Raushan new File

July 3, 2025

[13]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[14]:
```python
df = pd.read_csv(r"D:\Zaalima project\telecom churn\Raushan␣
↪project\telecom_customer_churn 1.csv")
```

[15]:
```python
df.head()
```

[15]:
```
  Customer ID  Gender  Age Married  Number of Dependents          City  \
0  0002-ORFBO  Female   37     Yes                     0  Frazier Park
1  0003-MKNFE    Male   46      No                     0      Glendale
2  0004-TLHLJ    Male   50      No                     0    Costa Mesa
3  0011-IGKFF    Male   78     Yes                     0      Martinez
4  0013-EXCHZ  Female   75     Yes                     0     Camarillo

   Zip Code   Latitude   Longitude  Number of Referrals  …   Payment Method  \
0     93225  34.827662 -118.999073                    2  …      Credit Card
1     91206  34.162515 -118.203869                    0  …      Credit Card
2     92627  33.645672 -117.922613                    0  …  Bank Withdrawal
3     94553  38.014457 -122.115432                    1  …  Bank Withdrawal
4     93010  34.227846 -119.079903                    3  …      Credit Card

  Monthly Charge Total Charges  Total Refunds Total Extra Data Charges  \
0           65.6        593.30           0.00                        0
1           -4.0        542.40          38.33                       10
2           73.9        280.85           0.00                        0
3           98.0       1237.85           0.00                        0
4           83.9        267.40           0.00                        0

  Total Long Distance Charges Total Revenue  Customer Status   Churn Category  \
0                      381.51        974.81           Stayed              NaN
1                       96.21        610.28           Stayed              NaN
2                      134.60        415.45          Churned       Competitor
3                      361.66       1599.51          Churned  Dissatisfaction
4                       22.14        289.54          Churned  Dissatisfaction
```

```
                 Churn Reason
0                         NaN
1                         NaN
2  Competitor had better devices
3        Product dissatisfaction
4            Network reliability

[5 rows x 38 columns]
```

[16]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 38 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   Customer ID                        7043 non-null   object
 1   Gender                             7043 non-null   object
 2   Age                                7043 non-null   int64
 3   Married                            7043 non-null   object
 4   Number of Dependents               7043 non-null   int64
 5   City                               7043 non-null   object
 6   Zip Code                           7043 non-null   int64
 7   Latitude                           7043 non-null   float64
 8   Longitude                          7043 non-null   float64
 9   Number of Referrals                7043 non-null   int64
 10  Tenure in Months                   7043 non-null   int64
 11  Offer                              3166 non-null   object
 12  Phone Service                      7043 non-null   object
 13  Avg Monthly Long Distance Charges  6361 non-null   float64
 14  Multiple Lines                     6361 non-null   object
 15  Internet Service                   7043 non-null   object
 16  Internet Type                      5517 non-null   object
 17  Avg Monthly GB Download            5517 non-null   float64
 18  Online Security                    5517 non-null   object
 19  Online Backup                      5517 non-null   object
 20  Device Protection Plan             5517 non-null   object
 21  Premium Tech Support               5517 non-null   object
 22  Streaming TV                       5517 non-null   object
 23  Streaming Movies                   5517 non-null   object
 24  Streaming Music                    5517 non-null   object
 25  Unlimited Data                     5517 non-null   object
 26  Contract                           7043 non-null   object
 27  Paperless Billing                  7043 non-null   object
 28  Payment Method                     7043 non-null   object
 29  Monthly Charge                     7043 non-null   float64
 30  Total Charges                      7043 non-null   float64
 31  Total Refunds                      7043 non-null   float64
```

```
 32  Total Extra Data Charges           7043 non-null   int64
 33  Total Long Distance Charges        7043 non-null   float64
 34  Total Revenue                      7043 non-null   float64
 35  Customer Status                    7043 non-null   object
 36  Churn Category                     1869 non-null   object
 37  Churn Reason                       1869 non-null   object
dtypes: float64(9), int64(6), object(23)
memory usage: 2.0+ MB
```

[17]:
```
df.isnull().sum()/df.shape[0]*100
```

[17]:
```
Customer ID                           0.000000
Gender                                0.000000
Age                                   0.000000
Married                               0.000000
Number of Dependents                  0.000000
City                                  0.000000
Zip Code                              0.000000
Latitude                              0.000000
Longitude                             0.000000
Number of Referrals                   0.000000
Tenure in Months                      0.000000
Offer                                55.047565
Phone Service                         0.000000
Avg Monthly Long Distance Charges     9.683374
Multiple Lines                        9.683374
Internet Service                      0.000000
Internet Type                        21.666903
Avg Monthly GB Download              21.666903
Online Security                      21.666903
Online Backup                        21.666903
Device Protection Plan               21.666903
Premium Tech Support                 21.666903
Streaming TV                         21.666903
Streaming Movies                     21.666903
Streaming Music                      21.666903
Unlimited Data                       21.666903
Contract                              0.000000
Paperless Billing                     0.000000
Payment Method                        0.000000
Monthly Charge                        0.000000
Total Charges                         0.000000
Total Refunds                         0.000000
Total Extra Data Charges              0.000000
Total Long Distance Charges           0.000000
Total Revenue                         0.000000
Customer Status                       0.000000
```

```
Churn Category                        73.463013
Churn Reason                          73.463013
dtype: float64
```

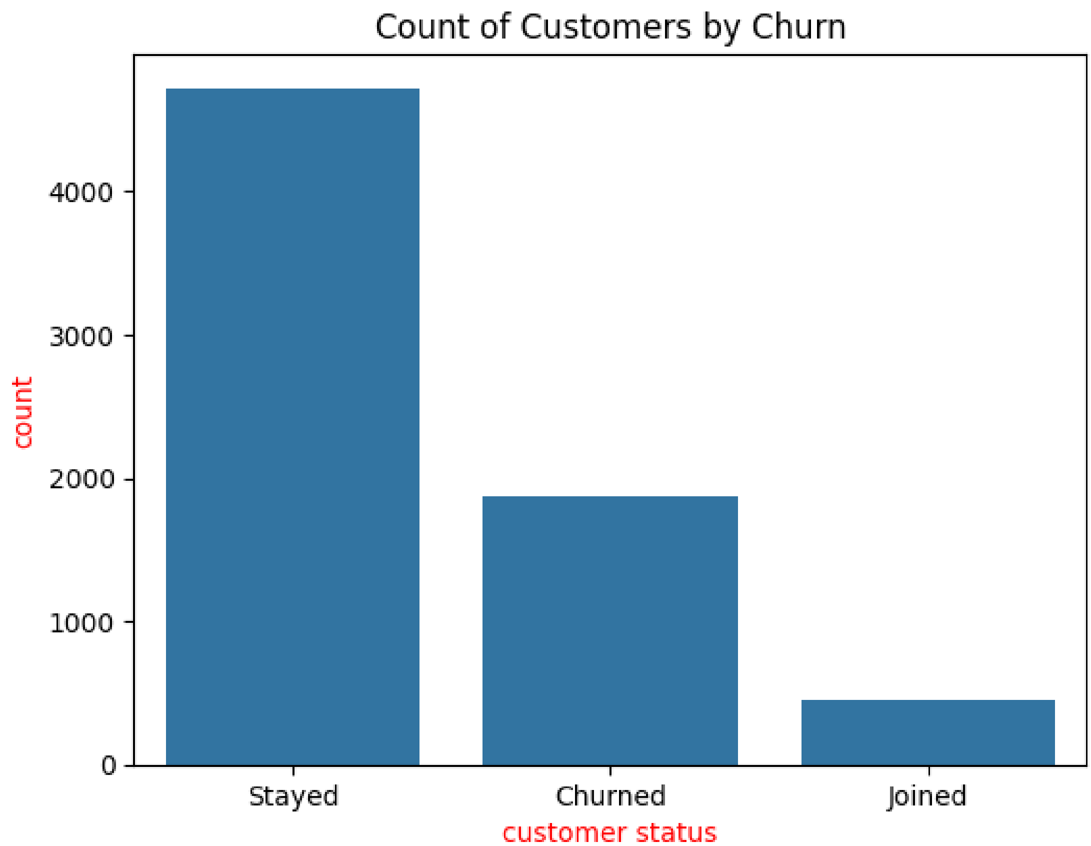
[18]:
```
# drop null attributes which have above 50% null value

