```
# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.
import kagglehub
blastchar_telco_customer_churn_path = kagglehub.dataset_download('blastchar/telco-customer-churn')

print('Data source import complete.')
```

```
Data source import complete.
```

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Sav
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/telco-customer-churn/WA_Fn-UseC_-Telco-Customer-Churn.csv
```

```
import warnings
warnings.filterwarnings("ignore")

df = pd.read_csv('/kaggle/input/telco-customer-churn/WA_Fn-UseC_-Telco-Customer-Churn.csv')
df.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...

5 rows × 21 columns

```
df.shape
```

```
(7043, 21)
```

```
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      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

```
df.describe()
```

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

```
df.duplicated()
```

	0
0	False
1	False
2	False
3	False
4	False
...	...
7038	False
7039	False
7040	False
7041	False
7042	False

7043 rows × 1 columns

dtype: bool

```
df.isna().sum()
```

	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

dtype: int64

```
df['SeniorCitizen']=df['SeniorCitizen'].astype(object) # Convert SeniorCitizen column into object type

# Convert the values in the TotalCharges column of a Pandas DataFrame (df) into numeric data type (e.g., float or integer)
df["TotalCharges"] = pd.to_numeric(df["TotalCharges"], errors='coerce')
```

```
df = df.drop('customerID', axis=1)
cat_cols=[col for col in df.columns if df[col].dtype=='object']
cat_cols
```

```
['gender',
 'SeniorCitizen',
 'Partner',
 'Dependents',
 'PhoneService',
 'MultipleLines',
 'InternetService',
 'OnlineSecurity',
 'OnlineBackup',
 'DeviceProtection',
 'TechSupport',
 'StreamingTV',
 'StreamingMovies',
 'Contract',
 'PaperlessBilling',
 'PaymentMethod',
 'Churn']
```

```
num_cols=[col for col in df.columns if df[col].dtype !='object']
num_cols
```

```
['tenure', 'MonthlyCharges', 'TotalCharges']
```

handling missing values

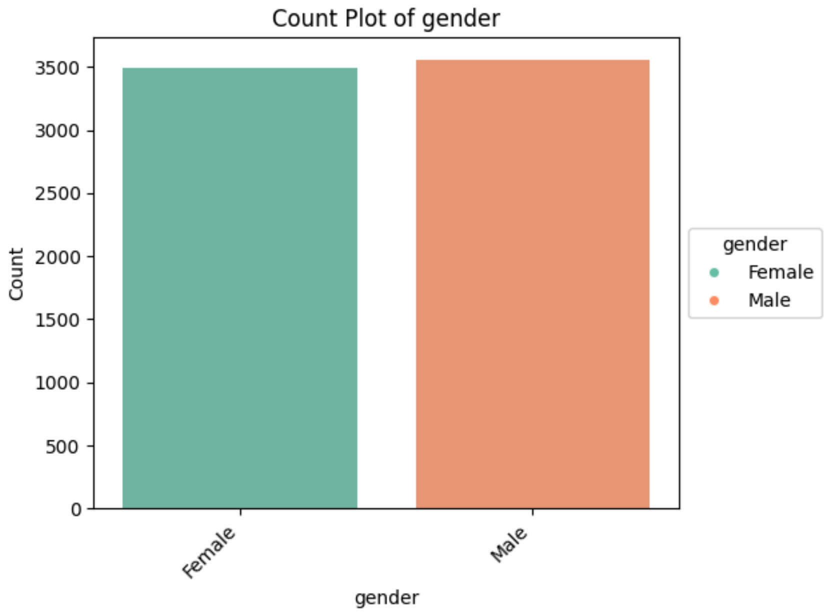
```
# Fill the NaN values with 0

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

```
df.info()
```

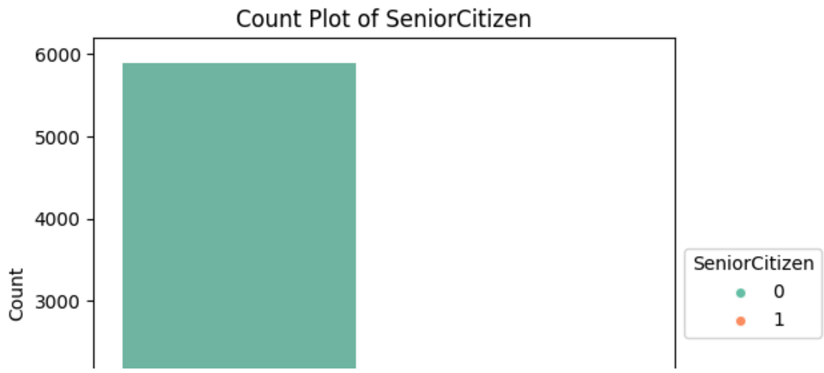
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 20 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   gender            7043 non-null   object 
 1   SeniorCitizen     7043 non-null   object 
 2   Partner           7043 non-null   object 
 3   Dependents        7043 non-null   object 
 4   tenure            7043 non-null   int64  
 5   PhoneService      7043 non-null   object 
 6   MultipleLines     7043 non-null   object 
 7   InternetService   7043 non-null   object 
 8   OnlineSecurity    7043 non-null   object 
 9   OnlineBackup      7043 non-null   object 
 10  DeviceProtection  7043 non-null   object 
 11  TechSupport       7043 non-null   object 
 12  StreamingTV       7043 non-null   object 
 13  StreamingMovies   7043 non-null   object 
 14  Contract          7043 non-null   object 
 15  PaperlessBilling  7043 non-null   object 
 16  PaymentMethod     7043 non-null   object 
 17  MonthlyCharges    7043 non-null   float64
 18  TotalCharges      7043 non-null   float64
 19  Churn             7043 non-null   object 
dtypes: float64(2), int64(1), object(17)
memory usage: 1.1+ MB
```

```python
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

def cat_summary(dataframe, col_name, plot=False):
    # Print summary table of value counts and their ratios
    print(pd.DataFrame({col_name: dataframe[col_name].value_counts(),
                        "Ratio": 100 * dataframe[col_name].value_counts() / len(dataframe)}))
    print("\n##########################################\n")

    # Plot if plot=True
    if plot:
        # Count plot without hue to avoid FutureWarning
        ax = sns.countplot(x=col_name, data=dataframe, palette="Set2", hue=col_name)

        # Set labels and title
        plt.xlabel(col_name)
        plt.ylabel("Count")
        plt.title(f"Count Plot of {col_name}")

        # Rotate x-axis labels for better readability
        plt.xticks(rotation=45, ha='right')

        # Manually create the legend
        unique_values = dataframe[col_name].unique()
        handles = [plt.Line2D([0], [0], marker='o', color='w', label=value,
                              markerfacecolor=sns.color_palette("Set2")[i])
                   for i, value in enumerate(unique_values)]

        # Adjust legend position to the right side of the plot
        plt.legend(title=col_name, handles=handles, loc="center left", bbox_to_anchor=(1, 0.5))

        # Adjust layout to prevent clipping
        plt.tight_layout()
        plt.show()

# Assuming cat_cols is a list of categorical columns
for col in cat_cols:
    cat_summary(df, col, plot=True)
```

```
        gender     Ratio
gender
Male      3555  50.47565
Female    3488  49.52435

##########################################
```




```
              SeniorCitizen      Ratio
SeniorCitizen
0                      5901  83.785319
1                      1142  16.214681

##########################################
```

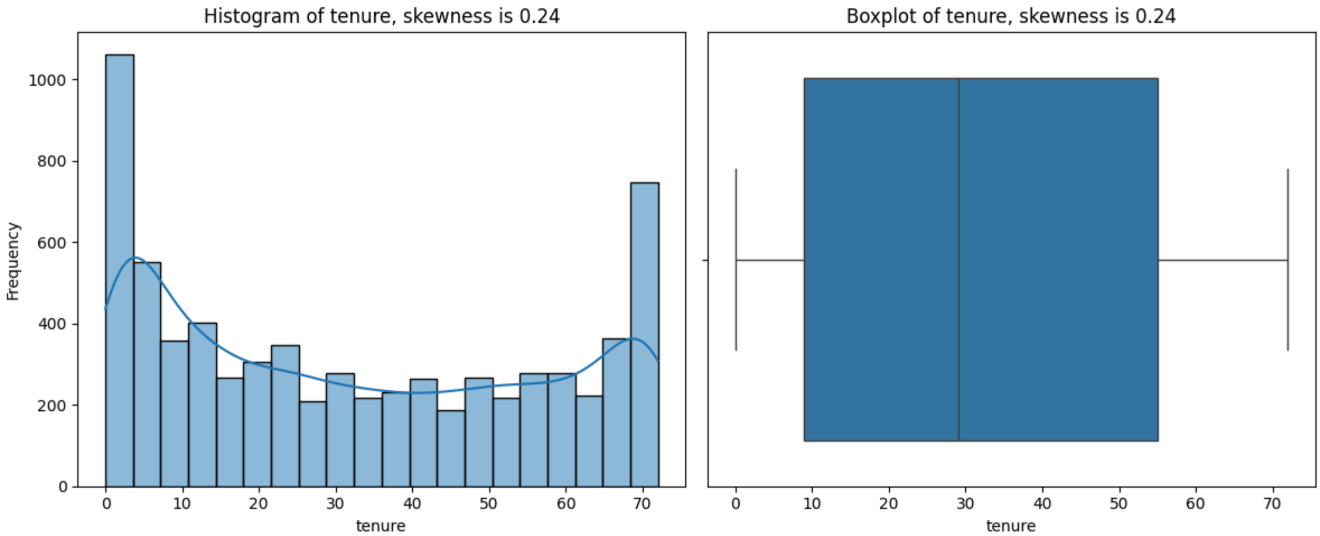



```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

def num_summary(dataframe, numerical_col):
    print('\n***************', numerical_col, '***************\n')
    print(dataframe[numerical_col].describe())

def univariate_plots(dataframe, numerical_cols):
    for col in numerical_cols:
        # Call num_summary to print statistics
        num_summary(dataframe, col)

        # Create a figure for the histogram
        plt.figure(figsize=(12, 5))

        # Histogram
        plt.subplot(1, 2, 1)
        sns.histplot(dataframe[col], bins=20, kde=True)
        plt.title(f'Histogram of {col}, skewness is {round(dataframe[col].skew(), 2)}')
        plt.xlabel(col)
        plt.ylabel('Frequency')

