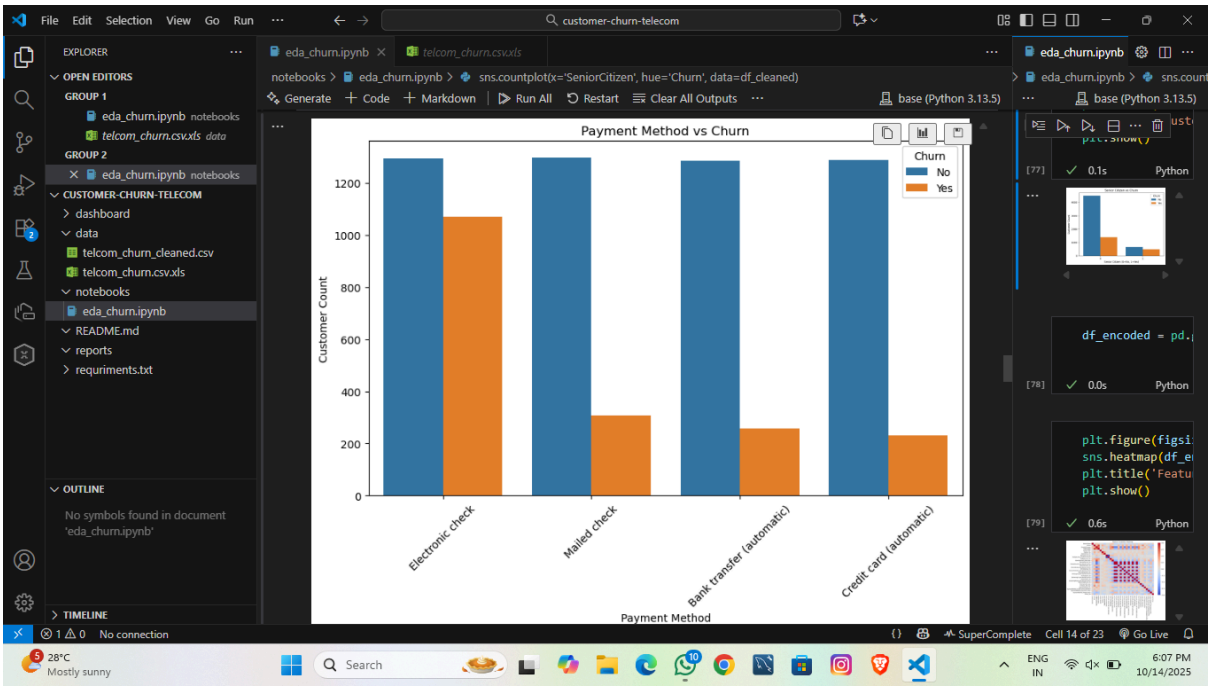
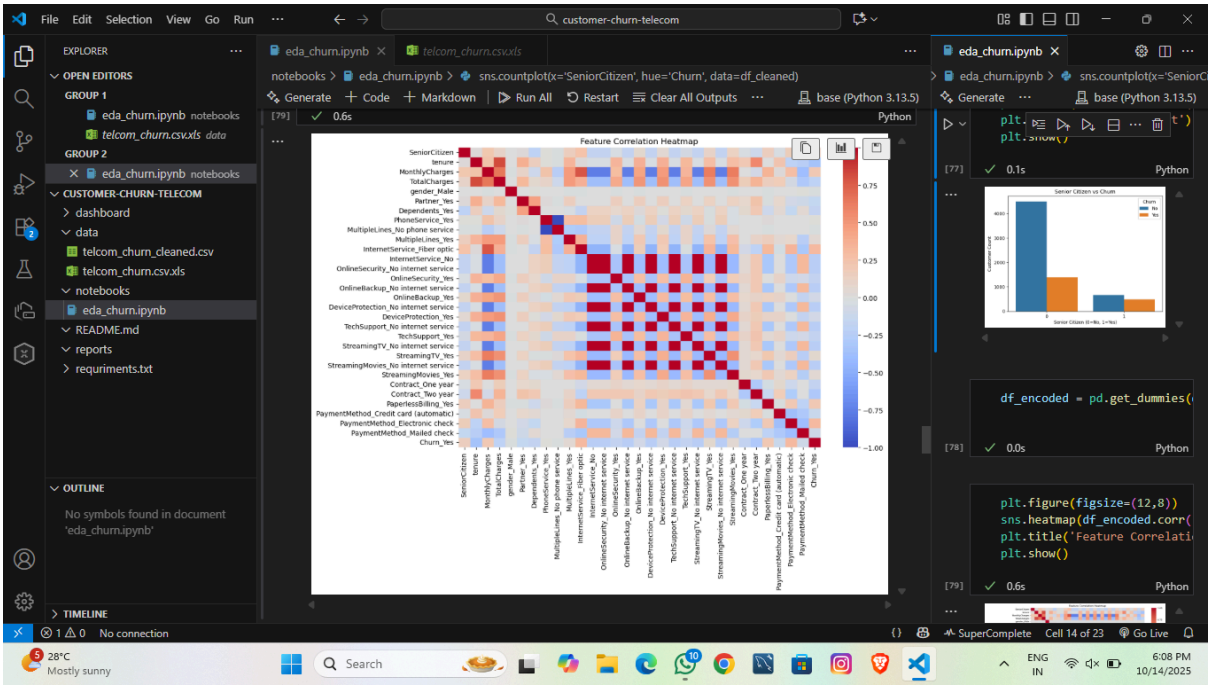
Generate Code Markdown Run All Restart Clear All Outputs Jupyter Variables Outline
base (Python 3.13.5)
sns.countplot(x='Contract', hue='Churn',data=df_cleaned)
plt.title('Contract Type vs Churn')
plt.show()
[74] 0.1s
Python
Contract Type vs Churn
Churn
No
Yes
count
Contract
Month-to-month
One year
Two year
0
500
1000
1500
2000
Spaces: 4 SuperComplete Cell 20 of 23 Go Live
28°C
Mostly sunny
Search
ENG
IN
6:04 PM
10/14/2025