df = df.drop(columns=['Churn Category','Churn Reason','Offer'],axis =1)
```

[19]:
```
df.head()
```

[19]:
```
  Customer ID  Gender  Age Married  Number of Dependents          City  \
0  0002-ORFBO  Female   37     Yes                     0  Frazier Park
1  0003-MKNFE    Male   46      No                     0      Glendale
2  0004-TLHLJ    Male   50      No                     0    Costa Mesa
3  0011-IGKFF    Male   78     Yes                     0      Martinez
4  0013-EXCHZ  Female   75     Yes                     0     Camarillo

   Zip Code   Latitude   Longitude  Number of Referrals  …        Contract  \
0     93225  34.827662 -118.999073                    2  …        One Year
1     91206  34.162515 -118.203869                    0  …  Month-to-Month
2     92627  33.645672 -117.922613                    0  …  Month-to-Month
3     94553  38.014457 -122.115432                    1  …  Month-to-Month
4     93010  34.227846 -119.079903                    3  …  Month-to-Month

  Paperless Billing   Payment Method Monthly Charge Total Charges  \
0               Yes      Credit Card           65.6        593.30
1                No      Credit Card           -4.0        542.40
2               Yes  Bank Withdrawal           73.9        280.85
3               Yes  Bank Withdrawal           98.0       1237.85
4               Yes      Credit Card           83.9        267.40

  Total Refunds  Total Extra Data Charges Total Long Distance Charges  \
0          0.00                         0                      381.51
1         38.33                        10                       96.21
2          0.00                         0                      134.60
3          0.00                         0                      361.66
4          0.00                         0                       22.14

  Total Revenue Customer Status
0        974.81          Stayed
1        610.28          Stayed
2        415.45         Churned
3       1599.51         Churned
4        289.54         Churned