        # Boxplot
        plt.subplot(1, 2, 2)
        sns.boxplot(x=dataframe[col])
        plt.title(f'Boxplot of {col}, skewness is {round(dataframe[col].skew(), 2)}')
        plt.xlabel(col)
```

```
        plt.tight_layout()
        plt.show()

# List of numerical columns to plot
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']

# Generate univariate plots
univariate_plots(df, num_cols)
```

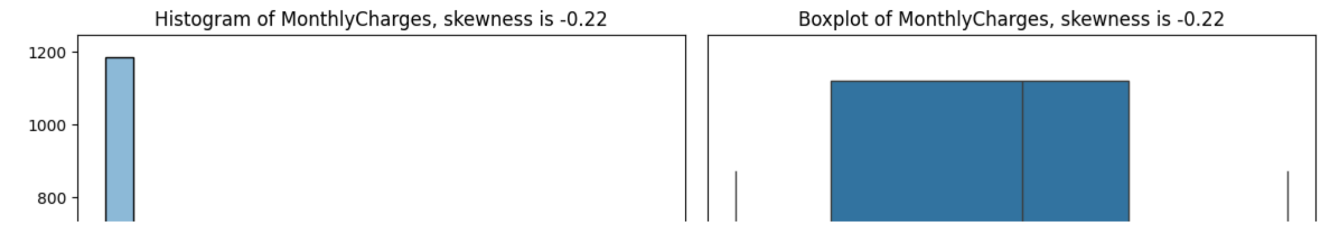
```
                          Partner
************** tenure ***************
            Dependents    Ratio
Dependents
No                4933  70.041176
Yes               2110  29.958824
##############################################
count    7043.000000
mean       32.371149
std        24.559481
min         0.000000
25%         9.000000
50%        29.000000
75%        55.000000
max        72.000000
Name: tenure, dtype: float64
```

Count Plot of Dependents

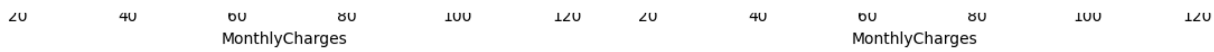



```
         PhoneService    Ratio
PhoneService
Yes              6361  90.316626
No                682   9.683374
************** MonthlyCharges ***************
count    7043.000000
mean       64.761692
std        30.090047
##############################################
min        18.250000
25%        35.500000
50%        70.350000
75%        89.850000
max       118.750000
Name: MonthlyCharges, dtype: float64
```

Count Plot of PhoneService

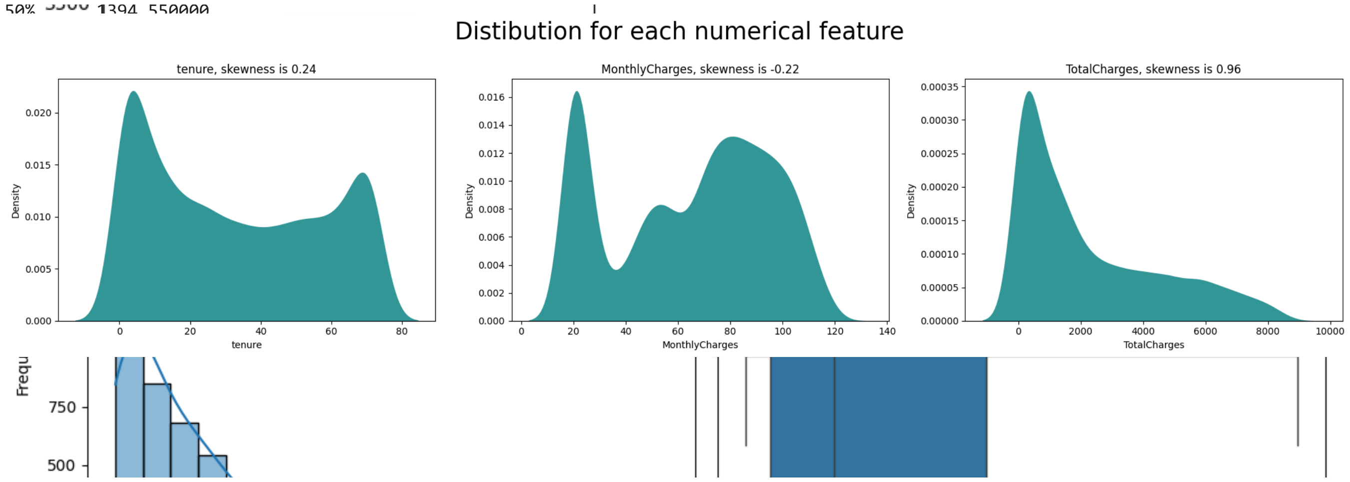



```
def dist_custom(dataset, columns_list, rows, cols, suptitle):
    fig, axs = plt.subplots(rows, cols,figsize=(20,5))
    fig.suptitle(suptitle,y=1, size=25)
    axs = axs.flatten()
    for i, data in enumerate(columns_list):
        sns.kdeplot(dataset[data], ax=axs[i], fill=True, alpha=0.8, linewidth=0, color='#008080')
        axs[i].set_title(data + ', skewness is '+str(round(dataset[data].skew(axis = 0, skipna = True),2)))

dist_custom(dataset=df, columns_list=num_cols, rows=1, cols=3, suptitle='Distibution for each numerical feature')
plt.tight_layout()
```



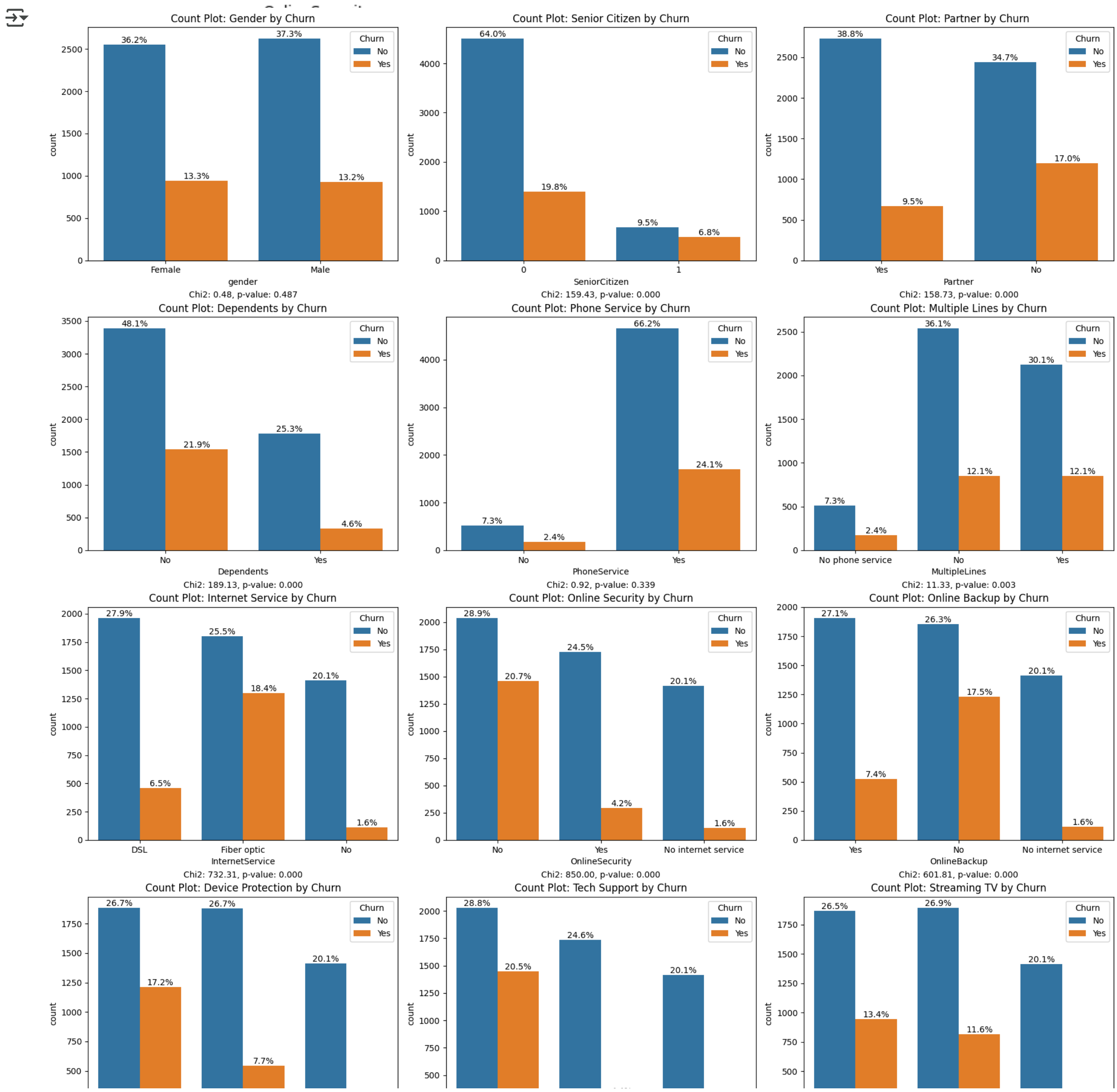

