

**SAIKET SYSTEMS INTERNSHIP SOLUTION**

**TOOL USED: PYTHON**

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SAIKET SYSTEM (BUSINESS ANALYSIS)

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## TASK1: Understand the Dataset Description:

- ❖ Familiarize yourself with the dataset.
- Steps:
- ❖ Load the dataset using pandas.
  - ❖ Display the first 10 rows.
  - ❖ Identify the data types of each column.
  - ❖ Check for missing values.

## SOLUTION

- ✓ Loading the dataset using pandas

```
[15] import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns

     # Option to display all rows
     pd.set_option('display.max_rows', None)

     # Loading the Excel file
     df = pd.read_excel('Telco_Customer_Churn_Dataset.xlsx')

     # data cleaning and preparation
     df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')
     df['TotalCharges'] = df['TotalCharges'].fillna(0)
     df.columns = df.columns.str.lower().str.replace(' ', '_')
     df['churn'] = df['churn'].map({'Yes': 1, 'No': 0})
```

- ✓ Display the first 10 rows.

```
[16] # To Show first 10 rows
display(df.head(10))

customerid  gender  seniorcitizen  partner  dependents  tenure  phoneservice  multiplelines  internetservice  onlinesecurity ... deviceprotection  techsupport  streamingtv  streamingmovies  contract  paperlessbilling  paymentmethod
0  7980-VHVEG  Female        0    Yes      No       1      No  No phone service      DSL      No  ...      No      No      No  Month-to-month      Yes  Electronic check
1  5575-GNVDE  Male         0    No      No      34     Yes      No  DSL      Yes  ...      Yes      No      No  No  One year      No  Mailed check
2  3668-QPYBK  Male         0    No      No       2     Yes      No  DSL      Yes  ...      No      No      No  Month-to-month      Yes  Mailed check
3  7795-CFOCW  Male         0    No      No      45      No  No phone service      DSL      Yes  ...      Yes      Yes      No  One year      No  Bank transfer (automatic)
4  9237-HQTIU  Female       0    No      No       2     Yes      No  Fiber optic      No  ...      No      No      No  Month-to-month      Yes  Electronic check
5  9305-CDSSKC  Female       0    No      No       8     Yes      Yes  Fiber optic      No  ...      Yes      No      Yes  Month-to-month      Yes  Electronic check
6  1452-KIOVK  Male         0    No      Yes      22     Yes      Yes  Fiber optic      No  ...      No      No      Yes  Month-to-month      Yes  Credit card (automatic)
7  6713-OKOMC  Female       0    No      No      10      No  No phone service      DSL      Yes  ...      No      No      No  Month-to-month      No  Mailed check
8  7892-POOKP  Female       0    Yes      No      28     Yes      Yes  Fiber optic      No  ...      Yes      Yes      Yes  Month-to-month      Yes  Electronic check
9  6388-TABGU  Male         0    No      Yes      62     Yes      No  DSL      Yes  ...      No      No      No  One year      No  Bank transfer (automatic)
```

10 rows × 21 columns

## ❖ Identification of the data types of each column

```
print(df.dtypes)
```

```
customerID    object
gender         object
SeniorCitizen  int64
Partner        object
Dependents     object
Tenure         int64
PhoneService   object
MultipleLines  object
InternetService object
OnlineSecurity object
OnlineBackup    object
DeviceProtection object
TechSupport    object
StreamingTV   object
StreamingMovies object
Contract       object
PaperlessBilling object
PaymentMethod   object
MonthlyCharges float64
TotalCharges   float64
Churn          object
dtype: object
```

- ❖ Customer ID – **object**
- ❖ Gender – **object**
- ❖ Senior Citizen – **int64**
- ❖ Partner – **object**
- ❖ Dependents – **object**
- ❖ Tenure – **int64**
- ❖ Phone Service – **object**
- ❖ Multiple Lines – **object**
- ❖ Internet Service – **object**
- ❖ Online Security – **object**
- ❖ Online Backup – **object**
- ❖ Device Protection – **object**
- ❖ Tech Support – **object**
- ❖ Streaming TV – **object**
- ❖ Streaming Movies – **object**
- ❖ Contract – **object**
- ❖ Paperless Billing – **object**
- ❖ Payment Method – **object**
- ❖ Monthly Charges – **float64**
- ❖ Total Charges – **float64**
- ❖ Churn – **object**

❖ Check for missing values.

```
print(df.isnull().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
dtype: int64
```

- **No Missing Data in Most Columns** – All columns except Total Charges have 0 missing values, meaning they are complete and ready for analysis.
- **Total Charges Has Missing Values** – This column has **11 missing entries**.

## TASK 2: DATA CLEANING

### QUESTION:

- ❖ Handle missing values appropriately (e.g., fill, drop, or impute).
- ❖ Remove duplicate records if any.
- ❖ Standardize column names (convert to lowercase and replace spaces with underscores)

### ANALYSIS & SOLUTION

The screenshot shows a Jupyter Notebook cell with the following code:

```
[ ] df['TotalCharges'] = df['TotalCharges'].fillna(0)
```

Below the code, there is a preview of a DataFrame. The columns include Partner, Dependents, tenure, PhoneService, MultipleLines, InternetService, OnlineSecurity, DeviceProtection, TechSupport, StreamingTV, StreamingMovies, Contract, PaperlessBilling, PaymentMethod, MonthlyCharges, TotalCharges, and Churn. The preview shows several rows of data with various service configurations and payment methods.

Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contract	PaperlessBilling	PaymentMethod	MonthlyCharges	TotalCharges	Churn	
Yes	Yes	0	No	No phone service	DSL	Yes	...	Yes	Yes	Yes	No	Two year	Yes	Bank transfer (automatic)	52.55	0.0	No
No	Yes	0	Yes	No	No	No internet service	...	No internet service	No internet service	No internet service	No internet service	Two year	No	Mailed check	20.25	0.0	No
Yes	Yes	0	Yes	No	DSL	Yes	...	Yes	No	Yes	Yes	Two year	No	Mailed check	80.85	0.0	No
Yes	Yes	0	Yes	Yes	No	No internet service	...	No internet service	No internet service	No internet service	No internet service	Two year	No	Mailed check	25.75	0.0	No
Yes	Yes	0	No	No phone service	DSL	Yes	...	Yes	Yes	Yes	No	Two year	No	Credit card (automatic)	56.05	0.0	No
Yes	Yes	0	Yes	No	No	No internet service	...	No internet service	No internet service	No internet service	No internet service	Two year	No	Mailed check	19.85	0.0	No
Yes	Yes	0	Yes	Yes	No	No internet service	...	No internet service	No internet service	No internet service	No internet service	Two year	No	Mailed check	25.35	0.0	No
Yes	Yes	0	Yes	No	No	No internet service	...	No internet service	No internet service	No internet service	No internet service	Two year	No	Mailed check	20.00	0.0	No
Yes	Yes	0	Yes	No	No	No internet service	...	No internet service	No internet service	No internet service	No internet service	One year	Yes	Mailed check	19.70	0.0	No
Yes	Yes	0	Yes	Yes	DSL	No	...	Yes	Yes	Yes	No	Two year	No	Mailed check	73.35	0.0	No
No	Yes	0	Yes	Yes	DSL	Yes	...	No	Yes	No	No	Two year	Yes	Bank transfer (automatic)	61.90	0.0	No

#### ✓ Handling missing values appropriately

**Note:** I replaced the 11 missing values in the **Total Charges** column with zero using a python function to do it. This ensures the dataset is complete and helps maintain accuracy when performing deeper analyses, such as the ones stated later in the task

#### ✓ Standardize column names (convert to lowercase and replace spaces with underscores)

The screenshot shows a Jupyter Notebook cell with the following code:

```
[ ] df.columns = df.columns.str.lower().str.replace(' ', '_')
```

Below the code, there is a preview of the DataFrame columns. The columns are now lowercase and separated by underscores:

```
Index(['customerid', 'gender', 'seniorcitizen', 'partner', 'dependents', 'tenure', 'phoneservice', 'multiplelines', 'internetservice', 'onlinesecurity', 'onlinebackup', 'deviceprotection', 'techsupport', 'streamingtv', 'streamingmovies', 'contract', 'paperlessbilling', 'paymentmethod', 'monthlycharges', 'totalcharges', 'churn'], dtype='object')
```

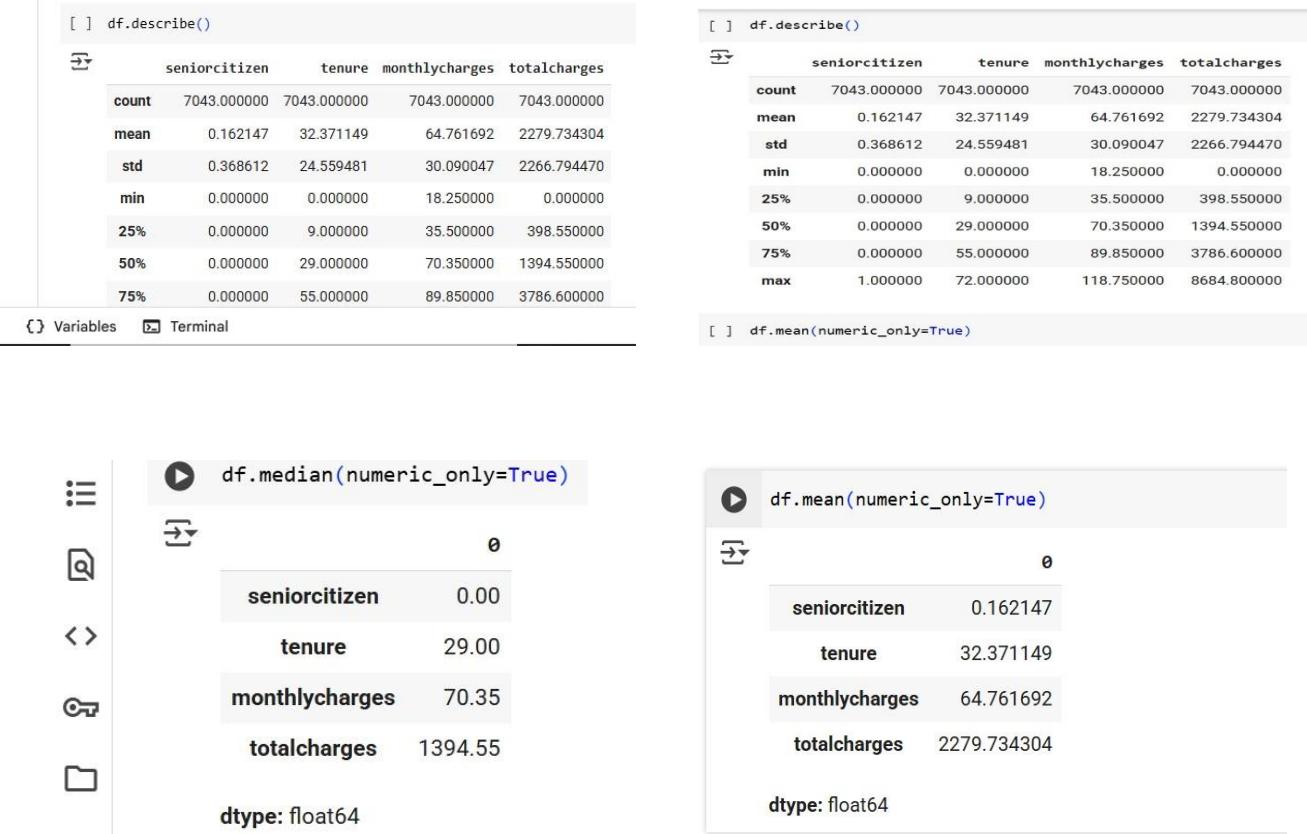
**Note:** The column names were converted to lowercase using a Python function, as shown in the uploaded image, to ensure consistency when running commands.