[5 rows x 35 columns]
```

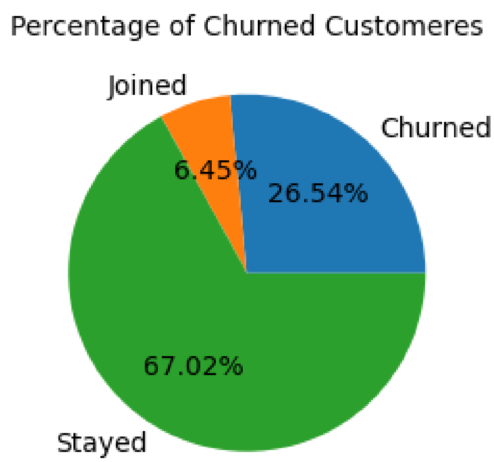
Count of Customer by Churn

[20]:
```
sns.countplot(x="Customer Status", data= df)
plt.xlabel("customer status",color="red")
plt.ylabel("count",color="red")
plt.title("Count of Customers by Churn")
plt.show()
```



Percentage of Churned Customer

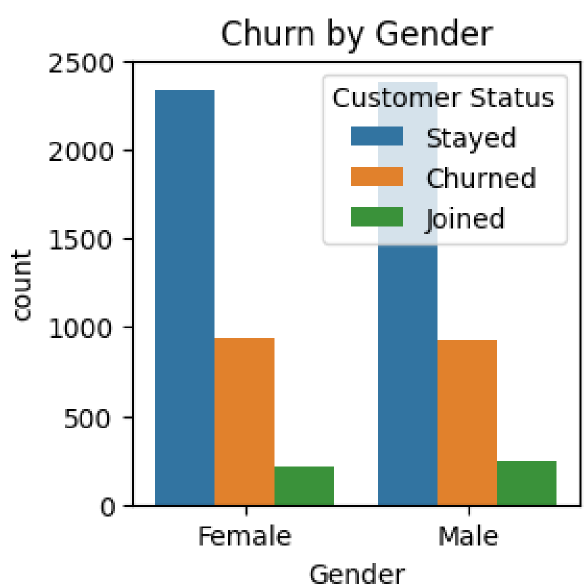
[21]:
```
plt.figure(figsize = (3,4))
gb = df.groupby("Customer Status").agg({'Customer Status':"count"})
plt.pie(gb['Customer Status'], labels = gb.index, autopct = "%1.2f%%")
plt.title("Percentage of Churned Customeres", fontsize = 10)
plt.show()
```



#from the given pie chart we can conclude that 26.54% of our customers have churned out

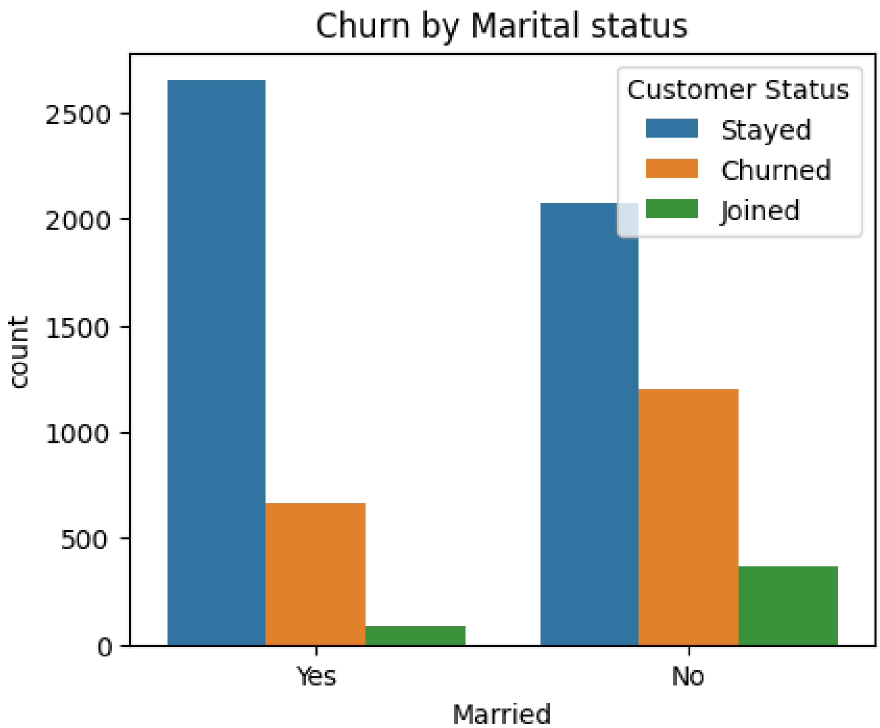
Count of churn by Gender

[22]:
```
plt.figure(figsize = (3,3))
sns.countplot(x = "Gender", data = df, hue = "Customer Status")
plt.title("Churn by Gender")
plt.show()
```



Count of Churn by Martial Status

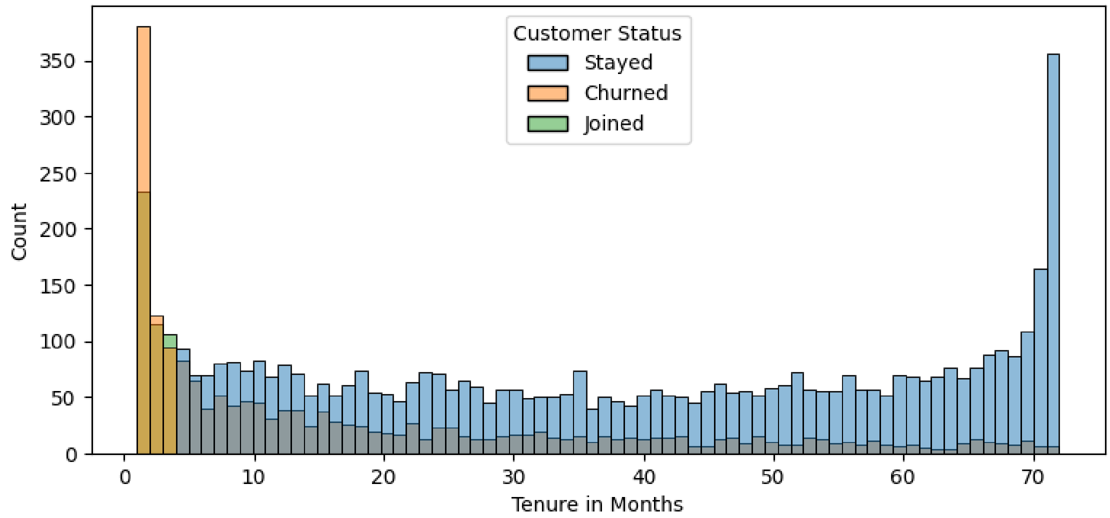
[23]:
```
plt.figure(figsize = (5,4))
sns.countplot(x = "Married", data = df, hue = "Customer Status")
plt.title("Churn by Marital status")
plt.show()
```



#comparative a greater pecentage of people in married category have churned

Tenure of churn in Months

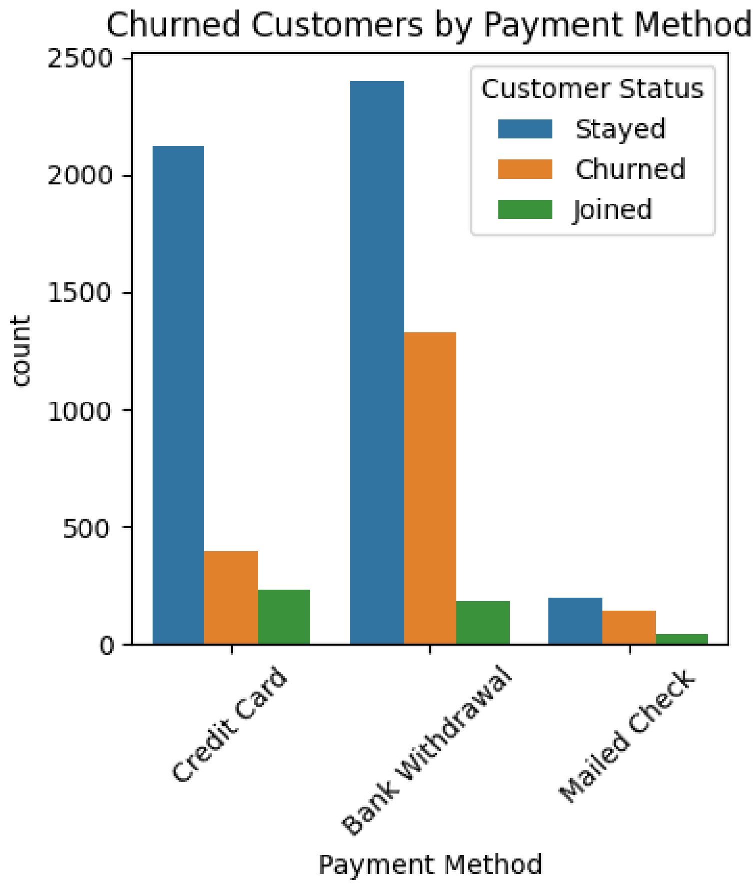
