D207

June 13, 2023

0.0.1 Backend Preparation and Imports

[1]:

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

0.0.2 A1. Provide one question that is relevant to your chosen data set.

The question that I wish to answer is the following: Is there a significant difference in the average monthly charges between customers who churn and those who do not churn?

0.0.3 A2. Explain how stakeholders in the organization could benefit from an analysis of the data.

Stakeholders can benefit from answering this question in serveral ways. By understanding if there is a significant difference in the average monthly charges between churned and non-churned customers, the company can gain insights into the pricing dynamics/strategies and its impact on customer retention. This information can be used to optimize pricing strategies, tailor offerings, and potentially reduce customer churn rates.

0.0.4 A3. Identify all of the data in your data set that are relevant to answering your question in part A1.

To answer the above question in section A2, I will be using the following variables from the churn_clean.csv data set: Monthly Charge, Churn, Timely Response, and Tenure.

0.0.5 B1. Using a T-Test to run an analysis of the Churn dataset.

[2]:

```
df = pd.read_csv('churn_clean.csv')
```

To make some variables human readable, I will rename the “Item” variables.

[3]:

```
df.rename(columns = {'Item1':'TimelyResponse',
                          'Item2':'TimelyFixes',
                          'Item3':'TimelyReplacements',
                          'Item4':'Reliability',
                          'Item5':'Options',
                          'Item6':'RespectfulResponses',
                          'Item7':'CourteousExchange',
                          'Item8':'ActiveListening'},
               inplace=True)
```

Now, in order to get a brief view of the dataframe, I will use the head() function.

```
[4]: df.head()
```

```
[4]:   CaseOrder Customer_id                           Interaction  \
     0          1     K409198  aa90260b-4141-4a24-8e36-b04ce1f4f77b
     1          2     S120509  fb76459f-c047-4a9d-8af9-e0f7d4ac2524
     2          3     K191035  344d114c-3736-4be5-98f7-c72c281e2d35
     3          4      D90850  abfa2b40-2d43-4994-b15a-989b8c79e311
     4          5     K662701  68a861fd-0d20-4e51-a587-8a90407ee574

                                     UID         City State                 County  \
     0  e885b299883d4f9fb18e39c75155d990  Point Baker    AK  Prince of Wales-Hyder
     1  f2de8bef964785f41a2959829830fb8a  West Branch    MI                 Ogemaw
     2  f1784cfa9f6d92ae816197eb175d3c71      Yamhill    OR                Yamhill
     3  dc8a365077241bb5cd5ccd305136b05e      Del Mar    CA              San Diego
     4  aabb64a116e83fdc4befc1fbab1663f9    Needville    TX              Fort Bend

          Zip       Lat        Lng  …  MonthlyCharge Bandwidth_GB_Year   \
     0  99927  56.25100 -133.37571  …     172.455519        904.536110
     1  48661  44.32893  -84.24080  …     242.632554        800.982766
     2  97148  45.35589 -123.24657  …     159.947583       2054.706961
     3  92014  32.96687 -117.24798  …     119.956840       2164.579412
     4  77461  29.38012  -95.80673  …     149.948316        271.493436

       TimelyResponse TimelyFixes  TimelyReplacements  Reliability  Options  \
     0              5           5                   5            3        4
     1              3           4                   3            3        4
     2              4           4                   2            4        4
     3              4           4                   4            2        5
     4              4           4                   4            3        4

       RespectfulResponses CourteousExchange ActiveListening
     0                   4                 3               4
     1                   3                 4               4
     2                   3                 3               3
     3                   4                 3               3
     4                   4                 4               5

     [5 rows x 50 columns]
```

For this section, I am interested in are MonthlyCharge and Churn, I will extract these variables into a separate table in order to perform futher comparison and analysis.

[5]:

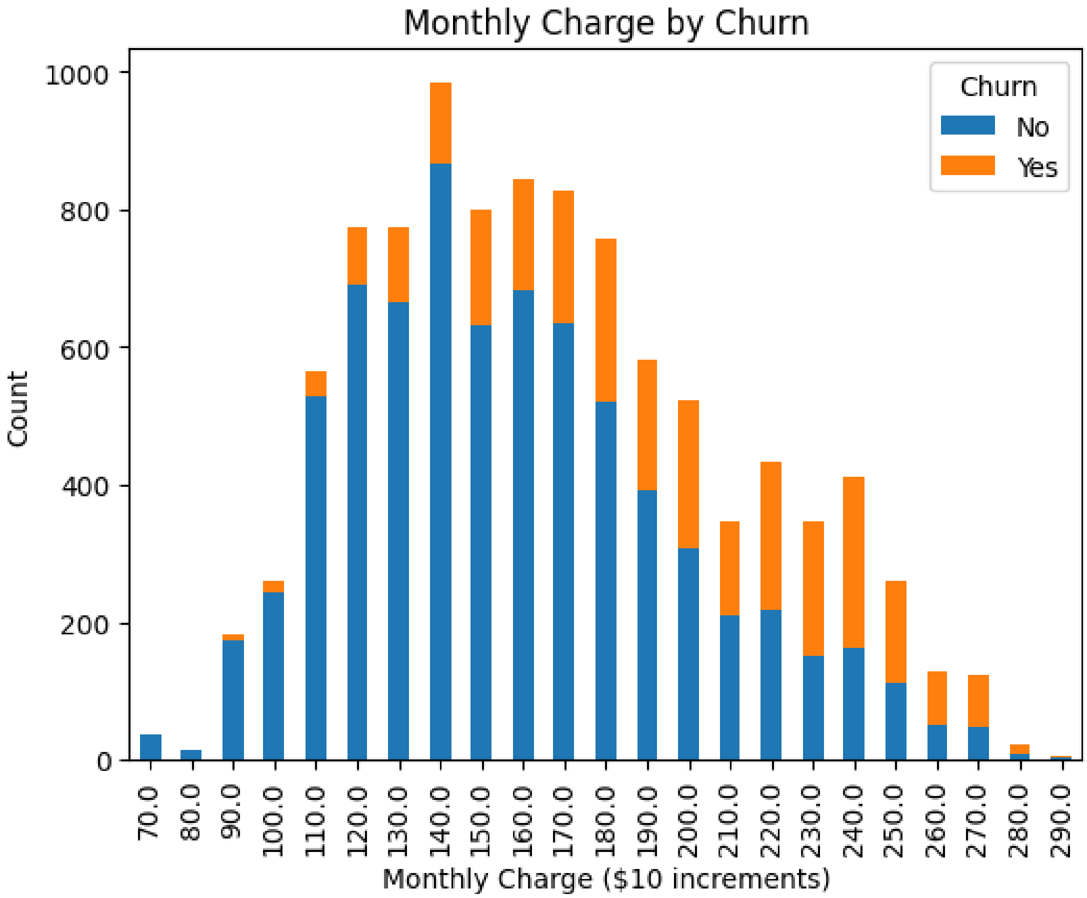
```
comparison_df = df[["MonthlyCharge", "Churn"]].copy()
comparison_df.head()
```

