

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

```
df = pd.read_excel('/content/E Commerce Dataset.xlsx', sheet_name = 'E Comm')
df
```

	CustomerID	Churn	Tenure	PreferredLoginDevice	CityTier	WarehouseToHome	Preferred
0	50001	1	4.0	Mobile Phone	3	6.0	
1	50002	1	NaN	Phone	1	8.0	
2	50003	1	NaN	Phone	1	30.0	
3	50004	1	0.0	Phone	3	15.0	
4	50005	1	0.0	Phone	1	12.0	
...
5625	55626	0	10.0	Computer	1	30.0	
5626	55627	0	13.0	Mobile Phone	1	13.0	
5627	55628	0	1.0	Mobile Phone	1	11.0	
5628	55629	0	23.0	Computer	3	9.0	
5629	55630	0	8.0	Mobile Phone	1	15.0	

5630 rows × 20 columns

Next steps: [View recommended plots](#)

```
df.shape
```

```
(5630, 20)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5630 entries, 0 to 5629
Data columns (total 20 columns):
```

#	Column	Non-Null Count	Dtype
0	CustomerID	5630 non-null	int64
1	Churn	5630 non-null	int64
2	Tenure	5366 non-null	float64
3	PreferredLoginDevice	5630 non-null	object
4	CityTier	5630 non-null	int64
5	WarehouseToHome	5379 non-null	float64
6	PreferredPaymentMode	5630 non-null	object
7	Gender	5630 non-null	object
8	HourSpendOnApp	5375 non-null	float64
9	NumberOfDeviceRegistered	5630 non-null	int64
10	PreferedOrderCat	5630 non-null	object
11	SatisfactionScore	5630 non-null	int64
12	MaritalStatus	5630 non-null	object
13	NumberOfAddress	5630 non-null	int64
14	Complain	5630 non-null	int64
15	OrderAmountHikeFromlastYear	5365 non-null	float64
16	CouponUsed	5374 non-null	float64
17	OrderCount	5372 non-null	float64
18	DaySinceLastOrder	5323 non-null	float64
19	CashbackAmount	5630 non-null	float64

dtypes: float64(8), int64(7), object(5)
memory usage: 879.8+ KB

```
df.nunique()
```

CustomerID	5630
Churn	2
Tenure	36
PreferredLoginDevice	3
CityTier	3
WarehouseToHome	34
PreferredPaymentMode	7
Gender	2
HourSpendOnApp	6
NumberOfDeviceRegistered	6
PreferedOrderCat	6
SatisfactionScore	5
MaritalStatus	3
NumberOfAddress	15
Complain	2
OrderAmountHikeFromlastYear	16
CouponUsed	17
OrderCount	16
DaySinceLastOrder	22
CashbackAmount	2586

dtype: int64

```
columns = df.columns.to_list()
columns
```

```
['CustomerID',
 'Churn',
```

```
'Tenure',
'PreferredLoginDevice',
'CityTier',
'WarehouseToHome',
'PreferredPaymentMode',
'Gender',
'HourSpendOnApp',
'NumberOfDeviceRegistered',
'PreferedOrderCat',
'SatisfactionScore',
'MaritalStatus',
'NumberOfAddress',
'Complain',
'OrderAmountHikeFromlastYear',
'CouponUsed',
'OrderCount',
'DaySinceLastOrder',
'CashbackAmount']
```

```
df.select_dtypes(exclude=np.number).columns
```

```
Index(['PreferredLoginDevice', 'PreferredPaymentMode', 'Gender',
      'PreferedOrderCat', 'MaritalStatus'],
      dtype='object')
```

```
for col in df.columns:
```

```
    if df[col].dtype == object:
```

```
        print(str(col) + ':' + str(df[col].unique()))
```

```
        print(df[col].value_counts())
```

```
        print('-----')
```

```
PreferredLoginDevice:['Mobile Phone' 'Phone' 'Computer']
```

```
PreferredLoginDevice
```

```
Mobile Phone      2765
```

```
Computer          1634
```

```
Phone             1231
```

```
Name: count, dtype: int64
```

```
PreferredPaymentMode:['Debit Card' 'UPI' 'CC' 'Cash on Delivery' 'E wallet' 'COD' 'Cred
```

```
PreferredPaymentMode
```

```
Debit Card        2314
```

```
Credit Card       1501
```

```
E wallet          614
```

```
UPI               414
```

```
COD               365
```

```
CC                273
```

```
Cash on Delivery  149
```

```
Name: count, dtype: int64
```

```
Gender:['Female' 'Male']
```

```
Gender
```

```
Male             3384
```

```
Female           2246
```

```
Name: count, dtype: int64
```

```

-----
PreferredOrderCat:['Laptop & Accessory' 'Mobile' 'Mobile Phone' 'Others' 'Fashion' 'Groc
PreferredOrderCat
Laptop & Accessory      2050
Mobile Phone           1271
Fashion                 826
Mobile                  809
Grocery                 410
Others                  264
Name: count, dtype: int64
-----
MaritalStatus:['Single' 'Divorced' 'Married']
MaritalStatus
Married      2986
Single       1796
Divorced      848
Name: count, dtype: int64
-----