[24]:
```
plt.figure(figsize = (9,4))
sns.histplot(x = "Tenure in Months", data = df, bins = 72, hue = "Customer␣
↪Status")
plt.show()
```



#people who have used our services for a long time have stayed and people who have used our sevices #1 or 2 months have churned

Count of Churned Customer by Payment Method

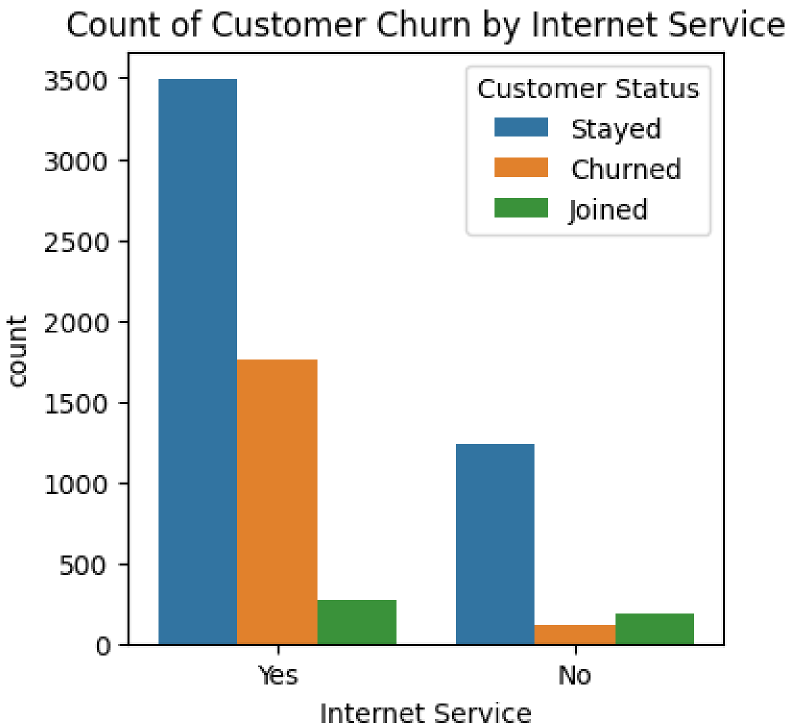
[31]:
```
plt.figure(figsize = (4,4))
sns.countplot(x = "Payment Method", data = df, hue = "Customer Status")
plt.title("Churned Customers by Payment Method")
plt.xticks(rotation = 45)
plt.show()
```



#Customer who have payed through bank withdrawal has churned in greater number.

Count of Customer Churn by Internet Service

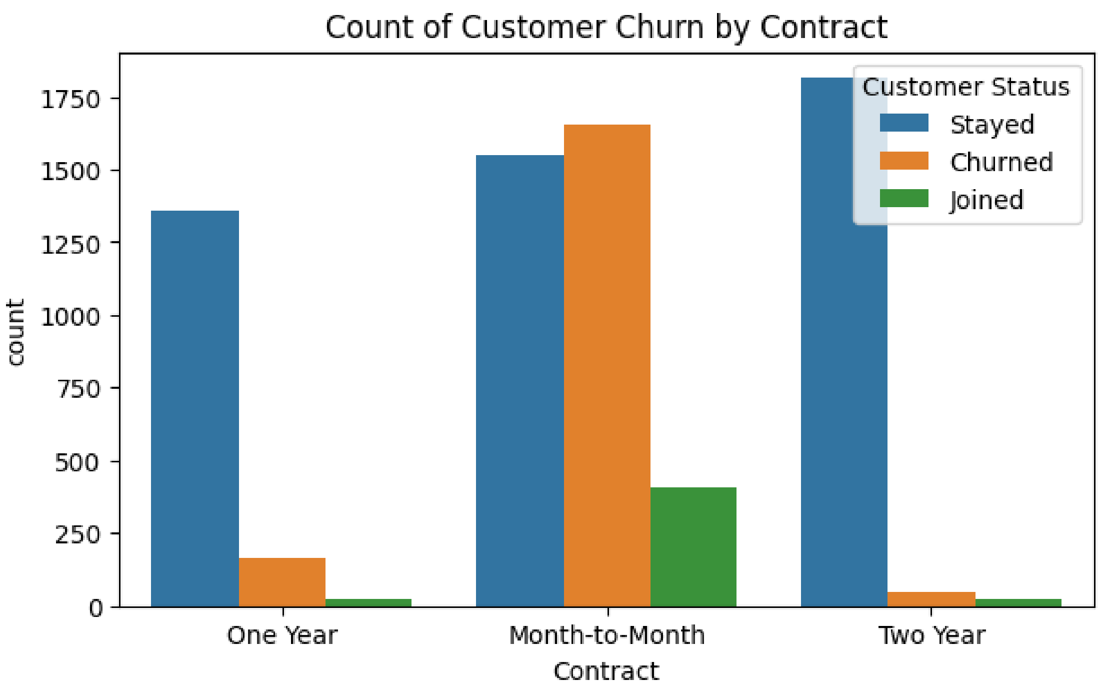
[32]:
```
plt.figure(figsize = (4,4))
sns.countplot(x = "Internet Service", data = df, hue= "Customer Status")
plt.title("Count of Customer Churn by Internet Service")
plt.show()
```



#Customer who have internet service have churned in larger amount.

Count of Customer Churn by Contract

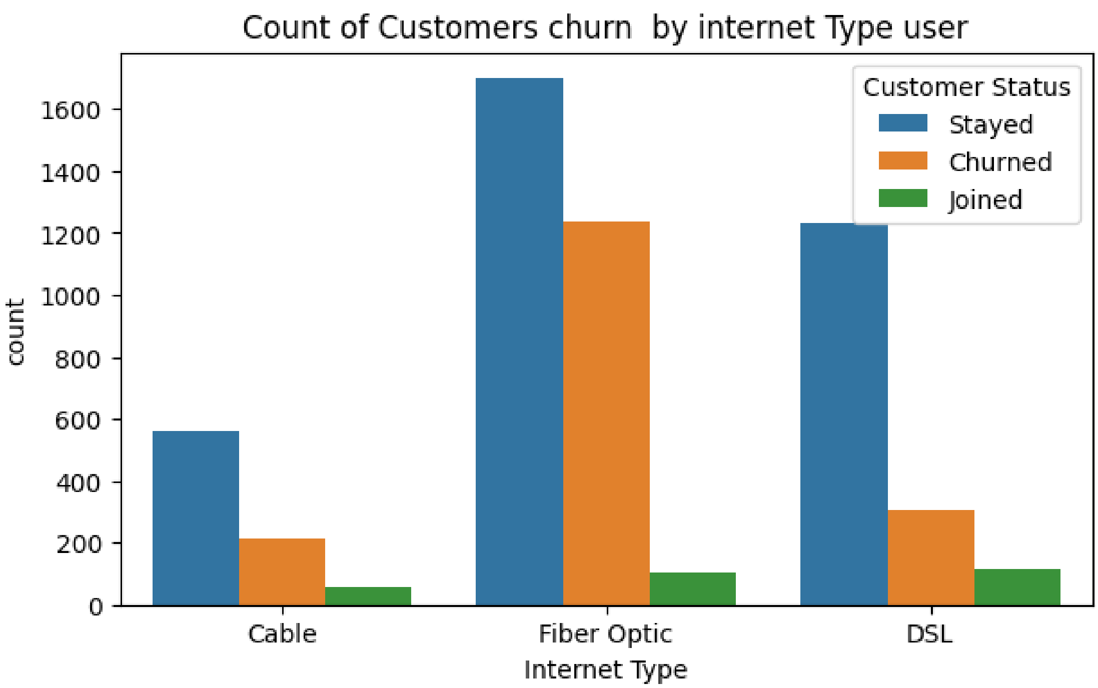
[33]:
```
plt.figure(figsize = (7,4))
sns.countplot(x = "Contract", data = df, hue= "Customer Status")
plt.title("Count of Customer Churn by Contract")
plt.show()
```



#It shows that Customer having month to month Contract has Churned in greater number.