[5]:

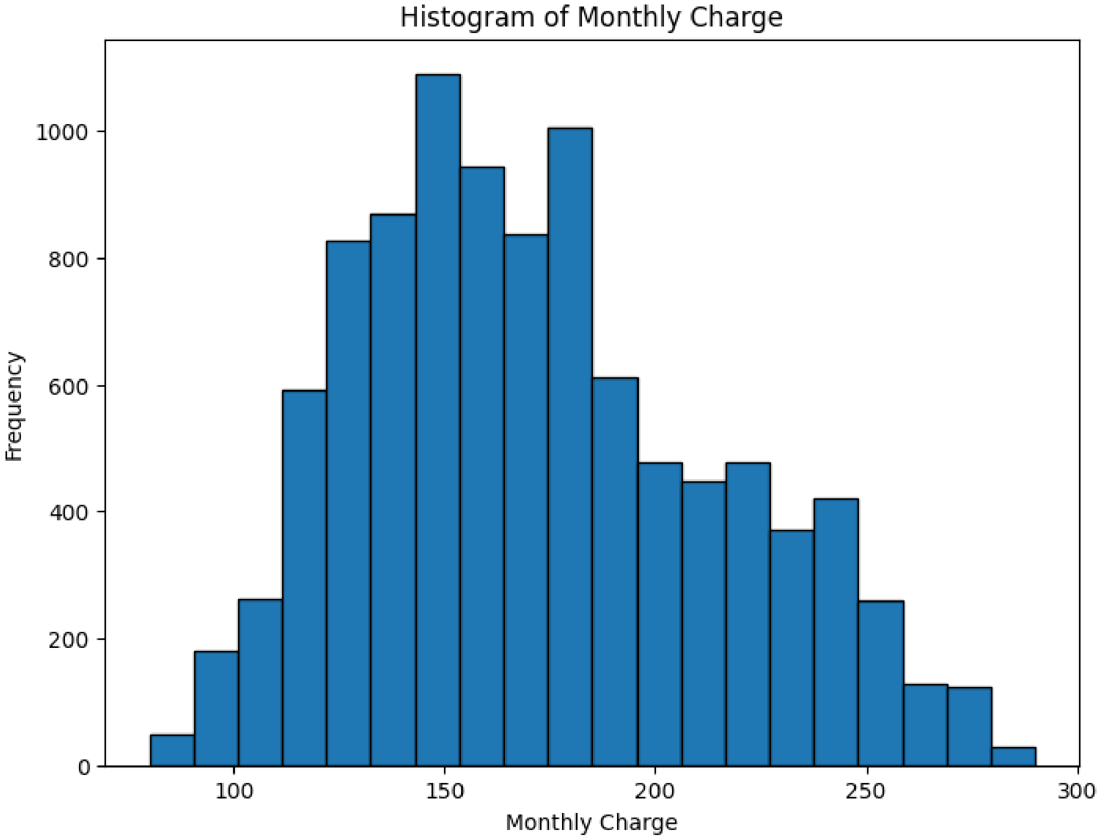
```
   MonthlyCharge Churn
0     172.455519    No
1     242.632554   Yes
2     159.947583    No
3     119.956840    No
4     149.948316   Yes
```