## TASK 3: EXPLORATORY DATA ANALYSIS (EDA)

- ❖ Understand trends and distributions in the data.
- ❖ Generate summary statistics (mean, median, and mode).
- ❖ Create visualizations for numerical columns (histograms, box plots).
- ❖ Analyze churn rates (e.g., churn vs. non-churn proportions)

### ANALYSIS & SOLUTION

- ✓ Generate summary statistics (mean, median, and mode).



The screenshot shows a Jupyter Notebook interface with three code cells and a sidebar.

**Code Cell 1:** [ ] df.describe()  
The output shows the describe() method for the DataFrame 'df'. It provides summary statistics for the columns: seniorcitizen, tenure, monthlycharges, and totalcharges. The output includes counts, mean, standard deviation (std), minimum (min), 25th percentile (25%), 50th percentile (50%), and 75th percentile (75%).

	seniorcitizen	tenure	monthlycharges	totalcharges
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692	2279.734304
std	0.368612	24.559481	30.090047	2266.794470
min	0.000000	0.000000	18.250000	0.000000
25%	0.000000	9.000000	35.500000	398.550000
50%	0.000000	29.000000	70.350000	1394.550000
75%	0.000000	55.000000	89.850000	3786.600000

**Code Cell 2:** [ ] df.mean(numeric\_only=True)  
The output shows the mean() method for the DataFrame 'df' with numeric\_only=True. It provides the mean value for each column: seniorcitizen (0.162147), tenure (32.371149), monthlycharges (64.761692), and totalcharges (2279.734304).  
dtype: float64

	seniorcitizen	tenure	monthlycharges	totalcharges
seniorcitizen	0.162147			
tenure		32.371149		
monthlycharges			64.761692	
totalcharges				2279.734304

**Code Cell 3:** [ ] df.median(numeric\_only=True)  
The output shows the median() method for the DataFrame 'df' with numeric\_only=True. It provides the median value for each column: seniorcitizen (0.00), tenure (29.00), monthlycharges (70.35), and totalcharges (1394.55).  
dtype: float64

	seniorcitizen	tenure	monthlycharges	totalcharges
seniorcitizen	0.00			
tenure		29.00		
monthlycharges			70.35	
totalcharges				1394.55

## **Summary of Tenure, Senior Citizen, Monthly Charges, and Total Charges**

### **1. Senior Citizen**

- **Mean:** 0.16 → about 16% of the customers are senior citizens.
- Since the median and 75% values are **0**, this confirms that the majority of customers are *not* senior citizens.

### **2. Tenure**

- **Mean:** 32.37 months → the average customer stays for about 2 years and 8 months.
- **Median:** 29 months → half of the customers have stayed less than 29 months.
- **Max:** 72 months → some customers have been with the company for the full 6 years.

### **3. Monthly Charges**

- **Mean:** \$64.76 → Average monthly bill is around \$65.
- **Median:** \$70.35 → half of customers pay less than this amount.
- The spread (min \$18.25 to max \$118.75) shows a wide range in plans and services.

### **4. Total Charges**

- **Mean:** \$2279.73 → on average, a customer has paid about \$2,280 in total.
- **Median:** \$1,394.55 → half of the customers have paid less than this over their tenure.
- The large range (0 to \$8,684.80) suggests big differences in how long customers stay and what plans they choose.

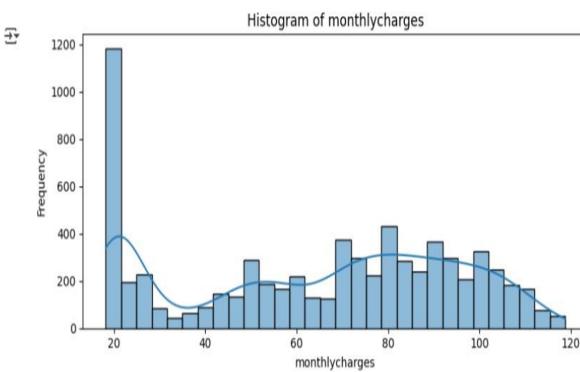
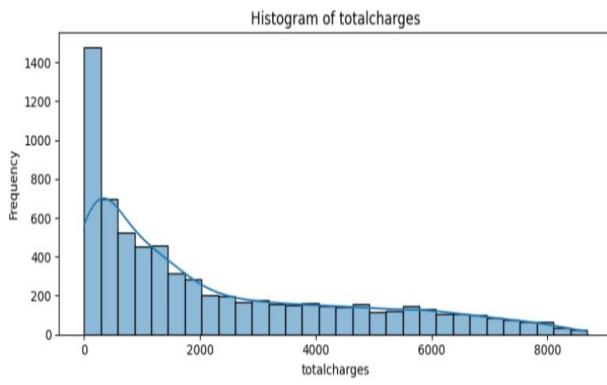
## **Key Observations**