Count of Customers churn by internet Type user

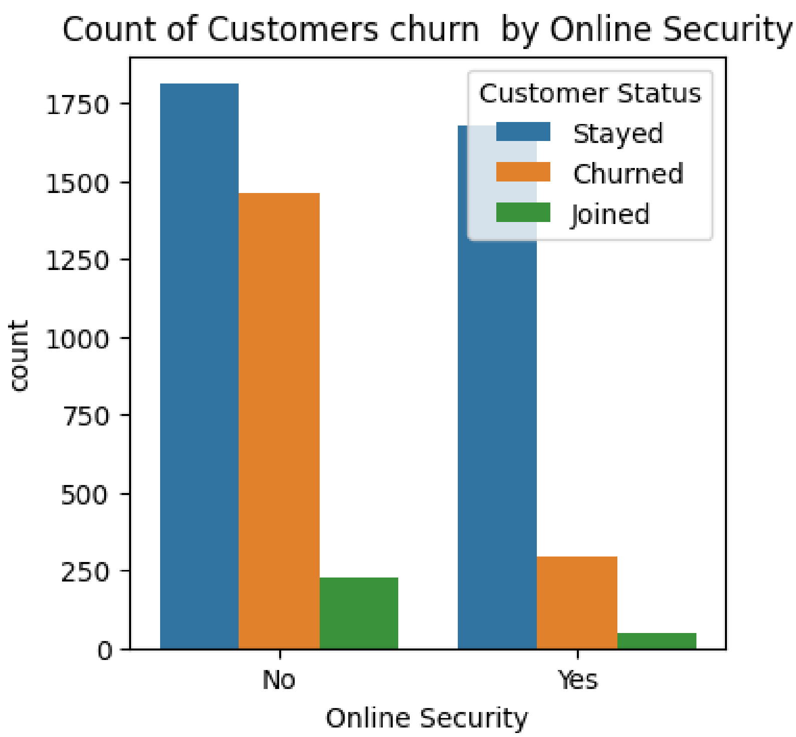
[34]:
```
plt.figure(figsize = (7,4))
sns.countplot(x = "Internet Type", data = df, hue= "Customer Status")
plt.title("Count of Customers churn  by internet Type user")
plt.show()
```



#Customer using Fiber Optic has churned in larger number.

Count of Customers churn by Online Security

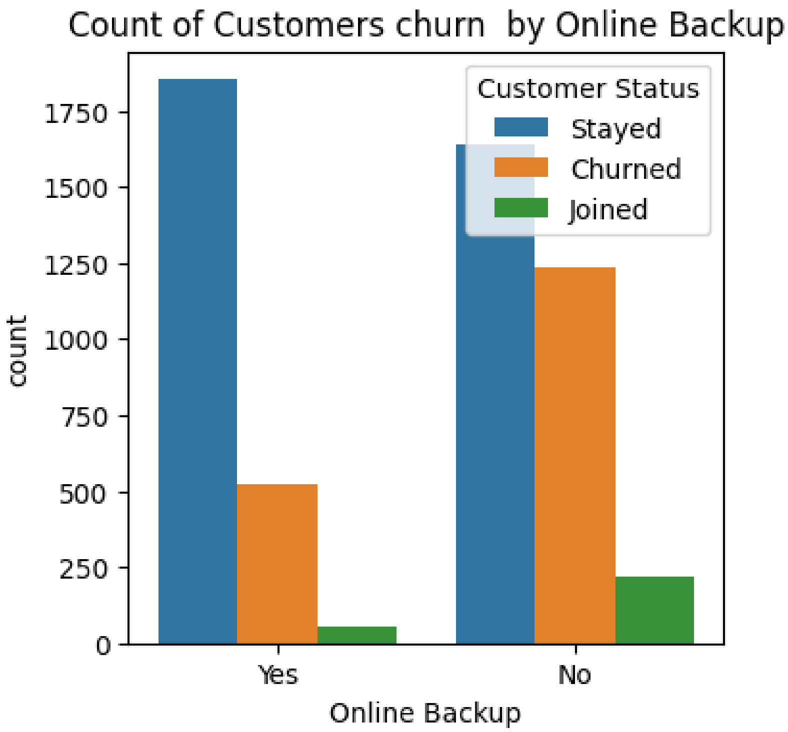
[35]:
```
plt.figure(figsize = (4,4))
sns.countplot(x = "Online Security", data = df, hue= "Customer Status")
plt.title("Count of Customers churn  by Online Security")
plt.show()
```



#Customer using no Online Security has churned.

Count of Customers churn by Online Backup

[36]:
```
plt.figure(figsize = (4,4))
sns.countplot(x = "Online Backup", data = df, hue= "Customer Status")
plt.title("Count of Customers churn  by Online Backup")
plt.show()
```



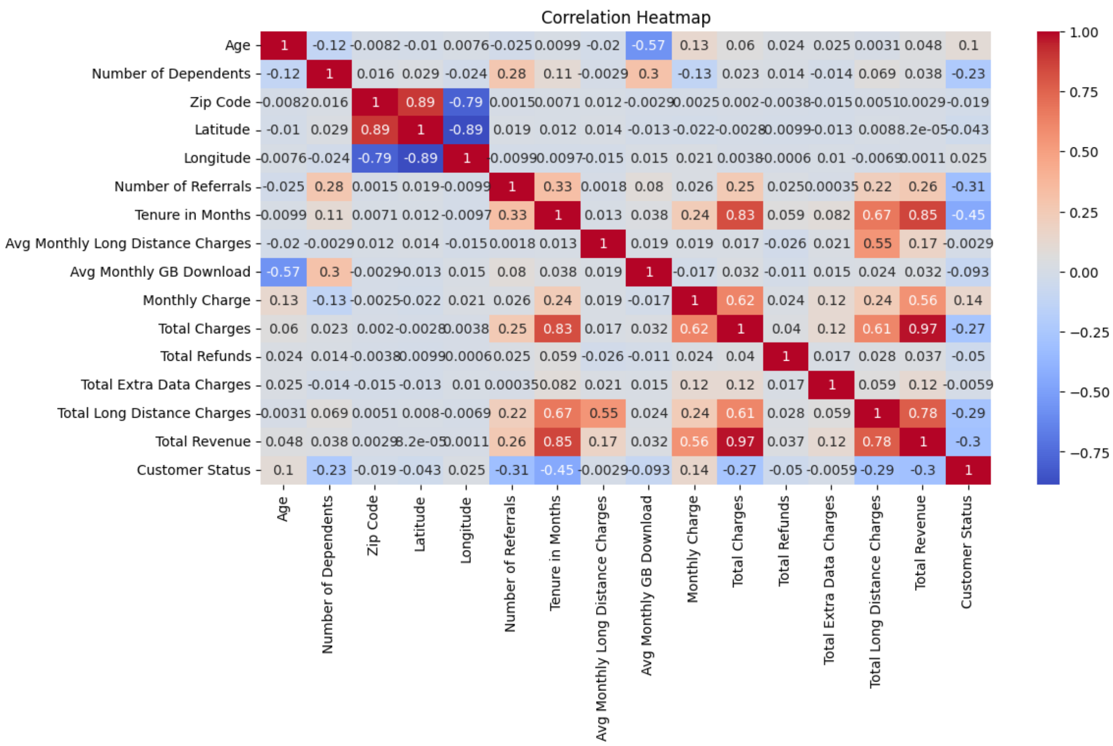
#Customer who does not uses Online Backup has churned.

Count of Customers by Churn Category

#Customer having better competitor has churned in larger number.

Correlation Heatmap

[37]:
```
# df['Customer Status']
# # Encode 'Churn' if needed
a = {'Stayed':0,'Joined':1,'Churned':2}
df['Customer Status'] = df['Customer Status'].map(a)