```

```
df.select_dtypes(include=np.number).columns
```

```

Index(['CustomerID', 'Churn', 'Tenure', 'CityTier', 'WarehouseToHome',
      'HourSpendOnApp', 'NumberOfDeviceRegistered', 'SatisfactionScore',
      'NumberOfAddress', 'Complain', 'OrderAmountHikeFromlastYear',
      'CouponUsed', 'OrderCount', 'DaySinceLastOrder', 'CashbackAmount'],
      dtype='object')

```

```

for col in df.columns:
    if df[col].dtype == float or df[col].dtype == int:
        print(str(col) + ' : ' + str(df[col].unique()))
        print(df[col].value_counts())
        print('-----')

```

```

...
1.0    614
8.0    538
0.0    496
7.0    447
4.0    431
9.0    299
5.0    228
10.0   157
6.0    113
11.0    91
12.0    69
13.0    51
14.0    35
15.0    19
17.0    17
16.0    13
18.0    10
30.0     1
46.0     1
31.0     1

```

Name: count, dtype: int64

CashbackAmount : [159.93 120.9 120.28 ... 173.77 287.91 173.78]

CashbackAmount

```

123.42    8
149.36    8
148.42    8
188.47    7
154.73    7
..
174.84    1
127.74    1
145.05    1
174.28    1
173.78    1

```

Name: count, Length: 2586, dtype: int64

```

df.loc[df['PreferredLoginDevice'] == 'Phone', 'PreferredLoginDevice' ] = 'Mobile Phone'
df.loc[df['PreferredOrderCat'] == 'Mobile', 'PreferredOrderCat' ] = 'Mobile Phone'

```

```
df['PreferredLoginDevice'].value_counts()
```

```

PreferredLoginDevice
Mobile Phone    3996
Computer       1634
Name: count, dtype: int64

```

#as cod is also cash on delivery

#as cc is also credit card so i merged them

```

df.loc[df['PreferredPaymentMode'] == 'COD', 'PreferredPaymentMode' ] = 'Cash on Delivery'
df.loc[df['PreferredPaymentMode'] == 'CC', 'PreferredPaymentMode' ] = 'Credit Card'

```

```
df['PreferredPaymentMode'].value_counts()
```

```
PreferredPaymentMode
Debit Card          2314
Credit Card        1774
E wallet            614
Cash on Delivery    514
UPI                 414
Name: count, dtype: int64
```

```
# convert num_cols to categories
```

```
df2 = df.copy()
```

```
for col in df2.columns:
```

```
    if col == 'CustomerID':
        continue
```

```
    else:
```

```
        if df2[col].dtype == 'int':
            df2[col] = df2[col].astype(str)
```

```
df2.dtypes
```

```
CustomerID          int64
Churn               object
Tenure              float64
PreferredLoginDevice  object
CityTier            object
WarehouseToHome     float64
PreferredPaymentMode  object
Gender              object
HourSpendOnApp       float64
NumberOfDeviceRegistered  object
PreferedOrderCat     object
SatisfactionScore    object
MaritalStatus        object
NumberOfAddress      object
Complain            object
OrderAmountHikeFromlastYear  float64
CouponUsed           float64
OrderCount           float64
DaySinceLastOrder    float64
CashbackAmount       float64
dtype: object
```

```
df.duplicated().sum()
```

```
0
```

```
# the sum of null values
grouped_data = []
for col in columns:
    n_missing = df[col].isnull().sum()
    percentage = n_missing / df.shape[0] * 100
    grouped_data.append([col, n_missing, percentage])

# Create a new DataFrame from the grouped data
grouped_df = pd.DataFrame(grouped_data, columns=['column', 'n_missing', 'percentage'])

# Group by 'col', 'n_missing', and 'percentage'
result = grouped_df.groupby(['column', 'n_missing', 'percentage']).size()
result
```