```
No                   3390  48.132898
Yes                  2971  42.183729
************** TotalCharges ***************
No phone service      682   9.683374
count    7043.000000
mean     2279.734304
##############################################
std      2266.794470
min         0.000000
25%       398.550000
```

Count Plot of MultipleLines

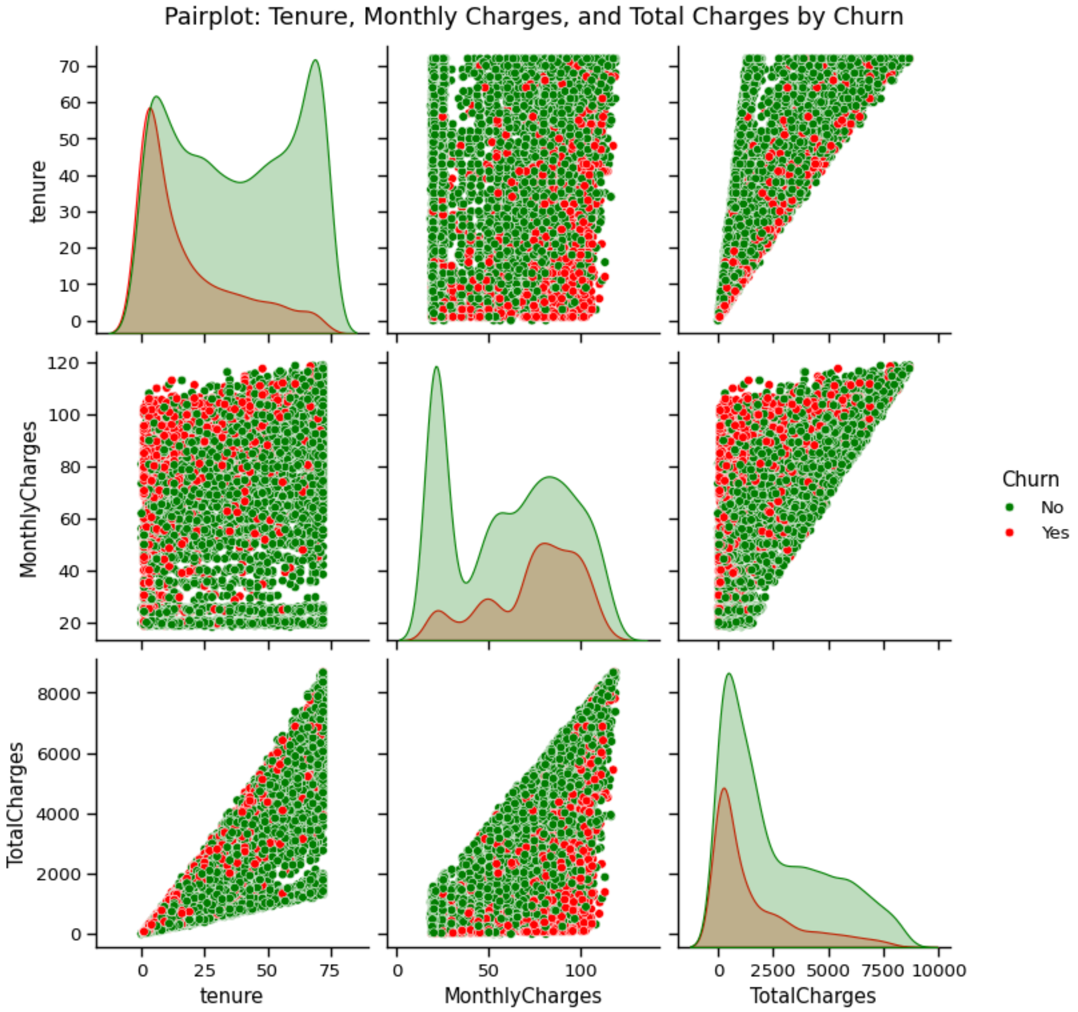



```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from scipy.stats import chi2_contingency

# Function to calculate Chi-Square and p-value
def chi_square_test(dataframe, feature, target):
    contingency_table = pd.crosstab(dataframe[feature], dataframe[target])
    chi2, p, _, _ = chi2_contingency(contingency_table)
    return chi2, p

# List of features to plot
features = [
    ('gender', 'Count Plot: Gender by Churn'),
    ('SeniorCitizen', 'Count Plot: Senior Citizen by Churn'),
    ('Partner', 'Count Plot: Partner by Churn '),
    ('Dependents', 'Count Plot: Dependents by Churn'),
    ('PhoneService', 'Count Plot: Phone Service by Churn'),
    ('MultipleLines', 'Count Plot: Multiple Lines by Churn'),
    ('InternetService', 'Count Plot: Internet Service by Churn'),
    ('OnlineSecurity', 'Count Plot: Online Security by Churn'),
    ('OnlineBackup', 'Count Plot: Online Backup by Churn'),
    ('DeviceProtection', 'Count Plot: Device Protection by Churn'),
    ('TechSupport', 'Count Plot: Tech Support by Churn'),
    ('StreamingTV', 'Count Plot: Streaming TV by Churn'),
    ('StreamingMovies', 'Count Plot: Streaming Movies by Churn'),
    ('Contract', 'Count Plot: Contract by Churn'),
    ('PaperlessBilling', 'Count Plot: Paperless Billing by Churn'),
    ('PaymentMethod', 'Count Plot: Payment Method by Churn'),
]

# Create subplots with enough space
fig, axes = plt.subplots(6, 3, figsize=(18, 30))

# Loop through the features for count plots
for i, (feature, title) in enumerate(features):
    ax = axes[i // 3, i % 3]  # Determine the correct subplot
    sns.countplot(data=df, x=feature, hue='Churn', ax=ax)
    ax.set_title(title)

    # Calculate total counts for percentages
    total = len(df)

    # Add percentage annotations on top of the bars
    for p in ax.patches:
        height = p.get_height()
        if height == 0:  # Skip if the bar height is 0 (0.0%)
            continue
        percentage = (height / total) * 100
        ax.annotate(f'{percentage:.1f}%',
                    (p.get_x() + p.get_width() / 2., height),
                    ha='center', va='bottom')

    # Perform Chi-Square test and get results
    chi2, p = chi_square_test(df, feature, 'Churn')
    ax.text(0.5, -0.15, f'Chi2: {chi2:.2f}, p-value: {p:.3f}', ha='center', va='center', transform=ax.transAxes)

    # Use plt.xticks() for proper x-tick label rotation if needed
    if feature == 'PaymentMethod':
        plt.setp(ax.xaxis.get_majorticklabels(), rotation=45, ha='right')

# Adjust layout
plt.tight_layout()
```

```
plt.show()
```

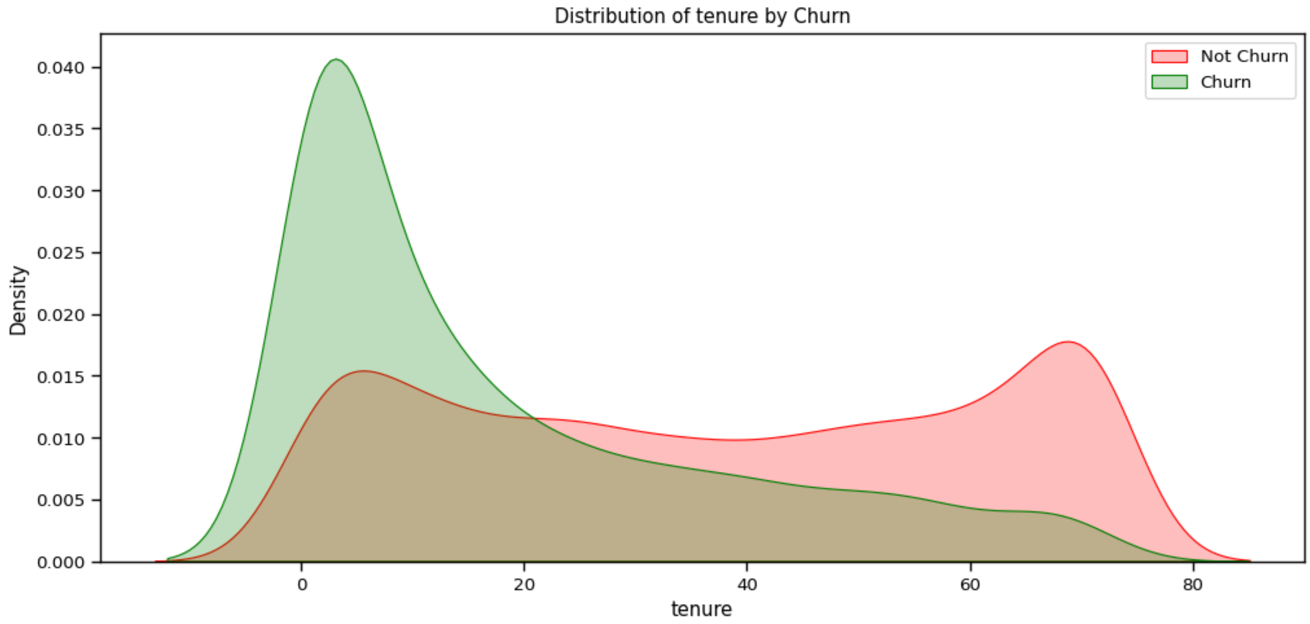


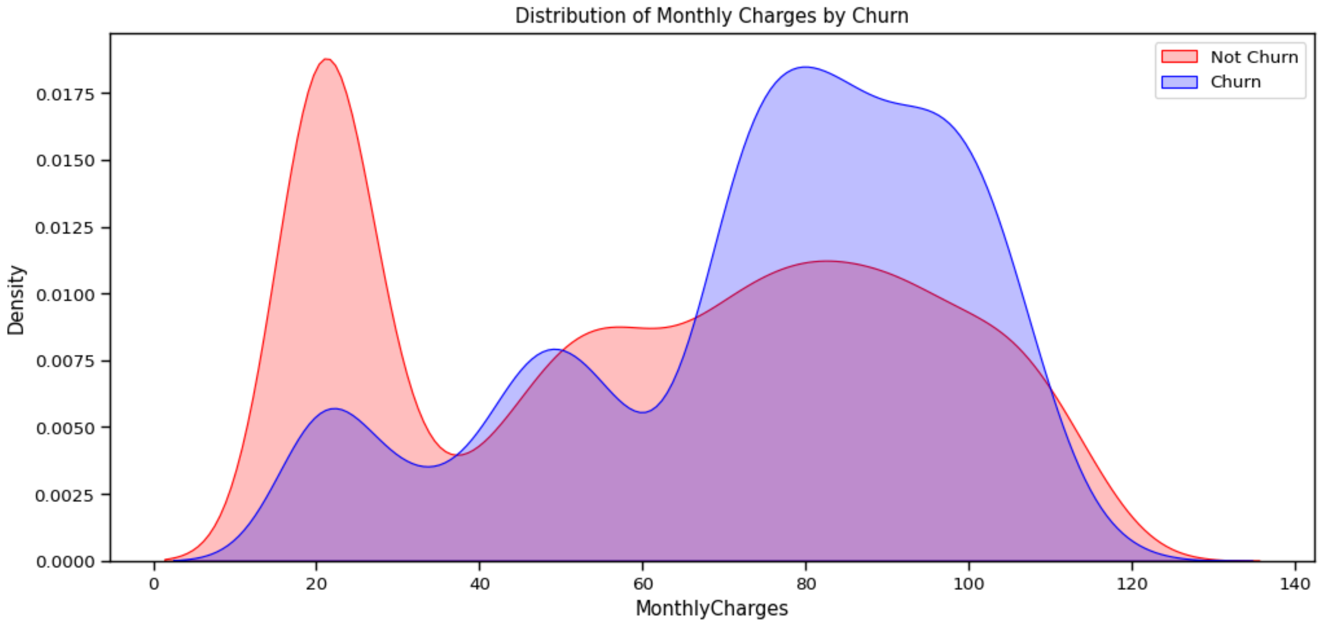