- The majority of customers are **not** senior citizens, but those who are may have different usage or churn behavior.
- Customers staying longer (higher tenure) naturally have higher total charges.
- Monthly charges vary greatly, likely due to differences in service packages, contract lengths, and optional add-ons.
- A small proportion of customers have zero total charges, possibly due to new sign-ups or incomplete billing data.

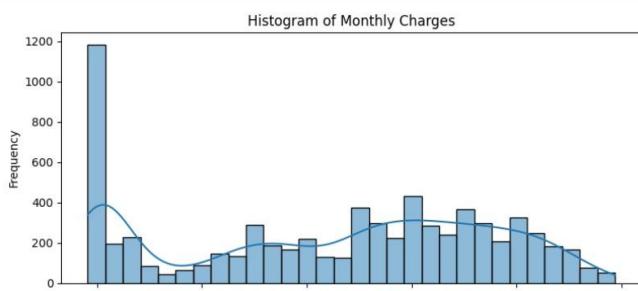
❖ Create visualizations for numerical columns (histograms, box plots).

```
[ ] import matplotlib.pyplot as plt
import seaborn as sns
```

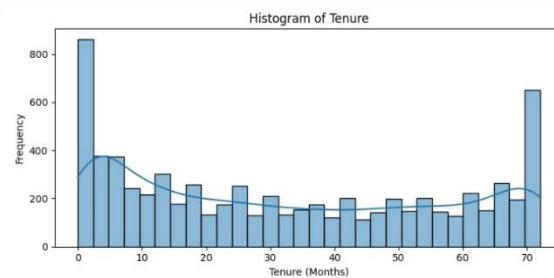
```
[ ] numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns
print(numerical_cols)
```



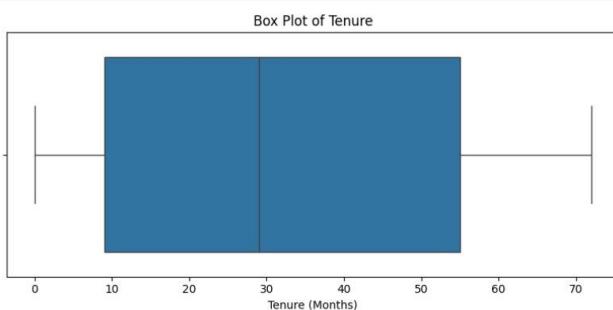
```
❷ plt.figure(figsize=(8, 4))
sns.histplot(df['monthlycharges'], bins=30, kde=True)
plt.title('Histogram of Monthly Charges')
plt.xlabel('Monthly Charges')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



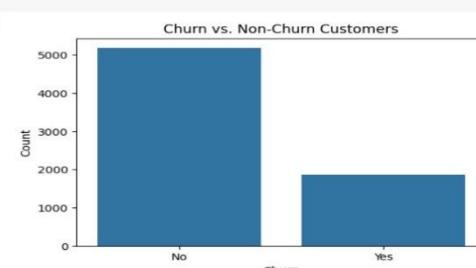
```
[ ] plt.figure(figsize=(8, 4))
sns.histplot(df['tenure'], bins=30, kde=True)
plt.title('Histogram of Tenure')
plt.xlabel('Tenure (Months)')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



```
❷ plt.figure(figsize=(8, 4))
sns.boxplot(x=df['tenure'])
plt.title('Box Plot of Tenure')
plt.xlabel('Tenure (Months)')
plt.tight_layout()
plt.show()
```