column	n_missing	percentage	
CashbackAmount	0	0.000000	1
Churn	0	0.000000	1
CityTier	0	0.000000	1
Complain	0	0.000000	1
CouponUsed	256	4.547069	1
CustomerID	0	0.000000	1
DaySinceLastOrder	307	5.452931	1
Gender	0	0.000000	1
HourSpendOnApp	255	4.529307	1
MaritalStatus	0	0.000000	1
NumberOfAddress	0	0.000000	1
NumberOfDeviceRegistered	0	0.000000	1
OrderAmountHikeFromlastYear	265	4.706927	1
OrderCount	258	4.582593	1
PreferredOrderCat	0	0.000000	1
PreferredLoginDevice	0	0.000000	1
PreferredPaymentMode	0	0.000000	1
SatisfactionScore	0	0.000000	1
Tenure	264	4.689165	1
WarehouseToHome	251	4.458259	1

dtype: int64

```
import plotly.graph_objects as go
from plotly.subplots import make_subplots
binary_cat_cols = ['Complain']
outcome = ['Churn']
cat_cols = ['PreferredLoginDevice', 'CityTier', 'PreferredPaymentMode',
            'Gender', 'NumberOfDeviceRegistered', 'PreferredOrderCat',
            'SatisfactionScore', 'MaritalStatus', 'NumberOfAddress', 'Complain']
num_cols = ['Tenure', 'WarehouseToHome', 'HourSpendOnApp', 'OrderAmountHikeFromlastYear', '']
```

```
df_c = df[df['Churn']==1].copy()
df_nc = df[df['Churn']==0].copy()

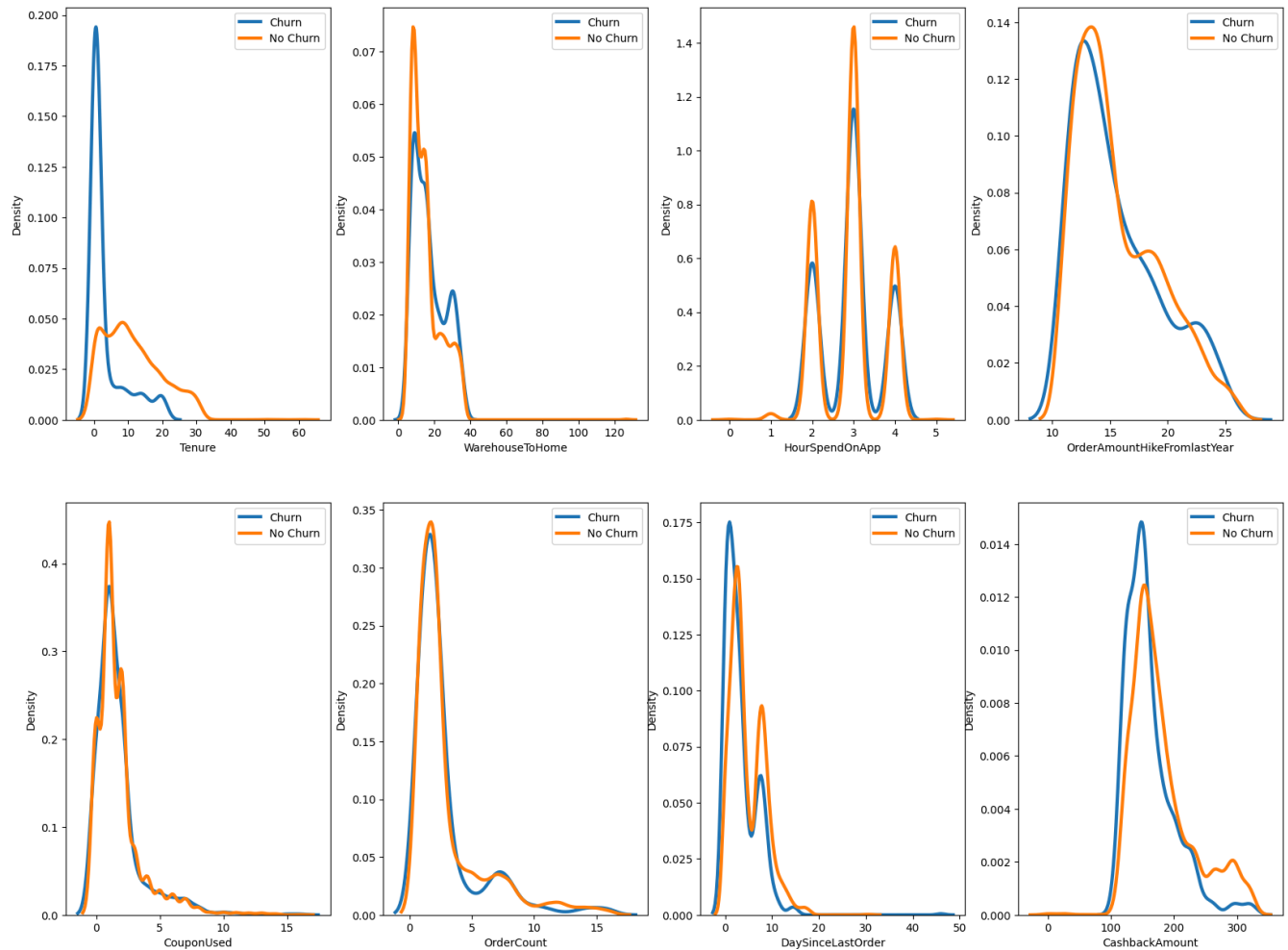
fig, ax = plt.subplots(2,4,figsize=(20, 15))
fig.suptitle('Density of Numeric Features by Churn', fontsize=20)
ax = ax.flatten()

for idx,c in enumerate(num_cols):
    sns.kdeplot(df_c[c], linewidth= 3,
                label = 'Churn',ax=ax[idx])
    sns.kdeplot(df_nc[c], linewidth= 3,
                label = 'No Churn',ax=ax[idx])

    ax[idx].legend(loc='upper right')

plt.show()
```