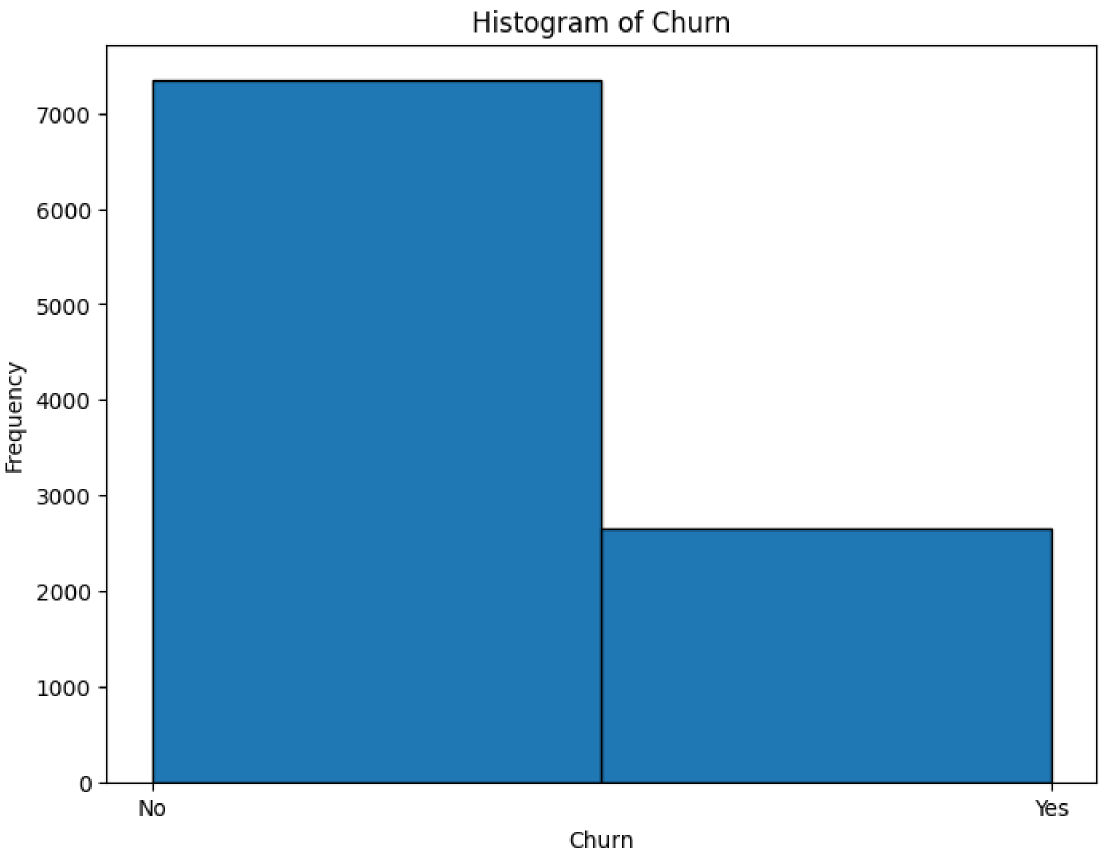
[6]:

```
# Round MonthlyCharge to the nearest $10 increment for easier visualization
comparison_df['MonthlyCharge_Bucket'] = np.floor(comparison_df['MonthlyCharge']␣
 ↪/ 10) * 10

# Create a pivot table with MonthlyCharge_Bucket and Churn
tbl = pd.pivot_table(comparison_df.groupby(['MonthlyCharge_Bucket', 'Churn']).
 ↪size().reset_index(),
                     values=0,
                     index='MonthlyCharge_Bucket',
                     columns=['Churn'],
                     aggfunc=sum)

# Plot the stacked bar chart
tbl.plot(kind='bar', stacked=True)

# Set the labels and title
plt.xlabel('Monthly Charge ($10 increments)')
plt.ylabel('Count')
plt.title('Monthly Charge by Churn')

plt.show()
```



[7]:
```python
# Create a histogram for MonthlyCharge
plt.figure(figsize=(8, 6))
plt.hist(comparison_df['MonthlyCharge'], bins=20, edgecolor='black')
plt.xlabel('Monthly Charge')
plt.ylabel('Frequency')
plt.title('Histogram of Monthly Charge')
plt.show()

# Create a histogram for Churn
plt.figure(figsize=(8, 6))
plt.hist(comparison_df['Churn'], bins=2, edgecolor='black')
plt.xlabel('Churn')
plt.ylabel('Frequency')
plt.title('Histogram of Churn')
plt.show()
```


Histogram of Monthly Charge
Frequency
1000
800
600
400
200
0
100
150
200
250
300
Monthly Charge



0.0.6 B2. Provide the output and the results of any calculations from the analysis you performed.

[8]:

```
# Separate the MonthlyCharge values for churned and non-churned customers
monthly_charge_churned = comparison_df[comparison_df['Churn'] ==␣
 ↪'Yes']['MonthlyCharge']
monthly_charge_non_churned = comparison_df[comparison_df['Churn'] ==␣
 ↪'No']['MonthlyCharge']

# Perform the t-test
t_statistic, p_value = stats.ttest_ind(monthly_charge_churned,␣
 ↪monthly_charge_non_churned)

# Print the results
print("T-Statistic: ", t_statistic)
print("P-Value: ", p_value)
```

```
T-Statistic:  40.18947672237426
P-Value:  0.0
```

0.0.7 B3. Justify why you chose this analysis technique.

I chose to use the T Test to compare two separate groups of data, Monthly Charge and Churn, to see the relationship between the two. I used it to determine if there is a statistically significant difference present in the churn_clean dataset. Additionally, in my professional life, I utilize T Test regularly so I have some familiarity with the process, and as to why this test should be used and under what circumstances.

0.0.8 C1. Identify the distribution of two continuous variables and two categorical variables using univariate statistics from your cleaned and prepared data.

I will analyze the following variables below:

Continuous Variables:

`MonthlyCharge`
`Tenure`

Categorical Variables:

`Churn`
`Timely Response`

[9]:

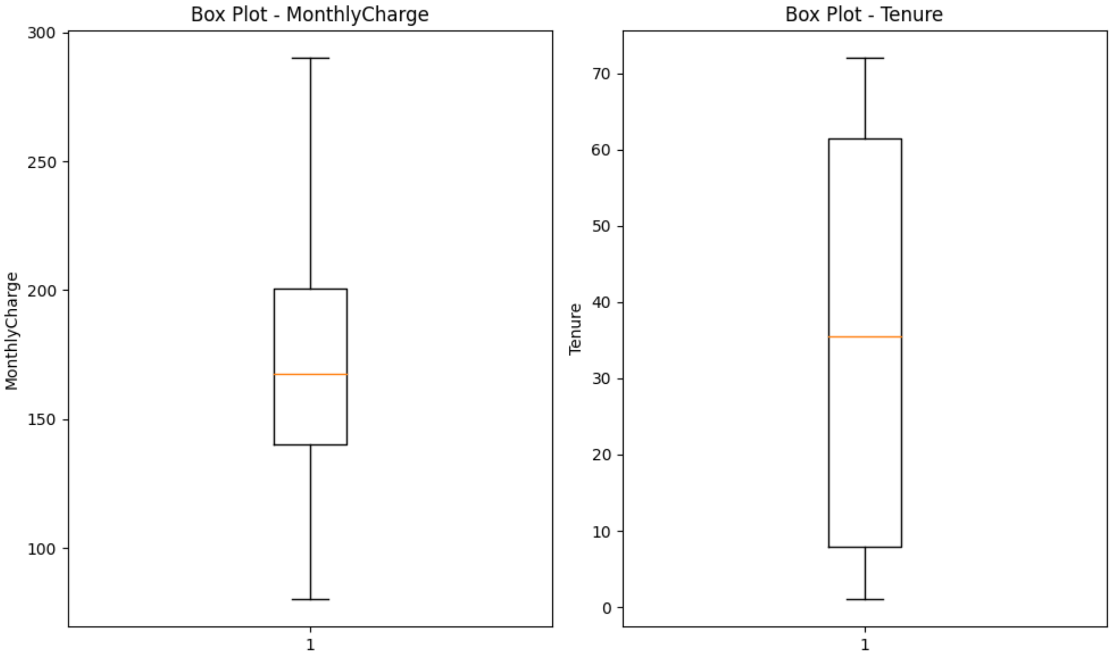
```python
# Create the data frames that I will use for analysis

continuous_df = df[['MonthlyCharge', 'Tenure']].copy()
categorical_df = df[['Churn', 'TimelyResponse']].copy()
```

[10]:

```python
# Summary statistics for MonthlyCharge and Tenure
monthly_charge_stats = continuous_df['MonthlyCharge'].describe()
tenure_stats = continuous_df['Tenure'].describe()

# Box plot for MonthlyCharge and Tenure
fig, axes = plt.subplots(1, 2, figsize=(10, 6))
axes[0].boxplot(continuous_df['MonthlyCharge'])
axes[0].set_title('Box Plot - MonthlyCharge')
axes[0].set_ylabel('MonthlyCharge')
axes[1].boxplot(continuous_df['Tenure'])
axes[1].set_title('Box Plot - Tenure')
axes[1].set_ylabel('Tenure')

# Display the summary statistics
print("Summary Statistics for MonthlyCharge:\n", monthly_charge_stats)
print("\nSummary Statistics for Tenure:\n", tenure_stats)

# Show the box plots
plt.tight_layout()
plt.show()
```

```
Summary Statistics for MonthlyCharge:
 count    10000.000000
```

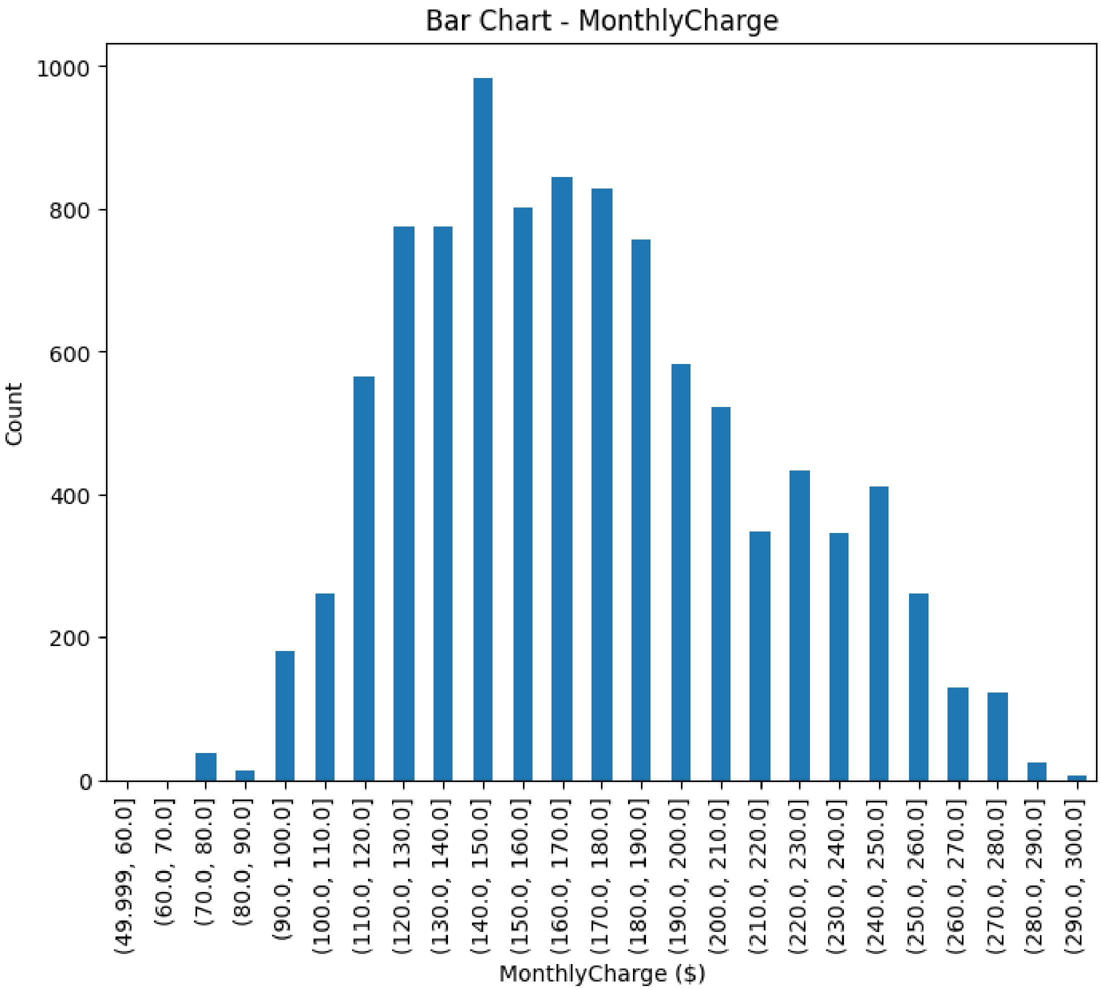
```
mean        172.624816
std          42.943094
min          79.978860
25%         139.979239
50%         167.484700
75%         200.734725
max         290.160419
Name: MonthlyCharge, dtype: float64

Summary Statistics for Tenure:
 count    10000.000000
mean        34.526188
std         26.443063
min          1.000259
25%          7.917694
50%         35.430507
75%         61.479795
max         71.999280
Name: Tenure, dtype: float64
```