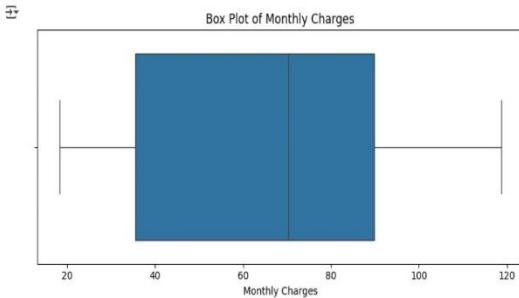
```
[ ] plt.figure(figsize=(8,4))
sns.countplot(x=df['churn'], data=df)
plt.title('Churn vs. Non-Churn Customers')
plt.xticks([0, 1], ['No', 'Yes'])
plt.xlabel('Churn')
plt.ylabel('Count')
plt.show()
```



```

❷ plt.figure(figsize=(8, 4))
sns.boxplot(x=df['monthlycharges'])
plt.title('Box Plot of Monthly Charges')
plt.xlabel('Monthly Charges')
plt.tight_layout()
plt.show()

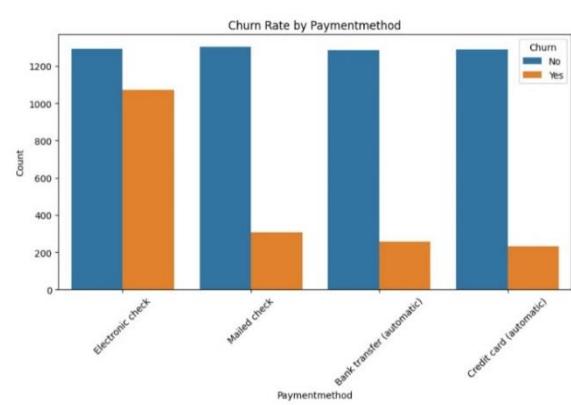
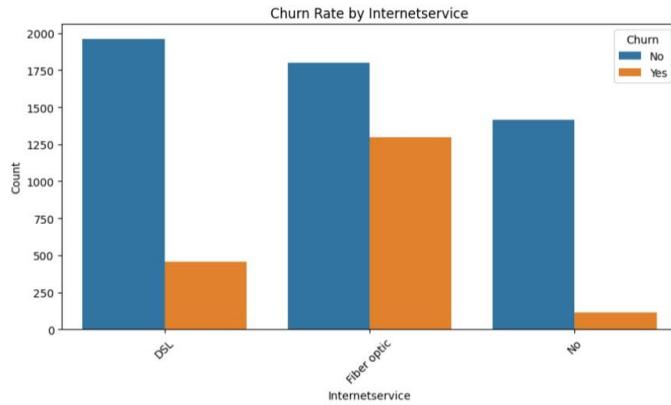
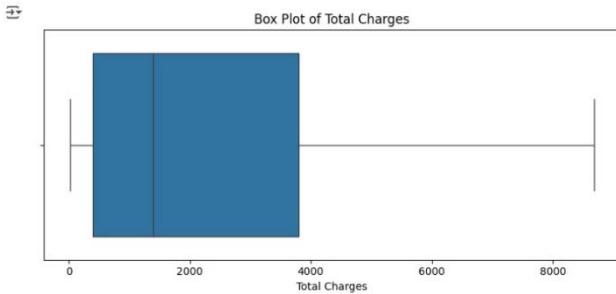
```



```

❷ plt.figure(figsize=(8, 4))
sns.boxplot(x=df['totalcharges'])
plt.title('Box Plot of Total Charges')
plt.xlabel('Total Charges')
plt.tight_layout()
plt.show()

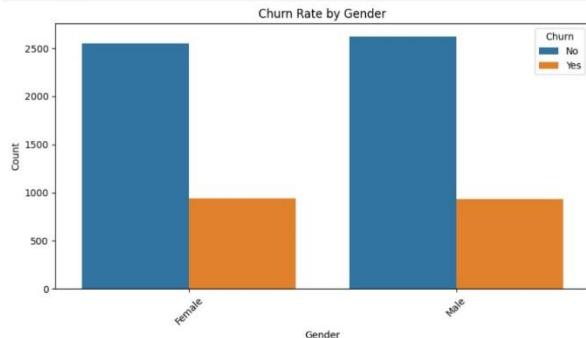
```



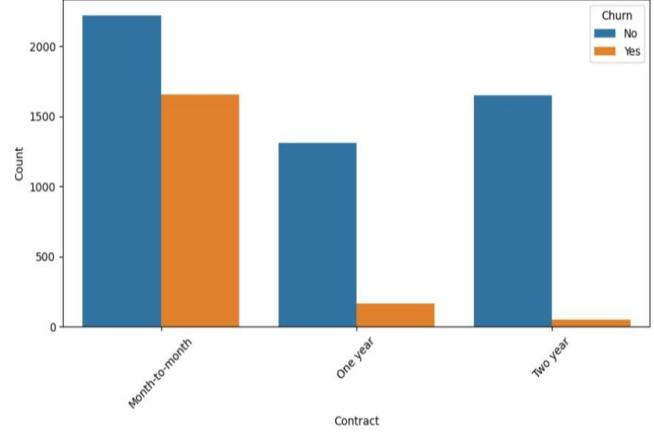
```

for col in ['gender', 'internetservice', 'contract', 'paymentmethod']:
    plt.figure(figsize=(10, 5))
    sns.countplot(x=col, hue='churn', data=df)
    plt.title(f'Churn Rate by {col.title()}')
    plt.xlabel(col.title())
    plt.ylabel('Count')
    plt.legend(title='Churn', labels=['No', 'Yes'])
    plt.show()