```
import seaborn as sns
import matplotlib.pyplot as plt

# Create a DataFrame for the selected columns
plot_data = df[['tenure', 'MonthlyCharges', 'TotalCharges', 'Churn']]

# Set the context for the plot
sns.set_context("paper", font_scale=1.1)

# Create pairplot
pair_plot = sns.pairplot(plot_data, hue='Churn', palette={'Yes': 'red', 'No': 'green'})

# Set titles
pair_plot.fig.suptitle('Pairplot: Tenure, Monthly Charges, and Total Charges by Churn', y=1.02)

# Show the plot
plt.show()
```

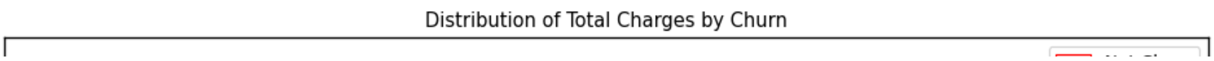



```
import seaborn as sns
import matplotlib.pyplot as plt

# Set the context for the plots
sns.set_context("paper", font_scale=1.1)

# List of features for KDE plots
features = [
    ('tenure', 'Red', 'Green', 'Distribution of tenure by Churn'),
    ('MonthlyCharges', 'Red', 'Blue', 'Distribution of Monthly Charges by Churn'),
    ('TotalCharges', 'Red', 'Green', 'Distribution of Total Charges by Churn')
]

# List of numerical columns for box plots
num_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']

# Create subplots with 2 rows for KDE and 3 for box plots
fig, axes = plt.subplots(3, 1, figsize=(12, 18))

# Loop through the features to create KDE plots
for i, (feature, color_no, color_yes, title) in enumerate(features):
    ax = sns.kdeplot(df[feature][df["Churn"] == 'No'], color=color_no, fill=True, ax=axes[i])
    ax = sns.kdeplot(df[feature][df["Churn"] == 'Yes'], ax=ax, color=color_yes, fill=True)

    # Add legend and labels
    ax.legend(["Not Churn", "Churn"], loc='upper right')
    ax.set_ylabel('Density')
    ax.set_xlabel(feature)
    ax.set_title(title)

# Create box plots for the numerical columns in a new figure
fig2, axes2 = plt.subplots(3, 1, figsize=(12, 18))

# Loop through numerical columns to create box plots
for i, col in enumerate(num_cols):
    ax = sns.boxplot(x='Churn', y=col, data=df, ax=axes2[i])
    ax.set_title(f'Bivariate Analysis: {col} vs Churn')

# Adjust layout for both figures
```

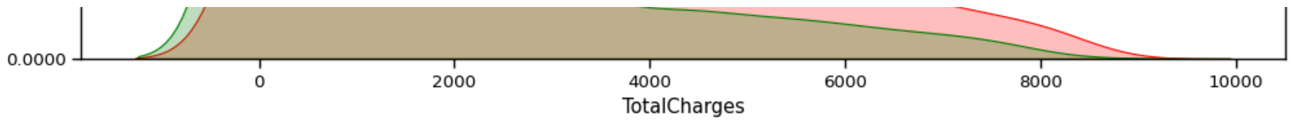
```
plt.tight_layout()
plt.show()
```

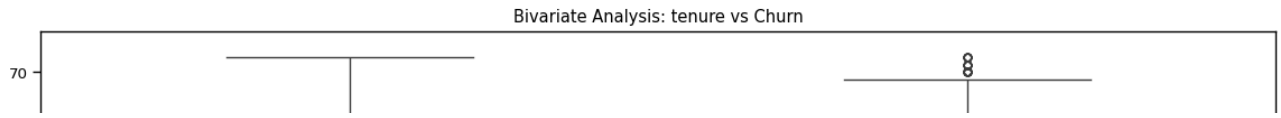


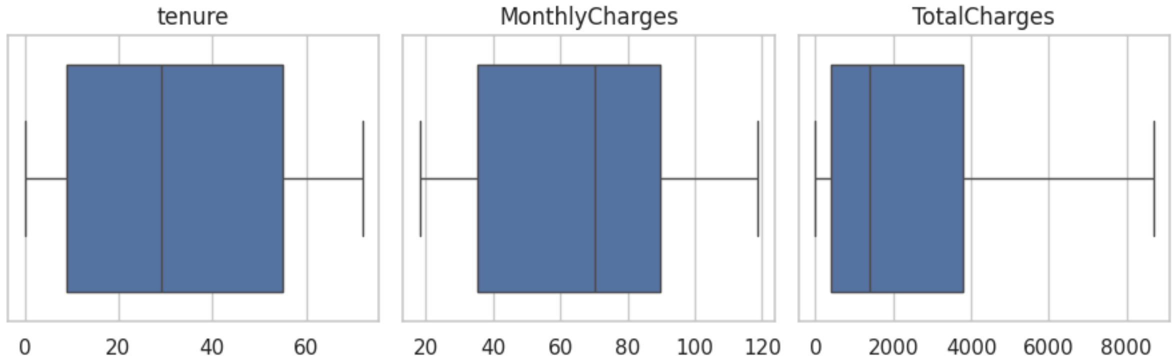





```
sns.set(style="whitegrid")

numerical_columns = [col for col in df.columns if df[col].dtype !='object']

num_columns = 5
num_rows = (len(numerical_columns) + num_columns - 1) // num_columns

plt.figure(figsize=(num_columns * 3, num_rows * 3))

for i, column in enumerate(numerical_columns, 1):
    plt.subplot(num_rows, num_columns, i)
    sns.boxplot(x=df[column])
    plt.title(column)
    plt.xlabel('')

plt.tight_layout()
plt.show()
```








```
for col in num_cols:
  print(f"Column: {col}")
  print(f"Minimum: {df[col].min()}")
  print(f"Maximum: {df[col].max()}")
  print("-" * 20)
```

```
Column: tenure
Minimum: 0
Maximum: 72
--------------------
Column: MonthlyCharges
Minimum: 18.25
Maximum: 118.75
--------------------
Column: TotalCharges
Minimum: 0.0
Maximum: 8684.8
--------------------
```

```
df.columns
```

```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity',
       'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV',
       'StreamingMovies', 'Contract', 'PaperlessBilling', 'PaymentMethod',
       'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

```
# Columns to apply the transformation
columns_to_update = ['OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies']

# Replace 'No internet service' with 'No' in the specified columns
df[columns_to_update] = df[columns_to_update].replace('No internet service', 'No')


# Replace 'No phone service' with 'No' in the 'MultipleLines' column
df['MultipleLines'] = df['MultipleLines'].replace('No phone service', 'No')
# Define the bins and corresponding labels
bins = [-1, 24, 48, 72]
labels = ['New', 'Mid', 'Long']

# Create the tenure_bin column
df['tenure_bin'] = pd.cut(df['tenure'], bins=bins, labels=labels, right=True)
```

```
df['ChurnRisk'] = ((df['tenure'] < 12) & (df['MonthlyCharges'] > df['MonthlyCharges'].median())).astype(int)
# Create interaction feature between Contract type and Internet service type
df['Contract_Internet'] = ((df['Contract'] == 'Month-to-month') & (df['InternetService'] == 'Fiber optic')).astype(int)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 23 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   gender            7043 non-null   object
 1   SeniorCitizen     7043 non-null   object
 2   Partner           7043 non-null   object
 3   Dependents        7043 non-null   object
 4   tenure            7043 non-null   int64
 5   PhoneService      7043 non-null   object
 6   MultipleLines     7043 non-null   object
 7   InternetService   7043 non-null   object
 8   OnlineSecurity    7043 non-null   object
 9   OnlineBackup      7043 non-null   object
 10  DeviceProtection  7043 non-null   object
 11  TechSupport       7043 non-null   object
```