# Select only numerical columns
corr = df.corr(numeric_only=True)

# Plot heatmap
plt.figure(figsize=(12, 6))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```

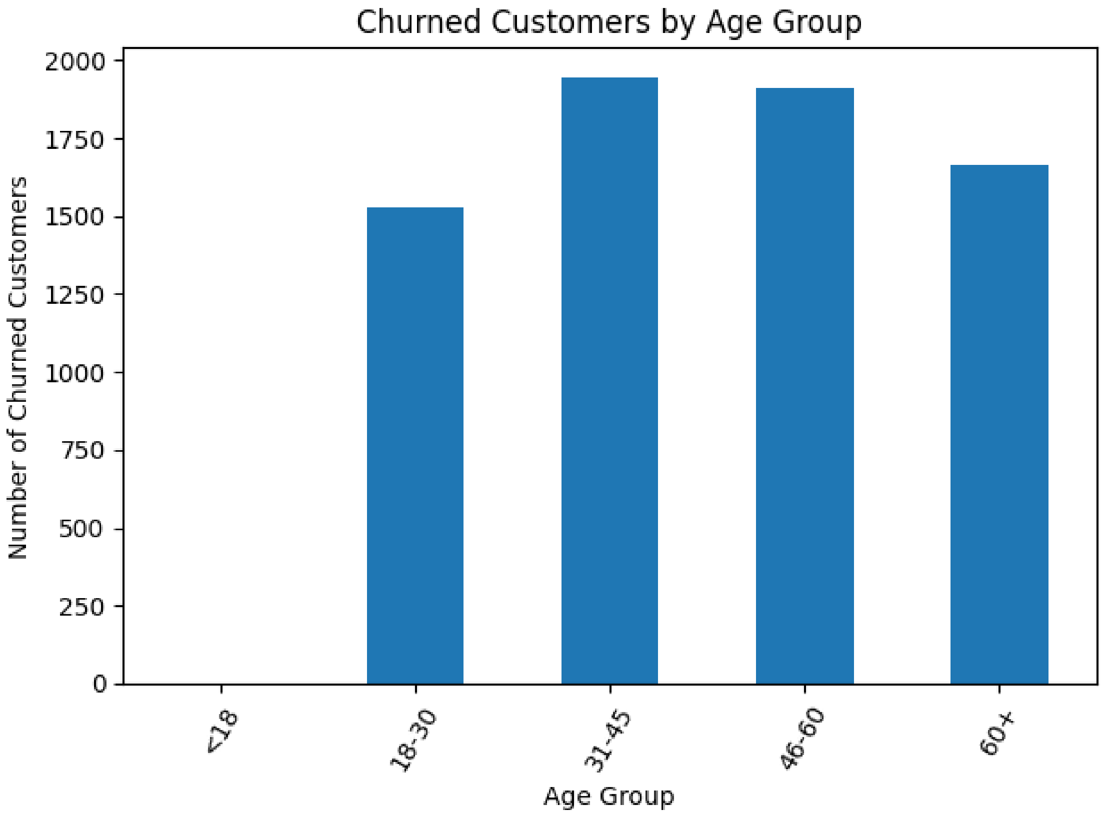


[38]:

```python
# 1. Create age bins and labels
age_bins = [0, 18, 30, 45, 60, float('inf')]
age_labels = ['<18', '18-30', '31-45', '46-60', '60+']

# 2. Ensure 'Age' is numeric
df['Age'] = pd.to_numeric(df['Age'], errors='coerce')

# 3. Create age group in a NEW column
df['AgeGroup'] = pd.cut(df['Age'], bins=age_bins, labels=age_labels)

# 4. Filter churned customers (assuming 'Yes' means churned)
df_churned = df[df['Customer Status'] == 'Yes'].copy()

# 5. Count churned customers by age group
churn_by_age = df['AgeGroup'].value_counts().sort_index()

# 6. Print and plot
print(churn_by_age)

# Optional: Plot
import matplotlib.pyplot as plt

churn_by_age.plot(kind='bar')
```

```
plt.title('Churned Customers by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Number of Churned Customers')
plt.xticks(rotation=60)
plt.tight_layout()
plt.show()
```

```
AgeGroup
<18          0
18-30     1529
31-45     1943
46-60     1909
60+       1662
Name: count, dtype: int64
```



[39]:
```
df['Customer Status']
```

[39]:
```
0        0
1        0
2        2
3        2
```

```
4       2
       ..
7038    0
7039    2
7040    1
7041    0
7042    0
Name: Customer Status, Length: 7043, dtype: int64
```

[40]:
```
df.head()
# For machine learning we do not need zip code,latitude,longitude so drop it.
df = df.drop(columns=['Zip Code','Longitude','Latitude','City','AgeGroup'],axis␣
 ↪= 1)
```

[41]:
```
df.drop(columns='Customer ID',axis=1,inplace=True)
```

[42]:
```
# df.head()
g = {'Female':0,'Male':1}
df['Gender'] = df['Gender'].map(g)
```

[43]:
```
df.head()
```

[43]:
```
   Gender  Age Married  Number of Dependents  Number of Referrals  \
0       0   37     Yes                     0                    2
1       1   46      No                     0                    0
2       1   50      No                     0                    0
3       1   78     Yes                     0                    1
4       0   75     Yes                     0                    3

   Tenure in Months Phone Service  Avg Monthly Long Distance Charges  \
0                 9           Yes                              42.39
1                 9           Yes                              10.69
2                 4           Yes                              33.65
3                13           Yes                              27.82
4                 3           Yes                               7.38

  Multiple Lines Internet Service  …        Contract  Paperless Billing  \
0             No              Yes  …        One Year                Yes
1            Yes              Yes  …  Month-to-Month                 No
2             No              Yes  …  Month-to-Month                Yes
3             No              Yes  …  Month-to-Month                Yes
4             No              Yes  …  Month-to-Month                Yes

    Payment Method Monthly Charge Total Charges Total Refunds  \
0      Credit Card           65.6        593.30          0.00
1      Credit Card           -4.0        542.40         38.33
2  Bank Withdrawal           73.9        280.85          0.00
```

```
3  Bank Withdrawal           98.0       1237.85          0.00
4      Credit Card           83.9        267.40          0.00

  Total Extra Data Charges Total Long Distance Charges Total Revenue  \
0                        0                      381.51        974.81
1                       10                       96.21        610.28
2                        0                      134.60        415.45
3                        0                      361.66       1599.51
4                        0                       22.14        289.54

  Customer Status
0               0
1               0
2               2
3               2
4               2

[5 rows x 30 columns]
```

[44]:
```
df['Payment Method'].unique()
```

[44]:
```
array(['Credit Card', 'Bank Withdrawal', 'Mailed Check'], dtype=object)
```

[45]:
```
u = {'Credit Card':1,'Bank Withdrawal':2,'Mailed Check':3}
df['Payment Method'] = df['Payment Method'].map(u)
```

[46]:
```
df['Contract'].unique()
c = {'One Year':3,'Month-to-Month':1,'Two Year':2}
df['Contract'] = df['Contract'].map(c)
```

#Tenure, total charges, and total revenue show strong positive correlations, indicating they move together. Age is moderately negatively correlated with data usage, while customer status shows weak correlation with all variables.