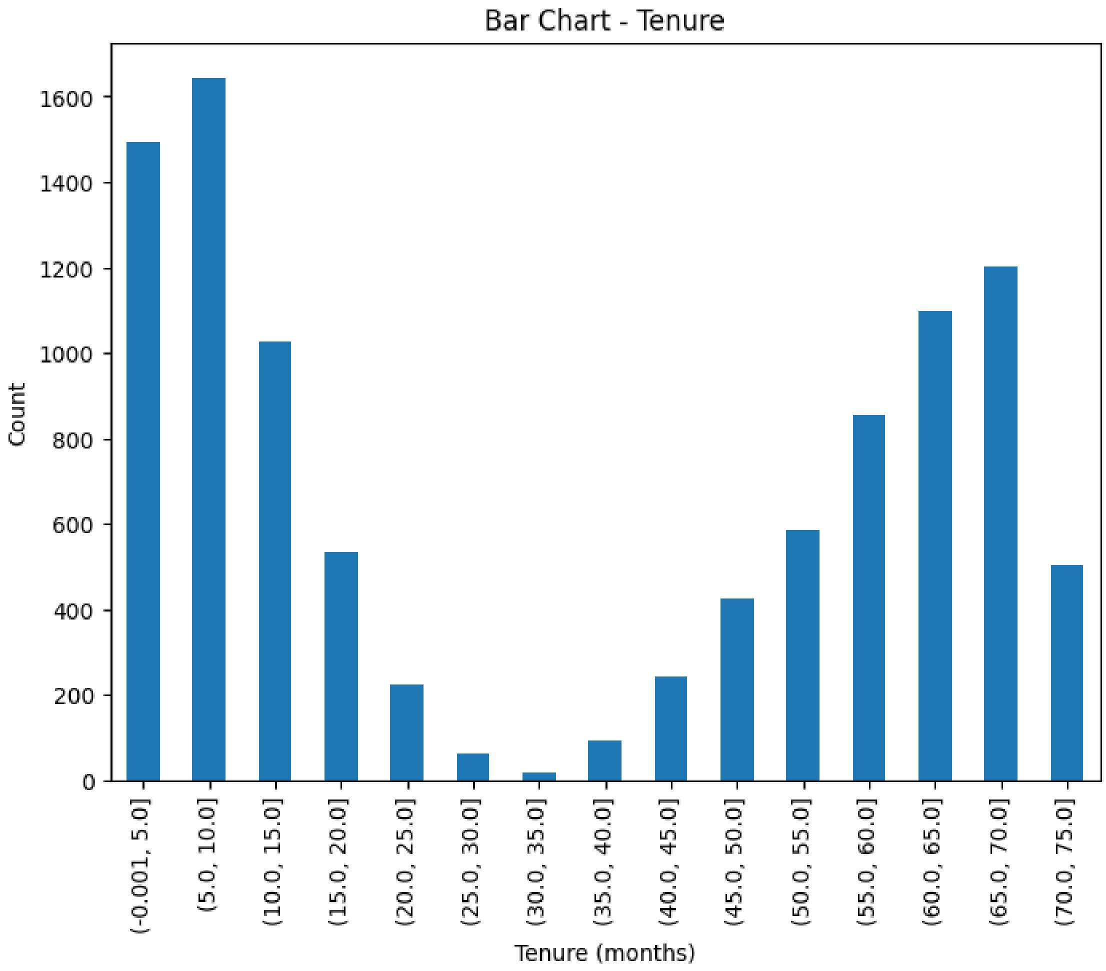


[11]:

```
# Define the bin sizes for MonthlyCharge and Tenure
monthly_charge_bins = np.arange(50, 310, 10)
tenure_bins = np.arange(0, continuous_df['Tenure'].max() + 5, 5)

# Bar chart for MonthlyCharge with $10 increments
```

```
monthly_charge_counts = pd.cut(continuous_df['MonthlyCharge'], bins=monthly_charge_bins, include_lowest=True).value_counts().sort_index()
monthly_charge_counts.plot(kind='bar', figsize=(8, 6))
plt.title('Bar Chart - MonthlyCharge')
plt.xlabel('MonthlyCharge ($)')
plt.ylabel('Count')

plt.show()

# Bar chart for Tenure with 5-year increments
tenure_counts = pd.cut(continuous_df['Tenure'], bins=tenure_bins, include_lowest=True).value_counts().sort_index()
tenure_counts.plot(kind='bar', figsize=(8, 6))
plt.title('Bar Chart - Tenure')
plt.xlabel('Tenure (months)')
plt.ylabel('Count')

plt.show()
```