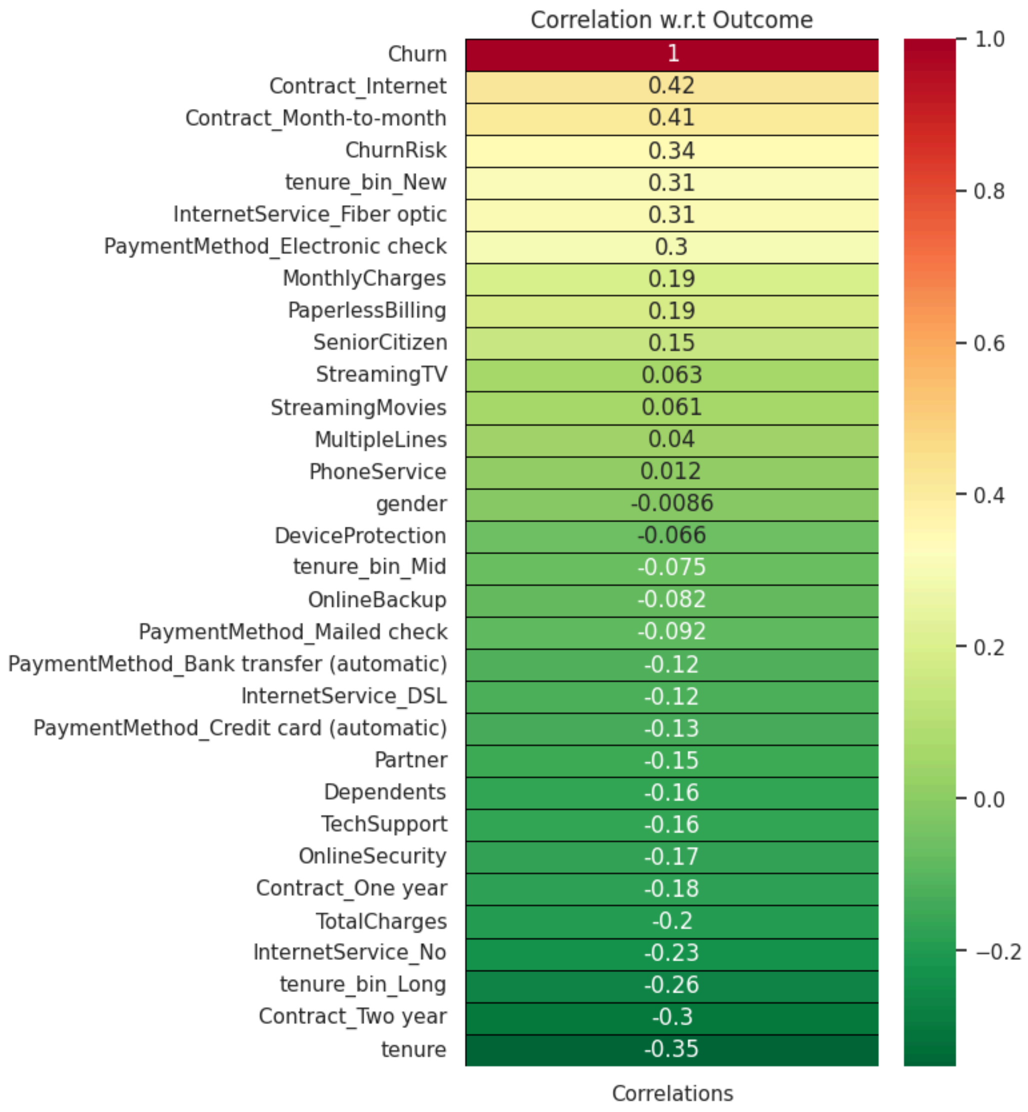
```
 12  StreamingTV        7043 non-null   object
 13  StreamingMovies    7043 non-null   object
 14  Contract           7043 non-null   object
 15  PaperlessBilling   7043 non-null   object
 16  PaymentMethod      7043 non-null   object
 17  MonthlyCharges     7043 non-null   float64
 18  TotalCharges       7043 non-null   float64
 19  Churn              7043 non-null   object
 20  tenure_bin         7043 non-null   category
 21  ChurnRisk          7043 non-null   int64
 22  Contract_Internet  7043 non-null   int64
dtypes: category(1), float64(2), int64(3), object(17)
memory usage: 1.2+ MB
```

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder

# Columns for Label Encoding (binary columns)
label_cols = ['gender', 'Partner', 'Dependents', 'PhoneService',
              'PaperlessBilling', 'Churn', 'OnlineSecurity',
              'OnlineBackup', 'DeviceProtection', 'TechSupport',
              'StreamingTV', 'StreamingMovies','MultipleLines','SeniorCitizen']

# Initialize the LabelEncoder
le = LabelEncoder()

# Apply Label Encoding to the binary columns, checking if they exist in the DataFrame
for col in label_cols:
    if col in df.columns:
        df[col] = le.fit_transform(df[col])
        # Columns for One Hot Encoding (nominal columns)
one_hot_cols = ['Contract', 'PaymentMethod', 'InternetService','tenure_bin']

# Initialize the OneHotEncoder
ohe = OneHotEncoder()
ohe_result = ohe.fit_transform(df[one_hot_cols])
ohe_columns = ohe.get_feature_names_out(one_hot_cols)
df = pd.concat([df.drop(columns=one_hot_cols), pd.DataFrame(ohe_result.toarray(), columns=ohe_columns)],axis=1)
```

```
from sklearn.preprocessing import MinMaxScaler,StandardScaler
mms = MinMaxScaler() # Normalization
mms1 = MinMaxScaler()
#ss = StandardScaler() # Standardization


df['tenure'] = mms.fit_transform(df[['tenure']])
df['MonthlyCharges'] = mms.fit_transform(df[['MonthlyCharges']])
df['TotalCharges'] = mms1.fit_transform(df[['TotalCharges']])
```

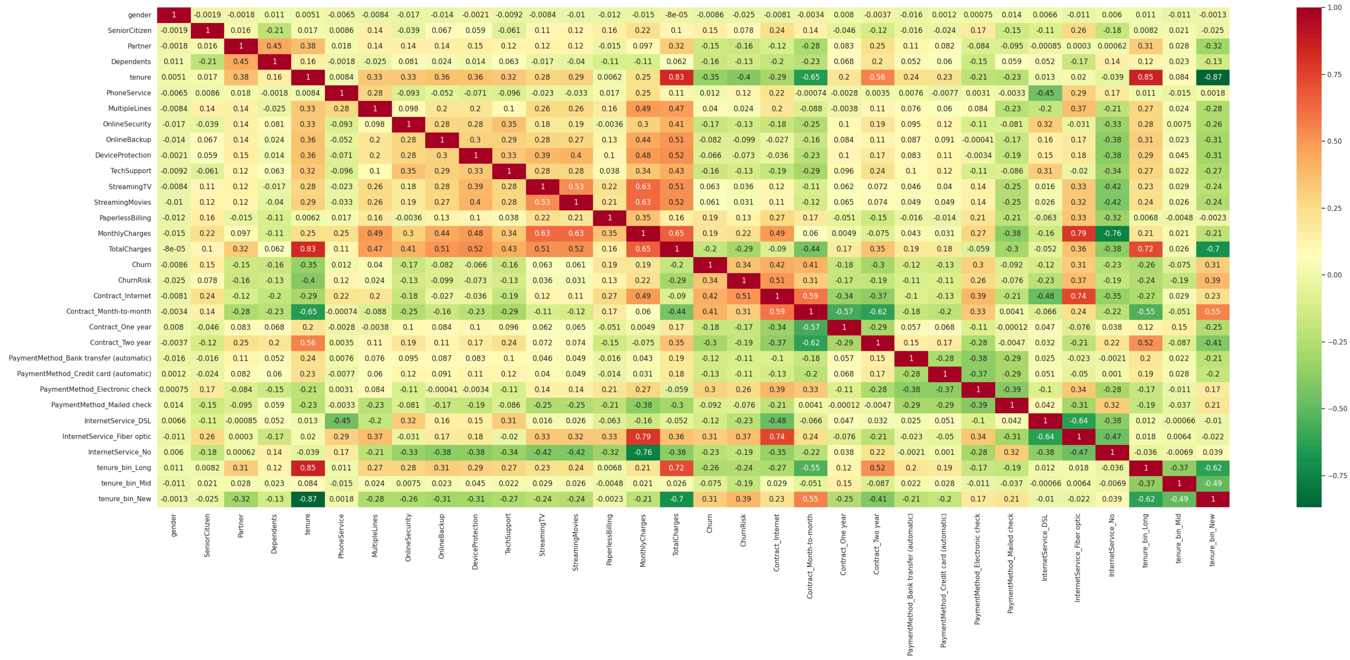
```
corr = df.corrwith(df['Churn']).sort_values(ascending = False).to_frame()
corr.columns = ['Correlations']
plt.subplots(figsize = (5,10))
sns.heatmap(corr,annot = True,cmap ='RdYlGn_r',linewidths = 0.4,linecolor = 'black');
plt.title('Correlation w.r.t Outcome')
```

```
Text(0.5, 1.0, 'Correlation w.r.t Outcome')
```

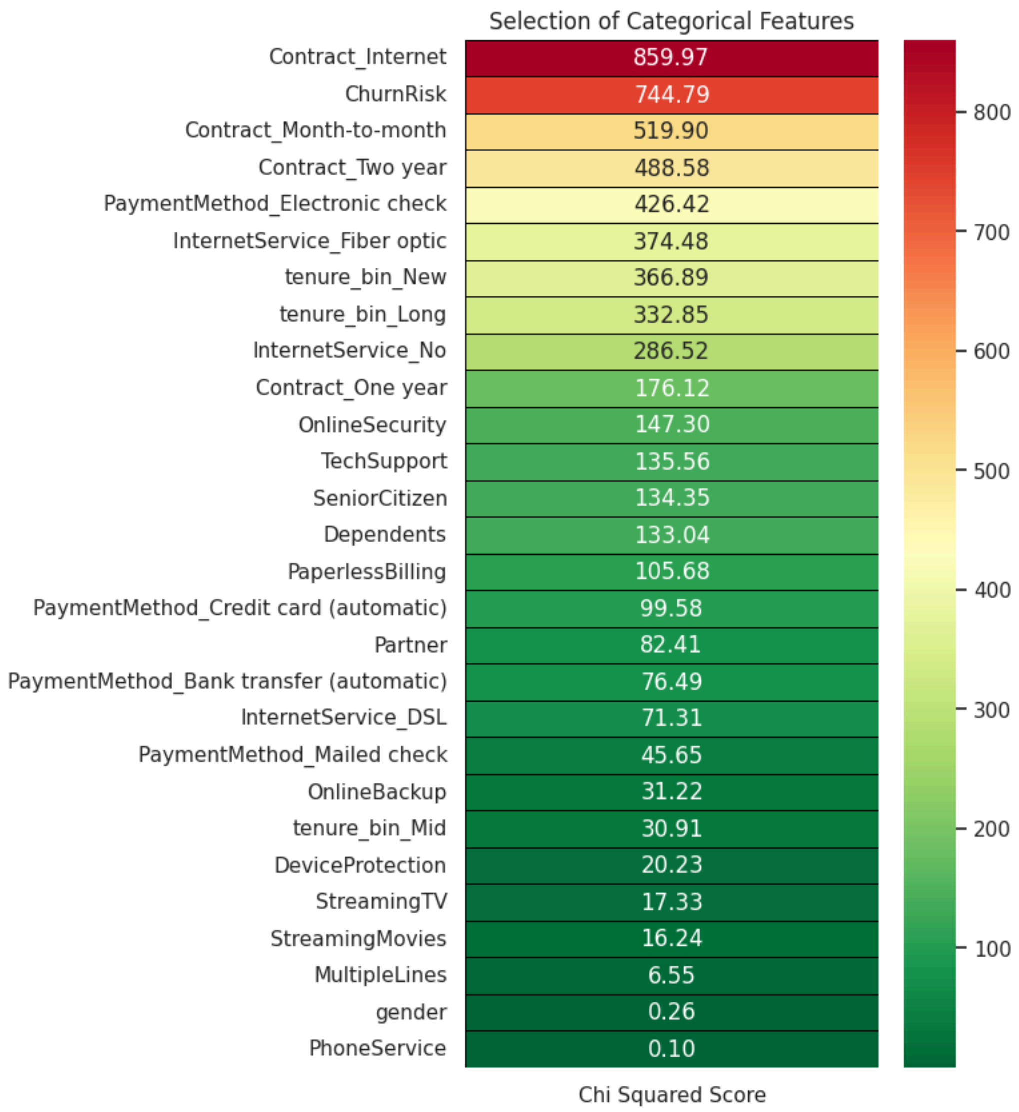