[47]:
```
df['Payment Method']
```

[47]:
```
0       1
1       1
2       2
3       2
4       1
       ..
7038    1
7039    2
7040    1
7041    1
7042    2
Name: Payment Method, Length: 7043, dtype: int64
```

[48]:
```
df = pd.get_dummies(df, columns=['Internet Service', 'Internet Type', 'Payment␣
↪Method'], drop_first=True)
```

[49]:
```
# Convert all boolean columns to 0 and 1
bool_cols = df.select_dtypes(include='bool').columns
df[bool_cols] = df[bool_cols].astype(int)
```

[50]:
```
df = df.replace({'Yes': 1, 'No': 0})
```

```
C:\Users\Raushan\AppData\Local\Temp\ipykernel_19712\3534361578.py:1:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  df = df.replace({'Yes': 1, 'No': 0})
```

[51]:
```
df.dtypes
```

[51]:
```
Gender                                int64
Age                                   int64
Married                               int64
Number of Dependents                  int64
Number of Referrals                   int64
Tenure in Months                      int64
Phone Service                         int64
Avg Monthly Long Distance Charges   float64
Multiple Lines                      float64
Avg Monthly GB Download             float64
Online Security                     float64
Online Backup                       float64
Device Protection Plan              float64
Premium Tech Support                float64
Streaming TV                        float64
Streaming Movies                    float64
Streaming Music                     float64
Unlimited Data                      float64
Contract                              int64
Paperless Billing                     int64
Monthly Charge                      float64
Total Charges                       float64
Total Refunds                       float64
Total Extra Data Charges              int64
Total Long Distance Charges         float64
Total Revenue                       float64
Customer Status                       int64
Internet Service_Yes                  int64
Internet Type_DSL                     int64
Internet Type_Fiber Optic             int64
```

```
Payment Method_2                        int64
Payment Method_3                        int64
dtype: object
```

Count of customer churn by age group

[52]:
```python
df['Avg Monthly Long Distance Charges']
```

[52]:
```
0       42.39
1       10.69
2       33.65
3       27.82
4        7.38
        …
7038    46.68
7039    16.20
7040    18.62
7041     2.12
7042      NaN
Name: Avg Monthly Long Distance Charges, Length: 7043, dtype: float64
```

[53]:
```python
from sklearn.preprocessing import MinMaxScaler

# List of columns to scale
cols_to_scale = [
    'Total Revenue',
    'Total Long Distance Charges',
    'Avg Monthly GB Download',
    'Avg Monthly Long Distance Charges'
]

# Initialize scaler
scaler = MinMaxScaler()

# Fit and transform the selected columns
scaled_values = scaler.fit_transform(df[cols_to_scale])

# Replace the original columns with scaled values
df[cols_to_scale] = scaled_values
```

[54]:
```python
cols_to_scale = [
    'Age',
    'Total Extra Data Charges',
    'Tenure in Months'
]

# Initialize scaler
scaler = MinMaxScaler()
```

```python
# Fit and transform the selected columns
scaled_values = scaler.fit_transform(df[cols_to_scale])

# Replace the original columns with scaled values
df[cols_to_scale] = scaled_values
```

[55]:
```python
df.head()
```

[55]:
```
   Gender       Age  Married  Number of Dependents  Number of Referrals  \
0       0  0.295082        1                     0                    2
1       1  0.442623        0                     0                    0
2       1  0.508197        0                     0                    0
3       1  0.967213        1                     0                    1
4       0  0.918033        1                     0                    3

   Tenure in Months  Phone Service  Avg Monthly Long Distance Charges  \
0          0.112676              1                           0.844835
1          0.112676              1                           0.197632
2          0.042254              1                           0.666394
3          0.169014              1                           0.547366
4          0.028169              1                           0.130053

   Multiple Lines  Avg Monthly GB Download  …  Total Refunds  \
0             0.0                 0.168675  …           0.00
1             1.0                 0.096386  …          38.33
2             0.0                 0.337349  …           0.00
3             0.0                 0.024096  …           0.00
4             0.0                 0.108434  …           0.00

   Total Extra Data Charges  Total Long Distance Charges  Total Revenue  \
0                  0.000000                     0.107024       0.079733
1                  0.066667                     0.026989       0.049249
2                  0.000000                     0.037759       0.032956
3                  0.000000                     0.101455       0.131975
4                  0.000000                     0.006211       0.022427

   Customer Status  Internet Service_Yes  Internet Type_DSL  \
0                0                     1                  0
1                0                     1                  0
2                2                     1                  0
3                2                     1                  0
4                2                     1                  0

   Internet Type_Fiber Optic  Payment Method_2  Payment Method_3
0                          0                 0                 0
1                          0                 0                 0
```

```
2                          1                 1                 0
3                          1                 1                 0
4                          1                 0                 0

[5 rows x 32 columns]
```

Customers aged 31–45 and 46–60 have the highest churn rates among all age groups.

[56]:
```python
df.head()
```

[56]:
```
   Gender       Age  Married  Number of Dependents  Number of Referrals  \
0       0  0.295082        1                     0                    2
1       1  0.442623        0                     0                    0
2       1  0.508197        0                     0                    0
3       1  0.967213        1                     0                    1
4       0  0.918033        1                     0                    3

   Tenure in Months  Phone Service  Avg Monthly Long Distance Charges  \
0          0.112676              1                           0.844835
1          0.112676              1                           0.197632
2          0.042254              1                           0.666394
3          0.169014              1                           0.547366
4          0.028169              1                           0.130053

   Multiple Lines  Avg Monthly GB Download  …  Total Refunds  \
0             0.0                 0.168675  …           0.00
1             1.0                 0.096386  …          38.33
2             0.0                 0.337349  …           0.00
3             0.0                 0.024096  …           0.00
4             0.0                 0.108434  …           0.00

   Total Extra Data Charges  Total Long Distance Charges  Total Revenue  \
0                  0.000000                     0.107024       0.079733
1                  0.066667                     0.026989       0.049249
2                  0.000000                     0.037759       0.032956
3                  0.000000                     0.101455       0.131975
4                  0.000000                     0.006211       0.022427

   Customer Status  Internet Service_Yes  Internet Type_DSL  \
0                0                     1                  0
1                0                     1                  0
2                2                     1                  0
3                2                     1                  0
4                2                     1                  0

   Internet Type_Fiber Optic  Payment Method_2  Payment Method_3
0                          0                 0                 0
1                          0                 0                 0
```

```
2                          1                 1                 0
3                          1                 1                 0
4                          1                 0                 0

[5 rows x 32 columns]
```