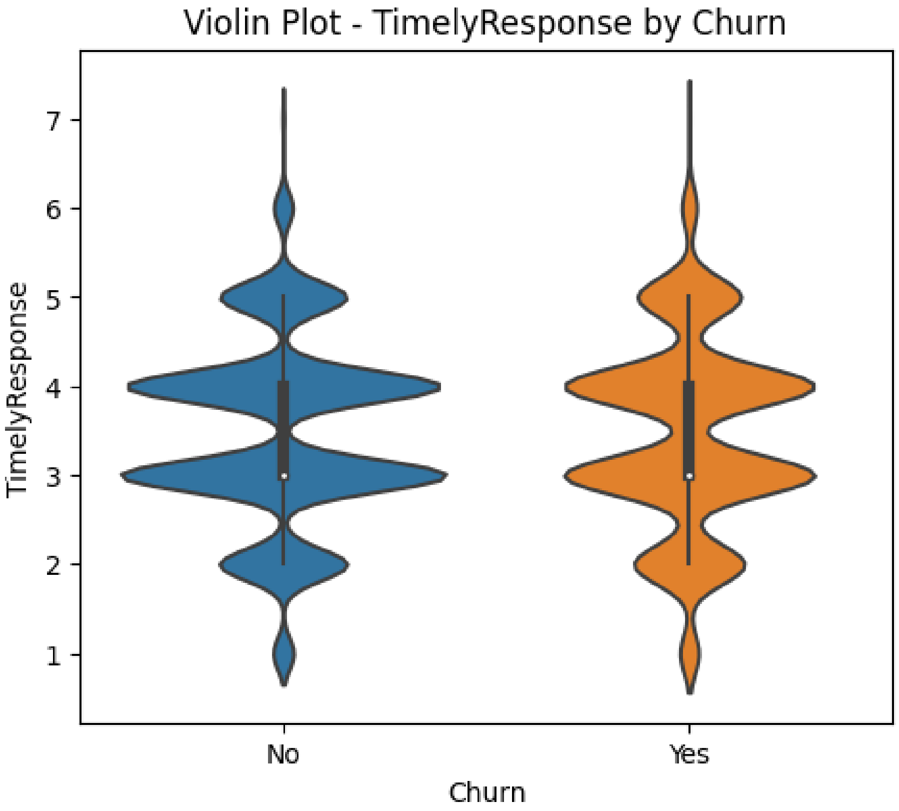


[12]:

```
plt.figure(figsize=(12, 10))

# Violin Plot
plt.subplot(2, 2, 1)
sns.violinplot(data=categorical_df, x='Churn', y='TimelyResponse')
plt.title('Violin Plot - TimelyResponse by Churn')
plt.xlabel('Churn')
plt.ylabel('TimelyResponse')
```

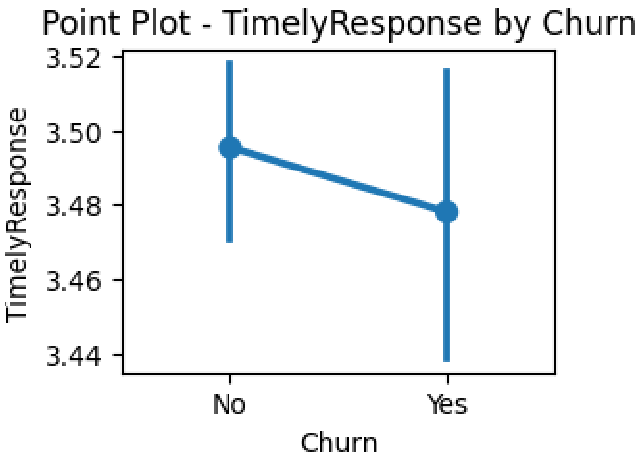
[12]:

```
Text(0, 0.5, 'TimelyResponse')
```

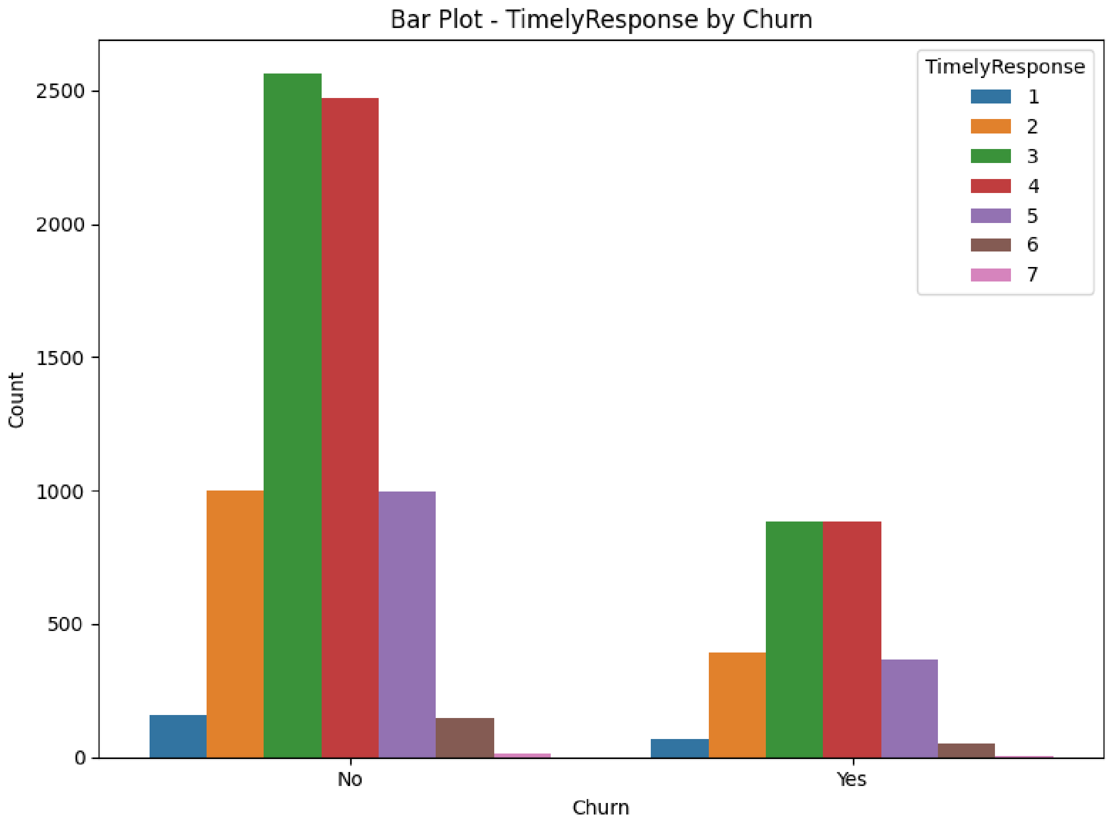


```
[13]: # point plot of categorical data
      plt.subplot(2, 2, 3)
      sns.pointplot(data=categorical_df, x='Churn', y='TimelyResponse')
      plt.title('Point Plot - TimelyResponse by Churn')
      plt.xlabel('Churn')
      plt.ylabel('TimelyResponse')
```

```
[13]: Text(0, 0.5, 'TimelyResponse')
```