```
plt.figure(figsize = (40,15))
sns.heatmap(df.corr(),cmap = 'RdYlGn_r',annot = True)
```

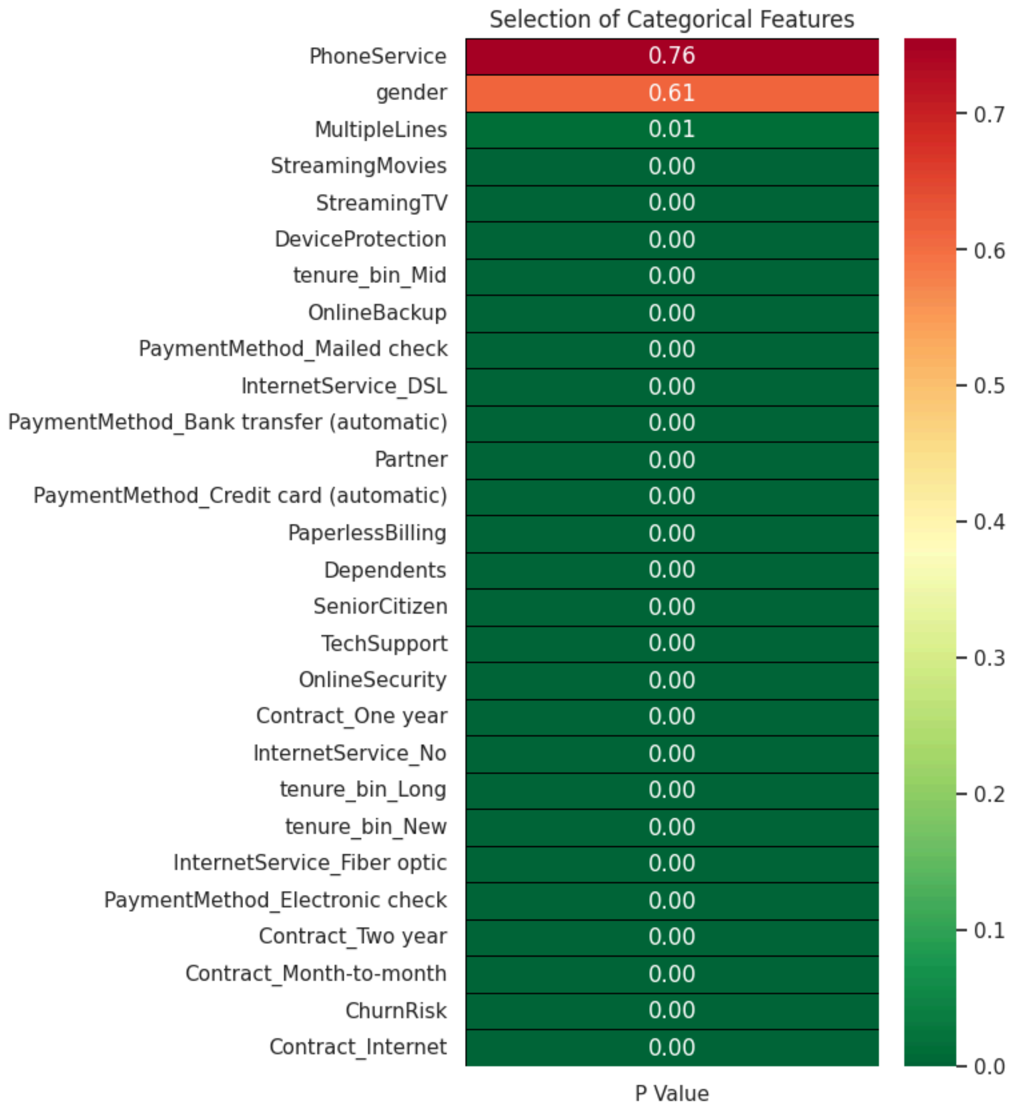
<Axes: >



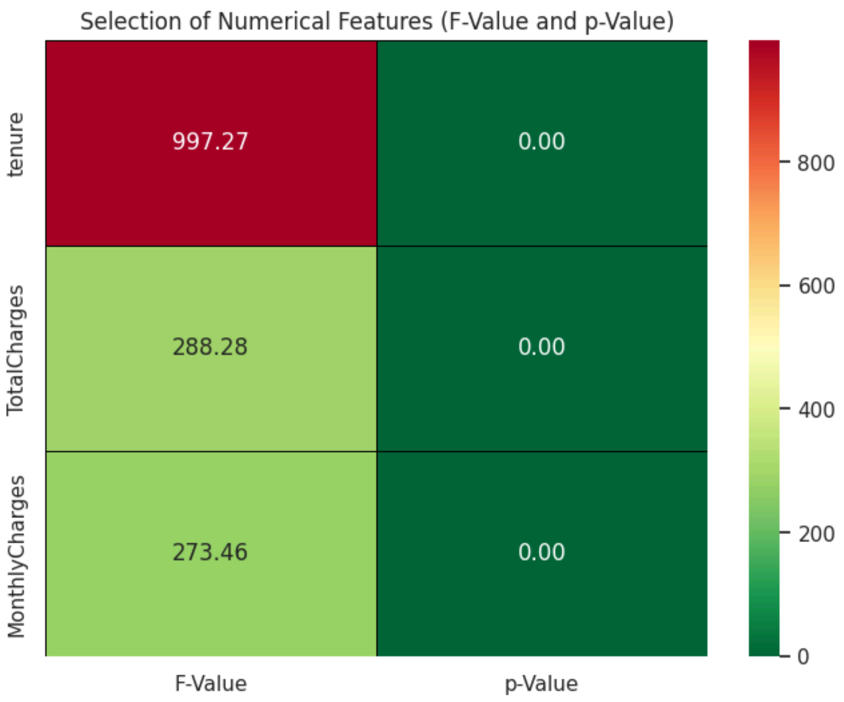

```
cat_new=['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'PhoneService',
       'MultipleLines', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'PaperlessBilling',
         'Contract_Month-to-month',
       'Contract_One year', 'Contract_Two year',
       'PaymentMethod_Bank transfer (automatic)',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check',
       'InternetService_DSL', 'InternetService_Fiber optic',
       'InternetService_No','tenure_bin_Long', 'tenure_bin_Mid',
       'tenure_bin_New','ChurnRisk', 'Contract_Internet']


from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2,mutual_info_classif
features = df.loc[:,cat_new]
target = df.loc[:,'Churn']

best_features = SelectKBest(score_func = chi2,k = 'all')
fit = best_features.fit(features,target)

featureScores = pd.DataFrame(data = fit.scores_,index = list(cat_new),columns = ['Chi Squared Score'])

plt.subplots(figsize = (5,10))
sns.heatmap(featureScores.sort_values(ascending = False,by = 'Chi Squared Score'),annot = True,cmap = 'RdYlGn_r',linewidths = 0.4,linec
plt.title('Selection of Categorical Features');
```




```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2,mutual_info_classif
features = df.loc[:,cat_new]
target = df.loc[:,'Churn']

best_features = SelectKBest(score_func = chi2,k = 'all')
fit = best_features.fit(features,target)

featureScores = pd.DataFrame(data = fit.pvalues_,index = list(cat_new),columns = ['P Value'])

plt.subplots(figsize = (5,10))
sns.heatmap(featureScores.sort_values(ascending = False,by = 'P Value'),annot = True,cmap = 'RdYlGn_r',linewidths = 0.4,linecolor = 'bla
plt.title('Selection of Categorical Features');
```




```
from sklearn.feature_selection import f_classif, SelectKBest
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Define features and target
features = df.loc[:, num_cols]
target = df.loc[:, 'Churn']

# Apply SelectKBest with f_classif as the score function
best_features = SelectKBest(score_func=f_classif, k='all')
fit = best_features.fit(features, target)

# Create a DataFrame for the F-scores and p-values
featureScores = pd.DataFrame({
    'F-Value': fit.scores_,
    'p-Value': fit.pvalues_
}, index=list(features.columns))

# Sort the DataFrame by F-Value
sorted_features = featureScores.sort_values(ascending=False, by='F-Value')

# Plot the heatmap
plt.subplots(figsize=(8, 6))
sns.heatmap(sorted_features, annot=True, cmap='RdYlGn_r', linewidths=0.4, linecolor='black', fmt='.2f')

# Add plot title
plt.title('Selection of Numerical Features (F-Value and p-Value)')
plt.show()
```




```
import pandas as pd
from sklearn.feature_selection import mutual_info_classif
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Assuming 'Churn' is the target variable and df1_tenure is your preprocessed DataFrame
X = df.drop('Churn', axis=1)
y = df['Churn']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Standardize the features (not strictly necessary for mutual_info_classif)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Calculate mutual information between each feature and the target variable
mi_scores = mutual_info_classif(X_train_scaled, y_train)

# Create a DataFrame to display the feature names and their mutual information scores
feature_scores_df = pd.DataFrame({'Feature': X.columns, 'Mutual_Information_Score': mi_scores})

# Sort the DataFrame by score in descending order
feature_scores_df = feature_scores_df.sort_values(by='Mutual_Information_Score', ascending=False)

# Print all feature scores
print("All Feature Mutual Information Scores:")
print(feature_scores_df)

# Select the features with non-zero mutual information scores
selected_features = feature_scores_df[feature_scores_df['Mutual_Information_Score'] > 0]['Feature'].tolist()