```



Churn Rate by Contract



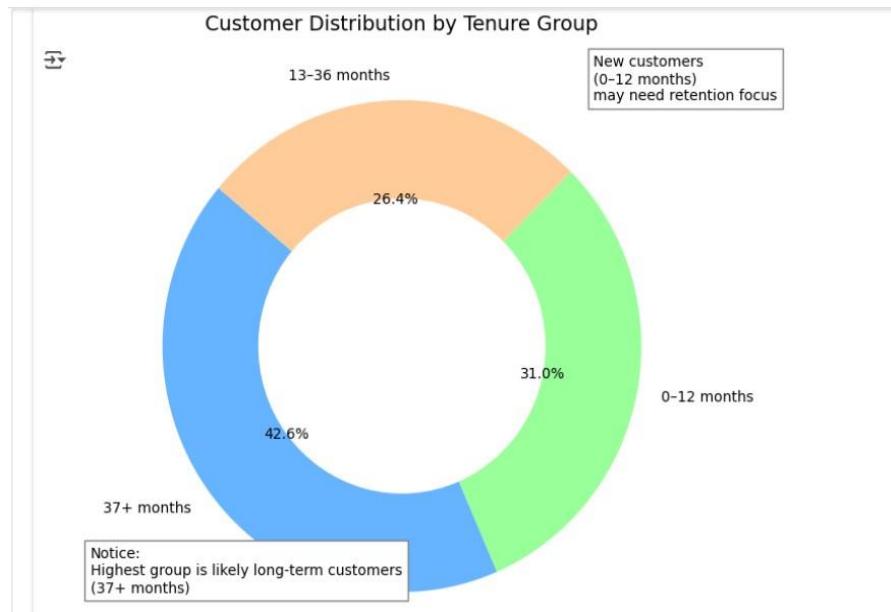
## TASK 4: CUSTOMER SEGMENTATION VISUALIZATION

- ❖ Visualize customer distribution by tenure using pie or donut charts. (e.g., 0-12 months, 13-36 months, 37+ months).
- ❖ Use a clustered bar chart to compare average monthly charges across tenure categories,
- ❖ adding annotations to highlight significant trends

```
[ ] tenure_counts = df['tenure_group'].value_counts()

▶ import matplotlib.pyplot as plt

tenure_counts = df['tenure_group'].value_counts()
colors = ['#66b3ff', '#99ff99', '#ffcc99']
plt.figure(figsize=(7, 7))
wedges, texts, autotexts = plt.pie(
    tenure_counts,
    labels=tenure_counts.index,
    autopct='%1.1f%%',
    startangle=140,
    colors=colors,
    wedgeprops=dict(width=0.4)
)
plt.title('Customer Distribution by Tenure Group', fontsize=14)
plt.text(-1.3, -1.0, 'Notice:\nHighest group is likely long-term customers\n(37+ months)', fontsize=10, bbox=dict(facecolor='white', edgecolor='gray'))
plt.text(0.8, 1.0, 'New customers\n(0-12 months)\nmay need retention focus', fontsize=10, bbox=dict(facecolor='white', edgecolor='gray'))
plt.tight_layout()
plt.show()
```



```

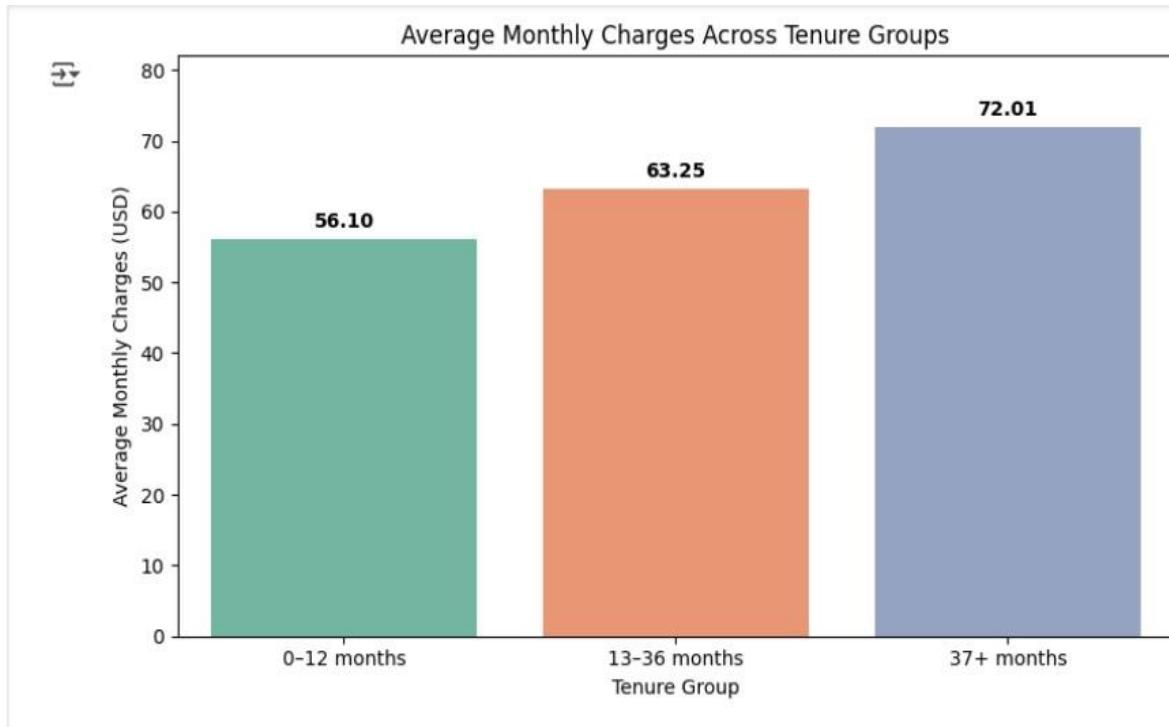
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 5))
bars = sns.barplot(x='Tenure Group', y='Churn_Rate', data=group_stats, hue='Tenure Group', palette='viridis', legend=False)

# Add value annotations on each bar
for bar in bars.patches:
    height = bar.get_height()
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        height,
        f'{height:.2%}',
        ha='center',
        va='bottom',
        fontsize=10,
        fontweight='bold'
    )

plt.title('Churn Rate by Tenure Group')
plt.xlabel('Tenure Group')
plt.ylabel('Churn Rate')
plt.ylim(0, group_stats['Churn_Rate'].max() * 1.1)
plt.tight_layout()
plt.show()