[57]:
```
x = df.drop('Customer Status',axis =1)
y = df['Customer Status']
```

[58]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.
 ↪3,random_state=1)
```

[59]:
```
from sklearn import tree
decision = tree.DecisionTreeClassifier()
decision.fit(x_train,y_train)
```

[59]:
```
DecisionTreeClassifier()
```

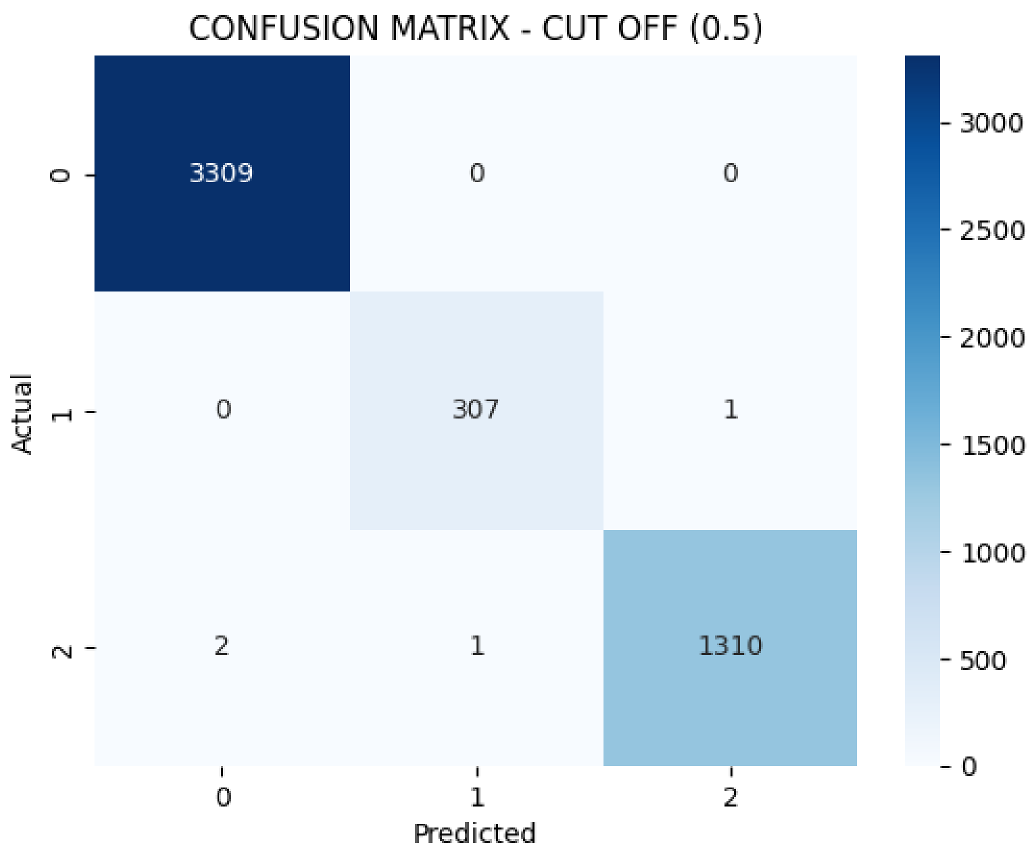
[62]:
```
#Train
```

[63]:
```
from sklearn import metrics
y_train_predict = decision.predict(x_train)

di_score = decision.score(x_train,y_train)


print(di_score)

print()

print(metrics.confusion_matrix(y_train,y_train_predict))

print()

print(metrics.classification_report(y_train,y_train_predict))
sns.heatmap(metrics.confusion_matrix(y_train,y_train_predict),annot = True,fmt␣
 ↪= '.5g',cmap = 'Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual');
plt.title('CONFUSION MATRIX - CUT OFF (0.5)')
```

```
0.9991886409736308

[[3309    0    0]
 [   0  307    1]
 [   2    1 1310]]
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3309
           1       1.00      1.00      1.00       308
           2       1.00      1.00      1.00      1313

    accuracy                           1.00      4930
   macro avg       1.00      1.00      1.00      4930
weighted avg       1.00      1.00      1.00      4930
```

[63]: Text(0.5, 1.0, 'CONFUSION MATRIX - CUT OFF (0.5)')



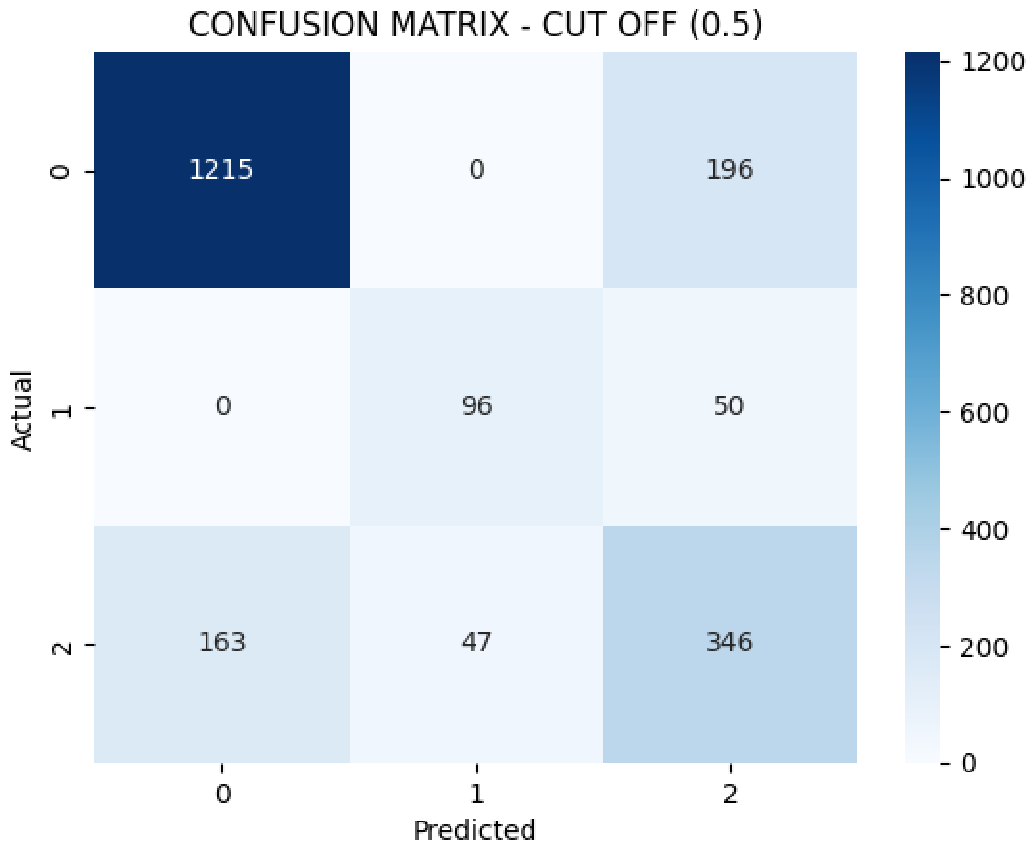
[64]:
```
# Test
```

[65]:
```
y_test_predict = decision.predict(x_test)

di_score = decision.score(x_test,y_test)
```

```
print(di_score)

print()

print(metrics.confusion_matrix(y_test,y_test_predict))

print()

print(metrics.classification_report(y_test,y_test_predict))

sns.heatmap(metrics.confusion_matrix(y_test,y_test_predict),annot = True,fmt =
 ↪'.5g',cmap = 'Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual');
plt.title('CONFUSION MATRIX - CUT OFF (0.5)')
#'Stayed': 0, 'Joined': 1, 'Churned': 2}
```

```
0.7841930903928065

[[1215    0  196]
 [   0   96   50]
 [ 163   47  346]]

              precision    recall  f1-score   support

           0       0.88      0.86      0.87      1411
           1       0.67      0.66      0.66       146
           2       0.58      0.62      0.60       556

    accuracy                           0.78      2113
   macro avg       0.71      0.71      0.71      2113
weighted avg       0.79      0.78      0.79      2113
```

[65]: Text(0.5, 1.0, 'CONFUSION MATRIX - CUT OFF (0.5)')


CONFUSION MATRIX - CUT OFF (0.5)
1215
0
196
0
96
50
163
47
346
Actual
Predicted
0
1
2
1200
1000
800
600
400
200
0

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```

```
[ ]:
```