# Print the selected features
print("\nSelected features:", selected_features)
```

```
All Feature Mutual Information Scores:
                        Feature  Mutual_Information_Score
18      Contract_Month-to-month                  0.099927
17            Contract_Internet                  0.078294
4                        tenure                  0.068584
20            Contract_Two year                  0.061272
30               tenure_bin_New                  0.050184
16                    ChurnRisk                  0.049950
15                 TotalCharges                  0.045921
23  PaymentMethod_Electronic check               0.045171
14               MonthlyCharges                  0.041497
26      InternetService_Fiber optic              0.040861
27           InternetService_No                  0.039556
28              tenure_bin_Long                  0.033160
2                       Partner                  0.020810
7                OnlineSecurity                  0.018228
29               tenure_bin_Mid                  0.017605
```

```
1                        SeniorCitizen              0.015476
3                           Dependents              0.014203
19                   Contract_One year              0.013204
10                         TechSupport              0.010700
25                 InternetService_DSL              0.008396
22    PaymentMethod_Credit card (automatic)         0.008184
13                    PaperlessBilling              0.007062
21  PaymentMethod_Bank transfer (automatic)         0.006653
24          PaymentMethod_Mailed check              0.004606
6                        MultipleLines              0.004378
11                         StreamingTV              0.002457
12                     StreamingMovies              0.000542
5                         PhoneService              0.000496
8                         OnlineBackup              0.000000
0                               gender              0.000000
9                     DeviceProtection              0.000000

Selected features: ['Contract_Month-to-month', 'Contract_Internet', 'tenure', 'Contract_Two year', 'tenure_bin_New', 'ChurnRisk', 'T
```

```
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Assuming 'Churn' is the target variable and df1_tenure is your preprocessed DataFrame
X = df.drop('Churn', axis=1)
y = df['Churn']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Standardize the features (important for Lasso, which is sensitive to feature scales)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the Lasso model (alpha controls the regularization strength)
lasso = Lasso(alpha=0.01)

# Fit the Lasso model to the training data
lasso.fit(X_train_scaled, y_train)

# Get the coefficients of the features
lasso_coefficients = lasso.coef_

# Create a DataFrame to display the feature names and their Lasso coefficients
feature_scores_df = pd.DataFrame({'Feature': X.columns, 'Lasso_Coefficient': lasso_coefficients})

# Sort the DataFrame by coefficient magnitude in descending order
feature_scores_df = feature_scores_df.reindex(feature_scores_df['Lasso_Coefficient'].abs().sort_values(ascending=False).index)

# Print all feature coefficients
print("All Feature Coefficients:")
print(feature_scores_df)

# Select the features with non-zero coefficients
selected_features = feature_scores_df[feature_scores_df['Lasso_Coefficient'] != 0]['Feature'].tolist()

# Print the selected features
print("\nSelected features:", selected_features)
```

```
All Feature Coefficients:
                          Feature  Lasso_Coefficient
4                          tenure          -0.069636
16                      ChurnRisk           0.045987
18        Contract_Month-to-month           0.043430
27             InternetService_No          -0.039935
17              Contract_Internet           0.038776
23  PaymentMethod_Electronic check           0.033652
7                  OnlineSecurity          -0.024634
26    InternetService_Fiber optic           0.023408
13               PaperlessBilling           0.016782
12                StreamingMovies           0.013598
1                   SeniorCitizen           0.012659
10                    TechSupport          -0.012535
29                 tenure_bin_Mid          -0.006281
8                    OnlineBackup          -0.004627
3                      Dependents          -0.002065
6                   MultipleLines           0.001244
5                    PhoneService          -0.000991
20              Contract_Two year          -0.000804
14                 MonthlyCharges           0.000000
2                         Partner          -0.000000
11                    StreamingTV           0.000000
9                DeviceProtection          -0.000000
0                          gender          -0.000000
```

```
22    PaymentMethod_Credit card (automatic)          -0.000000
21  PaymentMethod_Bank transfer (automatic)          -0.000000
19                         Contract_One year          -0.000000
15                              TotalCharges          -0.000000
25                       InternetService_DSL          -0.000000
24                PaymentMethod_Mailed check          -0.000000
28                           tenure_bin_Long           0.000000
30                            tenure_bin_New           0.000000

Selected features: ['tenure', 'ChurnRisk', 'Contract_Month-to-month', 'InternetService_No', 'Contract_Internet', 'PaymentMethod_Ele
```

information gain

```
import pandas as pd
from sklearn.feature_selection import mutual_info_classif
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Assuming 'Churn' is the target variable and df1_tenure is your preprocessed DataFrame
X = df.drop('Churn', axis=1)
y = df['Churn']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Standardize the features (optional, typically not necessary for tree models)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Calculate Information Gain (Mutual Information) for each feature
mutual_info = mutual_info_classif(X_train_scaled, y_train)

# Create a DataFrame to display the feature names and their Information Gain scores
feature_importance_df = pd.DataFrame({'Feature': X.columns, 'Information Gain': mutual_info})

# Sort the DataFrame by Information Gain in descending order
feature_importance_df = feature_importance_df.sort_values(by='Information Gain', ascending=False)

# Print all feature Information Gain scores
print("Feature Information Gain (Mutual Information):")
print(feature_importance_df)

# Select the top k features (for example, top 10)
num_features_to_select = 10  # Change this to select a different number of features
selected_features = feature_importance_df.head(num_features_to_select)['Feature'].tolist()

# Print the selected features
print("\nSelected features:", selected_features)
```

```
Feature Information Gain (Mutual Information):
                                    Feature  Information Gain
18                  Contract_Month-to-month          0.101083
17                        Contract_Internet          0.080022
4                                    tenure          0.075265
20                        Contract_Two year          0.058061
16                                ChurnRisk          0.050882
30                           tenure_bin_New          0.047540
15                             TotalCharges          0.045550
26             InternetService_Fiber optic          0.043741
23          PaymentMethod_Electronic check          0.043024
28                          tenure_bin_Long          0.037772
14                           MonthlyCharges          0.036991
27                       InternetService_No          0.031131
7                            OnlineSecurity          0.024908
3                                Dependents          0.016560
13                         PaperlessBilling          0.016278
22    PaymentMethod_Credit card (automatic)          0.012817
2                                   Partner          0.012255
10                              TechSupport          0.010204
21  PaymentMethod_Bank transfer (automatic)          0.007975
9                          DeviceProtection          0.007343
25                      InternetService_DSL          0.007155
1                             SeniorCitizen          0.005879
8                              OnlineBackup          0.005832
24               PaymentMethod_Mailed check          0.005725
29                           tenure_bin_Mid          0.005103
19                        Contract_One year          0.005075
5                              PhoneService          0.002896
12                          StreamingMovies          0.002408
6                             MultipleLines          0.001640
11                              StreamingTV          0.000000
0                                    gender          0.000000
```

```
Selected features: ['Contract_Month-to-month', 'Contract_Internet', 'tenure', 'Contract_Two year', 'ChurnRisk', 'tenure_bin_New', 'T
```

```
# List of final selected features
final_features = [
    'SeniorCitizen',
    'Dependents',
    'Contract_Month-to-month',
    'Contract_One year',
    'Contract_Two year',
    'tenure_bin_New',
    'tenure_bin_Mid',
    'tenure_bin_Long',
    'InternetService_Fiber optic',
    'OnlineSecurity',
    'TechSupport',
    'PaymentMethod_Electronic check',
    'PaperlessBilling',
    'MonthlyCharges',
    'TotalCharges',
    'Churn']

# Create a new DataFrame with the selected features
df_final = df[final_features]

# Display the new DataFrame
df_final.head()
```

	SeniorCitizen	Dependents	Contract_Month-to-month	Contract_One year	Contract_Two year	tenure_bin_New	tenure_bin_Mid	tenure_bin_Long	Internet
0	0	0	1.0	0.0	0.0	1.0	0.0	0.0	
1	0	0	0.0	1.0	0.0	0.0	1.0	0.0	
2	0	0	1.0	0.0	0.0	1.0	0.0	0.0	
3	0	0	0.0	1.0	0.0	0.0	1.0	0.0	
4	0	0	1.0	0.0	0.0	1.0	0.0	0.0	

```
df_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 16 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   SeniorCitizen                   7043 non-null   int64  
 1   Dependents                      7043 non-null   int64  
 2   Contract_Month-to-month         7043 non-null   float64
 3   Contract_One year               7043 non-null   float64
 4   Contract_Two year               7043 non-null   float64
 5   tenure_bin_New                  7043 non-null   float64
 6   tenure_bin_Mid                  7043 non-null   float64
 7   tenure_bin_Long                 7043 non-null   float64
 8   InternetService_Fiber optic     7043 non-null   float64
 9   OnlineSecurity                  7043 non-null   int64  
 10  TechSupport                     7043 non-null   int64  
 11  PaymentMethod_Electronic check  7043 non-null   float64
 12  PaperlessBilling                7043 non-null   int64  
 13  MonthlyCharges                  7043 non-null   float64
 14  TotalCharges                    7043 non-null   float64
 15  Churn                           7043 non-null   int64  
dtypes: float64(10), int64(6)
memory usage: 880.5 KB
```

```
pip install imblearn
```

```
Collecting imblearn
  Downloading imblearn-0.0-py2.py3-none-any.whl.metadata (355 bytes)
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.11/dist-packages (from imblearn) (0.13.0)
Requirement already satisfied: numpy<3,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn->imblearn) (2.0.2
Requirement already satisfied: scipy<2,>=1.10.1 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn->imblearn) (1.15.3
Requirement already satisfied: scikit-learn<2,>=1.3.2 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn->imblearn)
Requirement already satisfied: sklearn-compat<1,>=0.1 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn->imblearn)
Requirement already satisfied: joblib<2,>=1.1.1 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn->imblearn) (1.5.1
Requirement already satisfied: threadpoolctl<4,>=2.0.0 in /usr/local/lib/python3.11/dist-packages (from imbalanced-learn->imblearn)
Downloading imblearn-0.0-py2.py3-none-any.whl (1.9 kB)
Installing collected packages: imblearn
Successfully installed imblearn-0.0
```

```
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split

# Separate features and target
X = df_final.drop('Churn', axis=1)
y = df_final['Churn']

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Apply SMOTE to oversample the minority class
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)