```



```

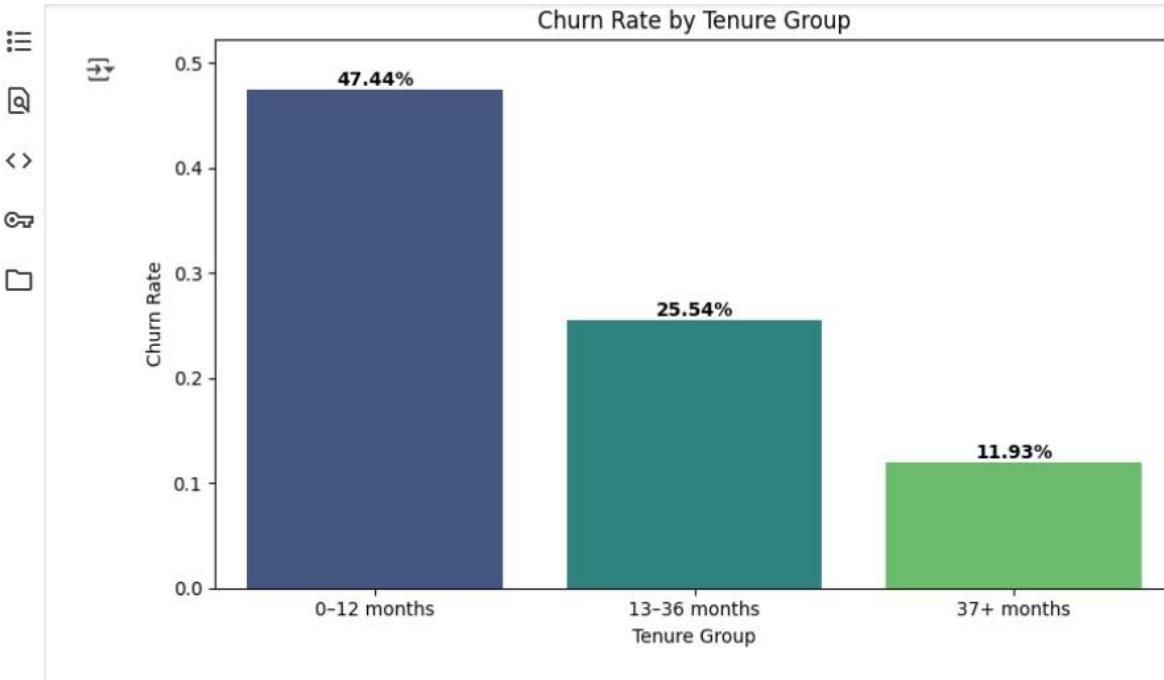
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 5))
bars = sns.barplot(x='tenure_group', y='monthlycharges', data=avg_monthly, hue='tenure_group', palette='Set2', legend=False)

# Add value annotations on each bar
for bar in bars.patches:
    height = bar.get_height()
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        height + 1,
        f'{height:.2f}',
        ha='center',
        va='bottom',
        fontsize=10,
        fontweight='bold'
    )

plt.title('Average Monthly Charges Across Tenure Groups')
plt.xlabel('Tenure Group')
plt.ylabel('Average Monthly Charges (USD)')
plt.ylim(0, avg_monthly['monthlycharges'].max() + 10)
plt.tight_layout()
plt.show()

```



## TASK 5: ADVANCED ANALYSIS

- ❖ Perform deeper analysis by grouping customers by tenure to compute statistics for charges and churn.
- ❖ Analyze churn rates by demographics (e.g., gender, senior citizen status).
- ❖ Payment methods and contract types. Visualize trends over time (if applicable) or lifecycle stages to identify patterns.

```
[19] # Create tenure groups
df['tenure_group'] = pd.cut(df['tenure'], bins=[0, 12, 36, 72], labels=['0-12', '13-36', '37+'])

# Group by tenure group and compute average charges and churn rate
tenure_analysis = df.groupby('tenure_group', observed=False).agg({
    'monthlycharges': 'mean',
    'totalcharges': 'mean',
    'churn': 'mean' # churn rate
}).reset_index()

print(tenure_analysis)

tenure_group  monthlycharges  totalcharges      churn
0           0-12       56.172023     276.621563  0.476782
1          13-36       63.248195    1513.541756  0.255388
2          37+        72.008730    4213.723192  0.119294
```

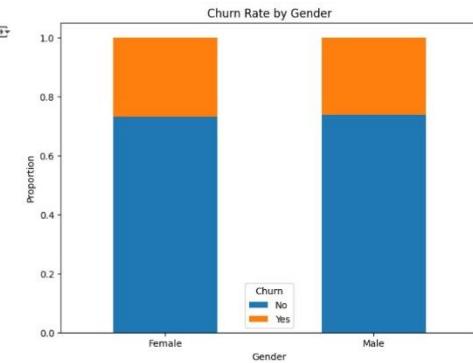
  

```
[20] # Churn rate by gender
gender_churn = df.groupby('gender')[['churn']].value_counts(normalize=True).unstack()
print(gender_churn)

# Churn rate by senior citizen status
senior_churn = df.groupby('seniorcitizen')[['churn']].value_counts(normalize=True).unstack()
print(senior_churn)

churn      0      1
gender
Female  0.738791  0.269208
Male   0.738397  0.261603
churn      0      1
seniorcitizen
0         0.763938  0.236062
```