[14]:
```
# bar plot of categorical data
plt.figure(figsize=(8, 6))
ax = sns.countplot(data=categorical_df, x='Churn', hue='TimelyResponse')
plt.title('Bar Plot - TimelyResponse by Churn')
plt.xlabel('Churn')
plt.ylabel('Count')
plt.legend(title='TimelyResponse', loc='upper right')
plt.tight_layout()  # Adjusts the plot's layout
plt.show()
```



0.0.9 D. Identify the distribution of two continuous variables and two categorical variables using bivariate statistics from your cleaned and prepared data.

I will be analyzing the same variables in section C1:

Continuous Variables:

```
MonthlyCharge
Tenure
```

Categorical Variables:

```
Churn
Timely Response
```

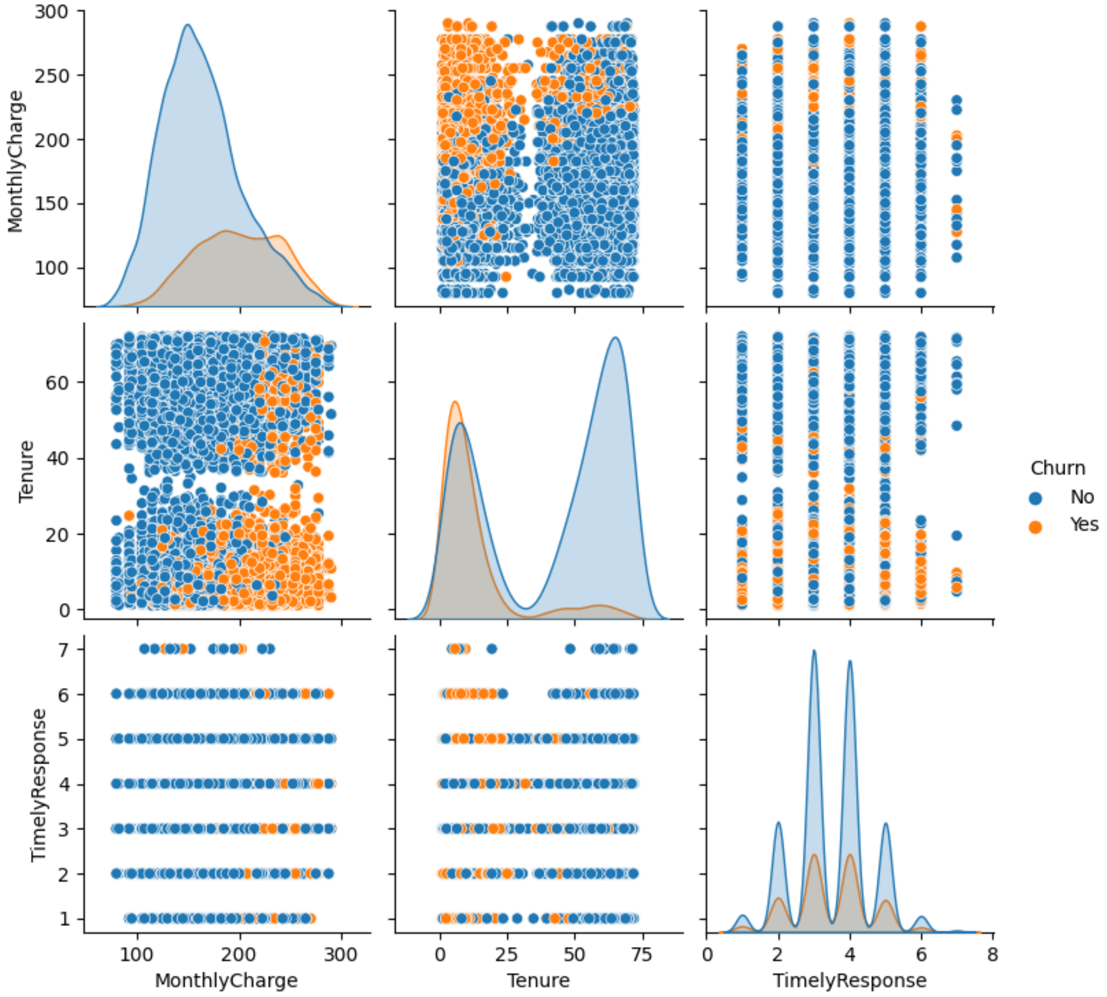
```
[15]: #Display dataframe for heatmap bivariate analysis of correlation
      bivariate_df = df[['MonthlyCharge', 'Tenure', 'Churn', 'TimelyResponse']]
      bivariate_df
```

```
[15]:       MonthlyCharge     Tenure Churn  TimelyResponse
      0        172.455519   6.795513    No               5
      1        242.632554   1.156681   Yes               3
      2        159.947583  15.754144    No               4
```

```
3         119.956840  17.087227    No                4
4         149.948316   1.670972   Yes                4
…              …          …    …               …
9995      159.979400  68.197130    No                3
9996      207.481100  61.040370    No                4
9997      169.974100  47.416890    No                4
9998      252.624000  71.095600    No                4
9999      217.484000  63.350860    No                2

[10000 rows x 4 columns]
```