# Check class distribution after SMOTE
print(y_train_smote.value_counts())

# Proceed with modeling using X_train_smote, y_train_smote
```

```
Churn
0    3635
1    3635
Name: count, dtype: int64
```

```
X_train_smote.shape, y_train_smote.shape, X_test.shape, y_test.shape
```

```
((7270, 15), (7270,), (2113, 15), (2113,))
```

MACHINE LEARNING ALGORITHMS

ADABOOST CLASSIFIER

```
# prompt: convert above code to Ada Boost

from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, precision_score, recall_score, f1_score
from sklearn.model_selection import cross_val_score


# Initialize the AdaBoost Classifier
model_ada = AdaBoostClassifier(n_estimators=200, random_state=42)

# Train the model with the training data
model_ada.fit(X_train_smote, y_train_smote)

# Make predictions on the test set
y_pred = model_ada.predict(X_test)


# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred)
print(f'\nAccuracy: {accuracy:.2f}')

# Manually compute precision, recall, and F1-score for each class
precision_0 = precision_score(y_test, y_pred, pos_label=0)
recall_0 = recall_score(y_test, y_pred, pos_label=0)
f1_0 = f1_score(y_test, y_pred, pos_label=0)

precision_1 = precision_score(y_test, y_pred, pos_label=1)
recall_1 = recall_score(y_test, y_pred, pos_label=1)
f1_1 = f1_score(y_test, y_pred, pos_label=1)

# Print the metrics for each class
print('\nClass 0 Metrics:')
print(f'Precision: {precision_0:.2f}')
print(f'Recall: {recall_0:.2f}')
print(f'F1-Score: {f1_0:.2f}')

print('\nClass 1 Metrics:')
print(f'Precision: {precision_1:.2f}')
print(f'Recall: {recall_1:.2f}')
print(f'F1-Score: {f1_1:.2f}')

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)
```

```
# Cross-validation score (using accuracy)
cv_scores = cross_val_score(model_ada, X_train_smote, y_train_smote, cv=5, scoring='accuracy')
print(f'\nCross-Validation Accuracy Score: {np.mean(cv_scores):.4f} ± {np.std(cv_scores):.4f}')
```

```
Accuracy: 0.75

Class 0 Metrics:
Precision: 0.93
Recall: 0.72
F1-Score: 0.81

Class 1 Metrics:
Precision: 0.53
Recall: 0.85
F1-Score: 0.65

Confusion Matrix:
[[1103  436]
 [  88  486]]

Cross-Validation Accuracy Score: 0.7622 ± 0.0039
```

GRADIENT BOOSTING CLASSIFIER

```
# prompt: convert above code to Gradient boost
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import GradientBoostingClassifier

# Initialize the Gradient Boosting Classifier
model_gb = GradientBoostingClassifier(n_estimators=200, random_state=42)

# Train the model with the training data
model_gb.fit(X_train_smote, y_train_smote)

# Make predictions on the test set
y_pred = model_gb.predict(X_test)

# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred)
print(f'\nAccuracy: {accuracy:.2f}')

# Manually compute precision, recall, and F1-score for each class
precision_0 = precision_score(y_test, y_pred, pos_label=0)
recall_0 = recall_score(y_test, y_pred, pos_label=0)
f1_0 = f1_score(y_test, y_pred, pos_label=0)

precision_1 = precision_score(y_test, y_pred, pos_label=1)
recall_1 = recall_score(y_test, y_pred, pos_label=1)
f1_1 = f1_score(y_test, y_pred, pos_label=1)

# Print the metrics for each class
print('\nClass 0 Metrics:')
print(f'Precision: {precision_0:.2f}')
print(f'Recall: {recall_0:.2f}')
print(f'F1-Score: {f1_0:.2f}')

print('\nClass 1 Metrics:')
print(f'Precision: {precision_1:.2f}')
print(f'Recall: {recall_1:.2f}')
print(f'F1-Score: {f1_1:.2f}')

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

# Cross-validation score (using accuracy)
cv_scores = cross_val_score(model_gb, X_train_smote, y_train_smote, cv=5, scoring='accuracy')
print(f'\nCross-Validation Accuracy Score: {np.mean(cv_scores):.4f} ± {np.std(cv_scores):.4f}')
```

```
Accuracy: 0.76

Class 0 Metrics:
Precision: 0.91
Recall: 0.75
F1-Score: 0.82

Class 1 Metrics:
Precision: 0.54
```

```
Recall: 0.80
F1-Score: 0.65

Confusion Matrix:
[[1153  386]
 [ 117  457]]

Cross-Validation Accuracy Score: 0.7801 ± 0.0105
```

LOGISTIC REGRESSION

```
# prompt: convert above code to Gradient boost
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression

# Initialize the Gradient Boosting Classifier
model_lr = LogisticRegression(max_iter=1000, random_state=42)

# Train the model with the training data
model_lr.fit(X_train_smote, y_train_smote)

# Make predictions on the test set
y_pred = model_lr.predict(X_test)

# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred)
print(f'\nAccuracy: {accuracy:.2f}')

# Manually compute precision, recall, and F1-score for each class
precision_0 = precision_score(y_test, y_pred, pos_label=0)
recall_0 = recall_score(y_test, y_pred, pos_label=0)
f1_0 = f1_score(y_test, y_pred, pos_label=0)

precision_1 = precision_score(y_test, y_pred, pos_label=1)
recall_1 = recall_score(y_test, y_pred, pos_label=1)
f1_1 = f1_score(y_test, y_pred, pos_label=1)

# Print the metrics for each class
print('\nClass 0 Metrics:')
print(f'Precision: {precision_0:.2f}')
print(f'Recall: {recall_0:.2f}')
print(f'F1-Score: {f1_0:.2f}')

print('\nClass 1 Metrics:')
print(f'Precision: {precision_1:.2f}')
print(f'Recall: {recall_1:.2f}')
print(f'F1-Score: {f1_1:.2f}')

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

# Cross-validation score (using accuracy)
cv_scores = cross_val_score(model_lr, X_train_smote, y_train_smote, cv=5, scoring='accuracy')
print(f'\nCross-Validation Accuracy Score: {np.mean(cv_scores):.4f} ± {np.std(cv_scores):.4f}')
```

```
Accuracy: 0.75

Class 0 Metrics:
Precision: 0.91
Recall: 0.73
F1-Score: 0.81

Class 1 Metrics:
Precision: 0.53
Recall: 0.80
F1-Score: 0.63

Confusion Matrix:
[[1130  409]
 [ 117  457]]

Cross-Validation Accuracy Score: 0.7539 ± 0.0072
```

RANDOM FOREST CLASSIFIER

```
# Import necessary libraries
import pandas as pd
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix


# Initialize the XGBoost Classifier
model_rfc = RandomForestClassifier(n_estimators=1000, max_depth=3, random_state=2)

# Train the model with the training data
model_rfc.fit(X_train_smote, y_train_smote)

# Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred)
print(f'\nAccuracy: {accuracy:.2f}')

# Manually compute precision, recall, and F1-score for each class
precision_0 = precision_score(y_test, y_pred, pos_label=0)
recall_0 = recall_score(y_test, y_pred, pos_label=0)
f1_0 = f1_score(y_test, y_pred, pos_label=0)

precision_1 = precision_score(y_test, y_pred, pos_label=1)
recall_1 = recall_score(y_test, y_pred, pos_label=1)
f1_1 = f1_score(y_test, y_pred, pos_label=1)

# Print the metrics for each class
print('\nClass 0 Metrics:')
print(f'Precision: {precision_0:.2f}')
print(f'Recall: {recall_0:.2f}')
print(f'F1-Score: {f1_0:.2f}')

print('\nClass 1 Metrics:')
print(f'Precision: {precision_1:.2f}')
print(f'Recall: {recall_1:.2f}')
print(f'F1-Score: {f1_1:.2f}')

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

# Cross-validation score (using accuracy)
cv_scores = cross_val_score(model_rfc, X_train_smote, y_train_smote, cv=5, scoring='accuracy')
print(f'\nCross-Validation Accuracy Score: {np.mean(cv_scores):.4f} ± {np.std(cv_scores):.4f}')
```

```
Accuracy: 0.75

Class 0 Metrics:
Precision: 0.91
Recall: 0.73
F1-Score: 0.81

Class 1 Metrics:
Precision: 0.53
Recall: 0.80
F1-Score: 0.63

Confusion Matrix:
[[1130  409]
 [ 117  457]]

Cross-Validation Accuracy Score: 0.7424 ± 0.0051
```

DECISION TREE CLASSIFIER

```
# Import necessary libraries
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix


# Initialize the XGBoost Classifier
model_dt = DecisionTreeClassifier(max_depth=3, random_state=2)

# Train the model with the training data
model_dt.fit(X_train_smote, y_train_smote)

# Make predictions on the test set
y_pred = model_dt.predict(X_test)

# Evaluate the model's performance
```

```
accuracy = accuracy_score(y_test, y_pred)
print(f'\nAccuracy: {accuracy:.2f}')

# Manually compute precision, recall, and F1-score for each class
precision_0 = precision_score(y_test, y_pred, pos_label=0)
recall_0 = recall_score(y_test, y_pred, pos_label=0)
f1_0 = f1_score(y_test, y_pred, pos_label=0)

precision_1 = precision_score(y_test, y_pred, pos_label=1)
recall_1 = recall_score(y_test, y_pred, pos_label=1)
f1_1 = f1_score(y_test, y_pred, pos_label=1)

# Print the metrics for each class
print('\nClass 0 Metrics:')
print(f'Precision: {precision_0:.2f}')
print(f'Recall: {recall_0:.2f}')
print(f'F1-Score: {f1_0:.2f}')

print('\nClass 1 Metrics:')
print(f'Precision: {precision_1:.2f}')
print(f'Recall: {recall_1:.2f}')
print(f'F1-Score: {f1_1:.2f}')

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("\nConfusion Matrix:")
print(cm)

# Cross-validation score (using accuracy)
cv_scores = cross_val_score(model_dt, X_train_smote, y_train_smote, cv=5, scoring='accuracy')
```

```
Accuracy: 0.74

Class 0 Metrics:
Precision: 0.91
Recall: 0.71
F1-Score: 0.80

Class 1 Metrics:
Precision: 0.51
Recall: 0.82
F1-Score: 0.63
```