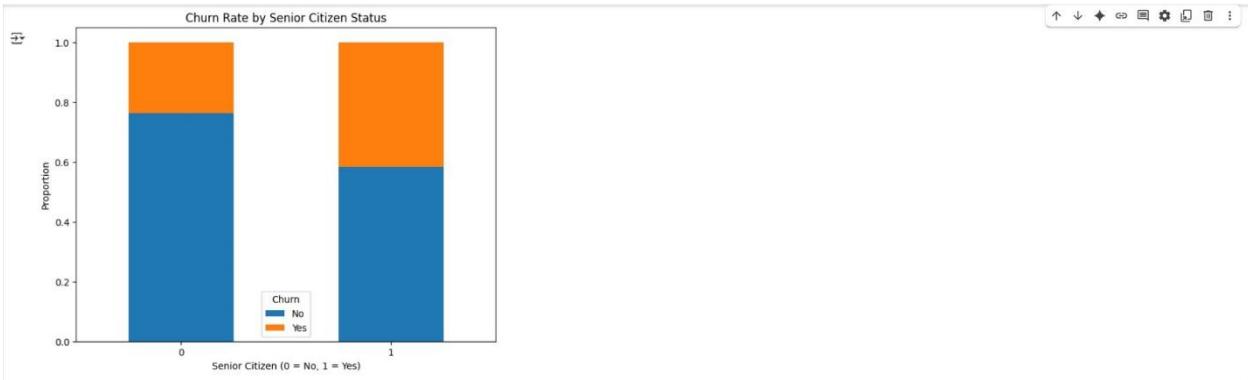
```
[23] # Churn rate by gender
gender_churn.plot(kind='bar', stacked=True, figsize=(8, 6))
plt.title('Churn Rate by Gender')
plt.xlabel('Gender')
plt.ylabel('Proportion')
plt.xticks(rotation=0)
plt.legend(title='Churn', labels=['No', 'Yes'])
plt.show()
```



```

# Churn rate by senior citizen status
senior_churn.plot(kind='bar', stacked=True, figsize=(8, 6))
plt.title('Churn Rate by Senior Citizen Status')
plt.xlabel('Senior Citizen (0 = No, 1 = Yes)')
plt.ylabel('Proportion')
plt.xticks(rotation=90)
plt.legend(title='Churn', labels=['No', 'Yes'])
plt.show()

```



```

# Churn rate by payment method
payment_churn = df.groupby('paymentmethod')[['churn']].value_counts(normalize=True).unstack()
print(payment_churn)

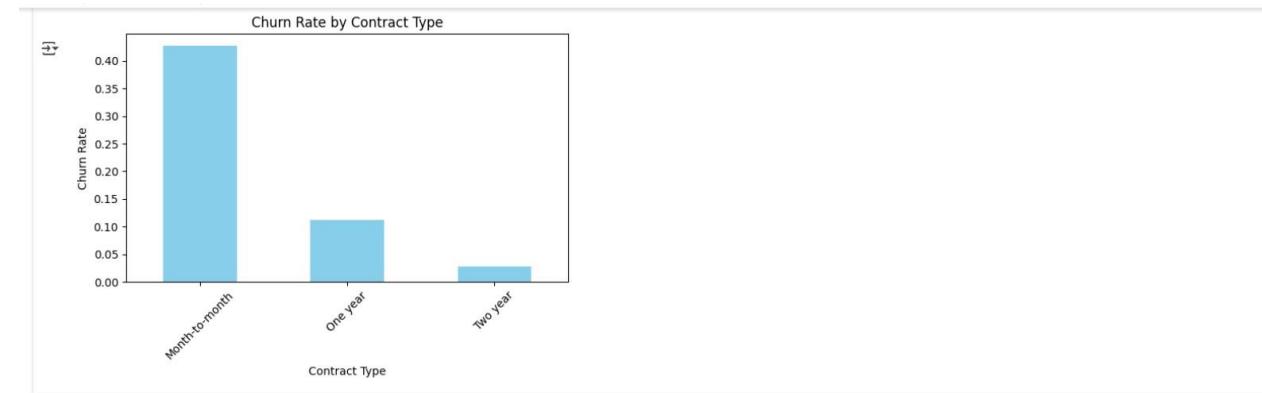
# Churn rate by contract type (barplot)
import seaborn as sns
import matplotlib.pyplot as plt

contract_churn = df.groupby('contract')[['churn']].value_counts(normalize=True).unstack()
contract_churn[1].plot(kind='bar', color='skyblue')

plt.title('Churn Rate by Contract Type')
plt.ylabel('Churn Rate')
plt.xlabel('Contract Type')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

churn
paymentmethod
Bank transfer (automatic) 0.832902 0.167098
Credit card (automatic) 0.847569 0.152431
Electronic check 0.547146 0.452854
Mailed check 0.808933 0.191067

```



```
❸ # Line plot of churn rate over tenure
tenure_churn = df.groupby('tenure')['churn'].apply(lambda x: (x == 1).mean())

plt.figure(figsize=(10,5))
tenure_churn.plot()
plt.title('Churn Rate Across Tenure (Months)')
plt.xlabel('Tenure (Months)')
plt.ylabel('Churn Rate')
plt.grid(True)
plt.tight_layout()
plt.show()
```