🤖 Modeling Summar• Algorithms Used: Logistic Regression and Random Forest

• Performance:• Random Forest outperformed Logistic Regression in precision and recall
• Feature importance revealed top churn drivers:• tenure
• MonthlyCharges
• Contract_Two year
• PaymentMethod_Electronic check




Payment Method vs Churn
Churn
No
Yes
Customer Count
0
200
400
600
800
1000
1200
Electronic check
Mailed check
Bank transfer (automatic)
Credit card (automatic)
Payment Method

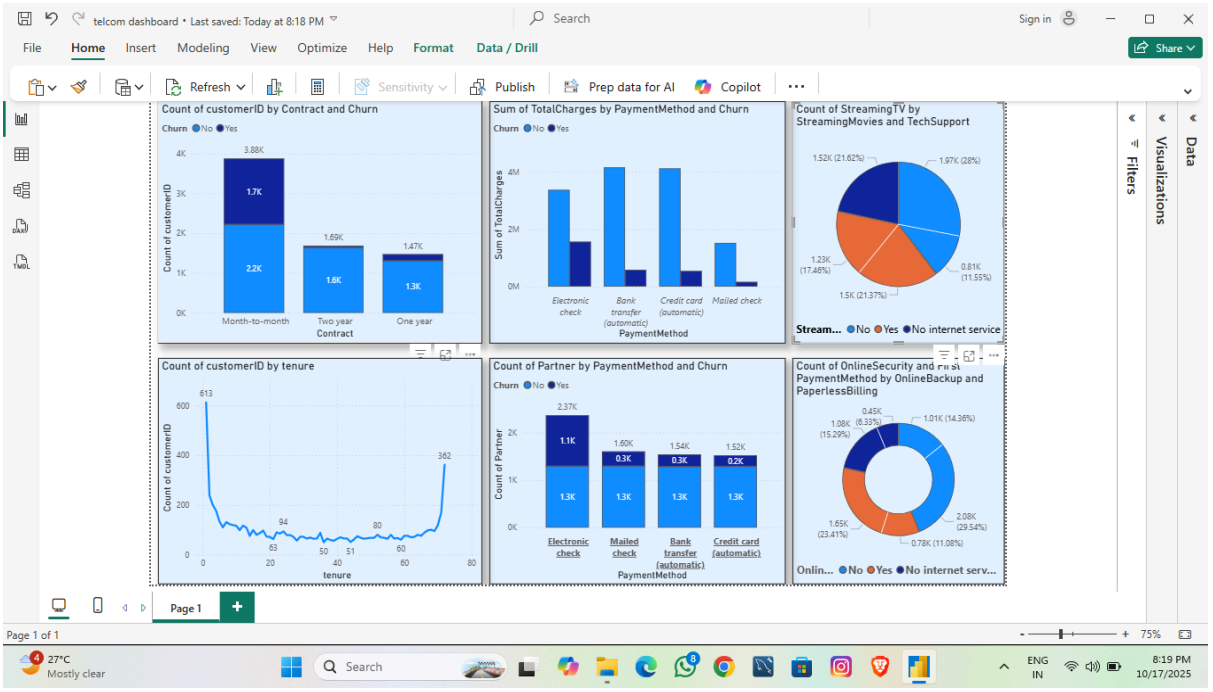

Feature Correlation Heatmap

📊 Dashboard Insights

Built using Power BI, the dashboard includes:

• Churn by Contract Type: Bar chart showing churn distribution across contract types
• Tenure Distribution: Line chart showing customer count by tenure
• TotalCharges by Payment Method: Bar chart comparing churned vs retained customers
• Streaming & Tech Support: Pie chart showing service combinations and churn risk
• Partner Status by Payment Method: Bar chart showing churn patterns among partnered customers
• Online Security & Backup: Pie chart showing tech support gaps tied to churn

Interactive slicers allow filtering by gender, internet service, contract type, and payment method.



✅ Recommendations

• Promote long-term contracts to reduce churn
• Incentivize auto-pay methods over electronic checks
• Improve onboarding experience for new customers
• Monitor high-risk segments (short tenure + electronic check users)
• Offer bundled services with tech support and streaming to increase retention

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📌 Conclusion

This analysis provides a data-driven foundation for reducing churn and improving customer retention in telecom services. By combining machine learning with interactive dashboards, we deliver insights that support strategic decision-making.