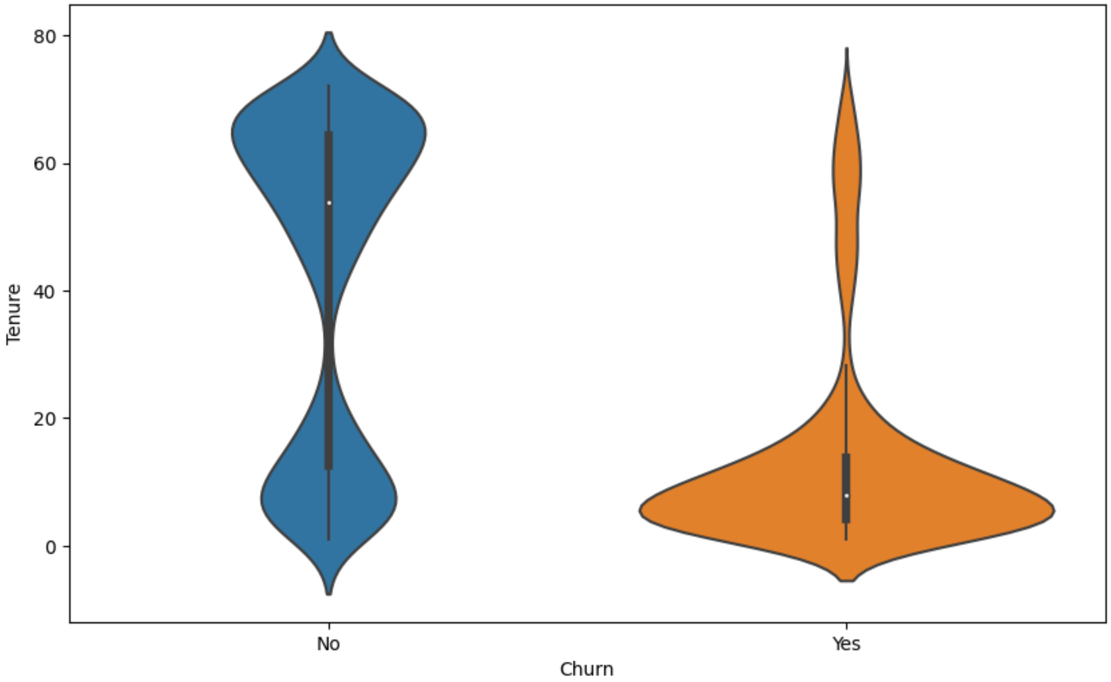
[16]:

```
# Create a new data frame for the below sns plots with the selected variables
bivariate_df = df[['MonthlyCharge', 'Tenure', 'Churn', 'TimelyResponse']].copy()

# scatter plot matrix
sns.pairplot(bivariate_df, hue='Churn')
plt.show()
```



[17]:

```
# violin plot
plt.figure(figsize=(10, 6))
sns.violinplot(data=bivariate_df, x='Churn', y='Tenure')
plt.show()
```



0.0.10 E1: Discuss the results of the hypothesis test.

The results of the hypothesis test indicated a significant difference in the Monthly Charge between customers who churned and customers who did not churn. The t-statistic of 40 and a p-value of 0 suggest that there is a strong association between the Monthly Charge and churn status. This is readily apparent by looking at the scatter plot matrix where there is a large visual difference between Monthly Charge and Churn status, and it implies that the Monthly Charge has a significant impact on the likelihood of churn.

0.0.11 E2: Discuss the limitations of your data analysis.

The following limitations exist in many datasets, but are highlighted below as they are likely to exist in the churn_cleaned dataset:

1. The data analysis does not accurately detail interactions between variables, or the strength to which those interactions exist. For example, Monthly Charge may be highly region specific as there are large variations in the cost of living in defferent regions.
2. The length of time in which this data was captured is surely to produce different results, depending on what time you look at. As an example, using the "COVID" timeframe where

individuals were often more at home would likely produce different data in amount of data consumed as well as other variables.

3. This data set is based on one Company. Different internet/TV providers might have different marketing approaches which would yield them different data. In short, while this dataset is large, it does not accurately reflect the entire consumer population of internet and TV.
4. Usage patterns in data were not included. The time a user uses the internet or TV, which channels and websites a user uses would allow for more nuanced analysis.

0.0.12 E3: Recommend a course of action based on your results.

Based on the results, it is recommended to further investigate the relationship between Monthly Charge and churn. The significant difference suggests that adjusting the Monthly Charge may impact customer churn rates. Further analysis could involve examining the relationship between other variables and churn, considering customer segmentation to identify specific customer groups with high churn rates, and exploring potential strategies to optimize pricing and minimize churn. Additionally, it is important to consider the limitations of the data analysis and conduct further research to gain a comprehensive understanding of the factors influencing churn and to inform actionable strategies.

G. Reference the web sources used to acquire segments of third-party code to support the analysis.

https://www.learndatasci.com/tutorials/python-pandas-tutorial-complete-introduction-for-beginners/

https://matplotlib.org/stable/gallery/index.html

https://seaborn.pydata.org/tutorial.html

https://numpy.org/learn/

https://seaborn.pydata.org/examples/index.html

https://matplotlib.org/

https://www.w3schools.com/python/matplotlib_intro.asp

https://docs.scipy.org/doc/scipy/reference/stats.html

https://www.w3schools.com/python/pandas/default.asp

https://www.w3schools.com/python/numpy/numpy_intro.asp

https://pythonguides.com/scipy-stats/