Density of Numeric Features by Churn



- **Tenure:** Customers with longer tenure seem less likely to churn. Makes sense as longer tenure indicates satisfaction
- **CityTier:** Churn rate looks similar across tiers. City tier does not seem predictive of churn
- **WarehouseToHome:** Shorter warehouse to home distances have a lower churn rate. Faster deliveries may improve satisfaction
- **HourSpendOnApp:** More time spent on app correlates with lower churn. App engagement is a good sign
- **NumberOfDeviceRegistered:** More registered devices associates with lower churn. Access across devices improves convenience
- **SatisfactionScore:** Higher satisfaction scores strongly associate with lower churn, as expected. Critical driver
- **NumberOfAddress:** Slight downward trend in churn as number of addresses increases. More addresses indicates loyalty
- **Complain:** More complaints associate with higher churn, though relationship isn't very strong. Complaints hurt satisfaction
- **OrderAmountHikeFromLastYear:** Big spenders from last year are less likely to churn. Good to retain big customers
- **CouponUsed:** Coupon usage correlates with lower churn. Coupons enhance loyalty
- **OrderCount:** Higher order counts associate with lower churn. Frequent usage builds habits
- **DaySinceLastOrder:** Longer since last order correlates with higher churn. Recency is a good predictor

```
df_c = df2[df2['Churn']=='1'].copy()
df_nc = df2[df2['Churn']=='0'].copy()

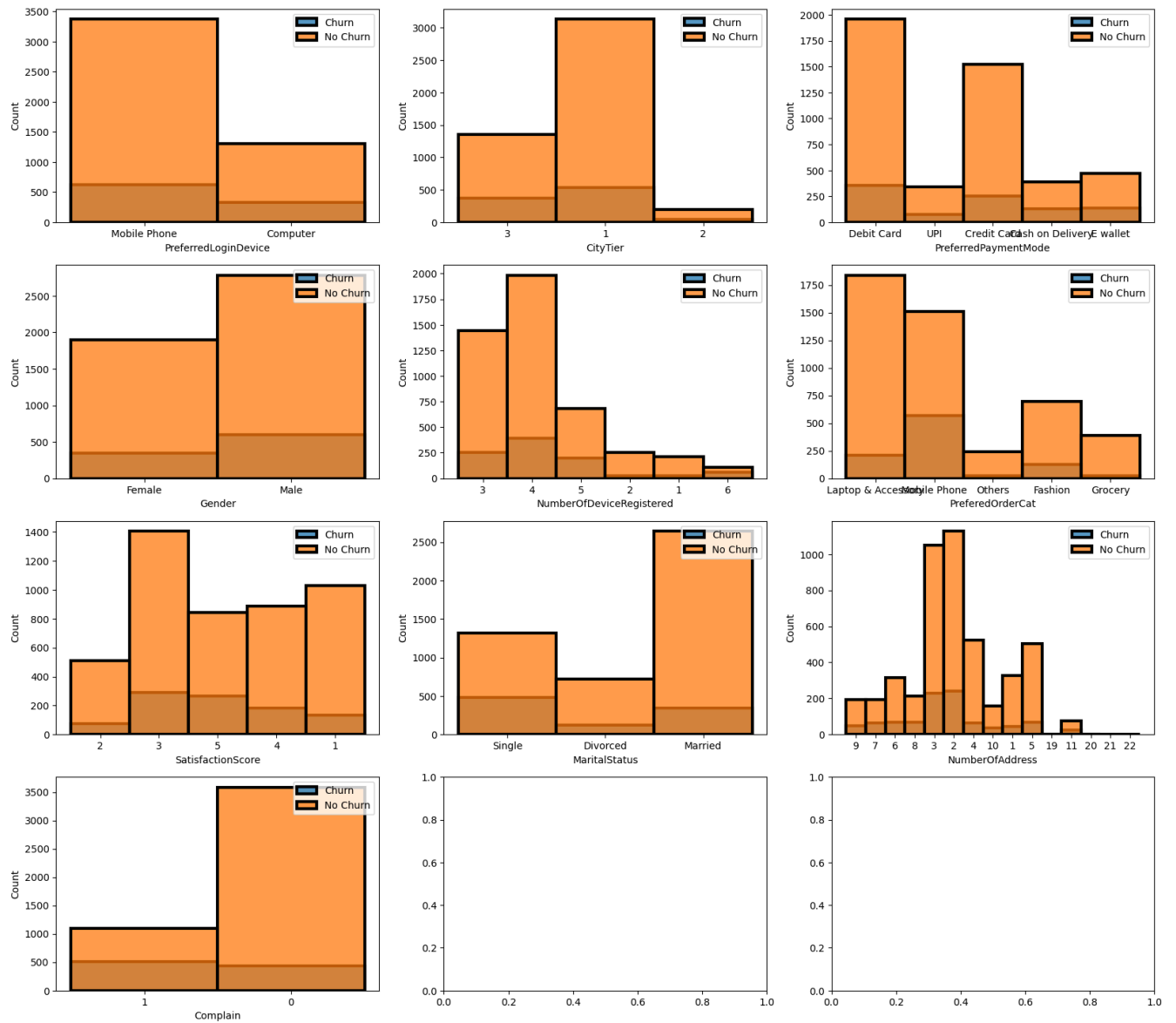
fig, ax = plt.subplots(4,3,figsize=(20, 18))
fig.suptitle('Density of Numeric Features by Churn', fontsize=20)
ax = ax.flatten()

for idx,c in enumerate(cat_cols):
    sns.histplot(df_c[c], linewidth= 3,
                label = 'Churn',ax=ax[idx])
    sns.histplot(df_nc[c], linewidth= 3,
                label = 'No Churn',ax=ax[idx])

    ax[idx].legend(loc='upper right')

plt.show()
```

Density of Numeric Features by Churn



Which Gender has more Orders?

```
df['Gender'].value_counts()
```

```
Gender
Male      3384
Female    2246
Name: count, dtype: int64
```

```
df.groupby("Churn")["Gender"].value_counts()
```

```
Churn  Gender
0      Male      2784
       Female    1898
1      Male       600
       Female     348
Name: count, dtype: int64
```

```
df.groupby("PreferredLoginDevice")["OrderCount"].value_counts()
```

```
PreferredLoginDevice  OrderCount
Computer
2.0                  573
1.0                  486
3.0                  132
4.0                   61
7.0                   59
5.0                   48
8.0                   44
6.0                   40
14.0                  20
9.0                   19
11.0                  16
10.0                  15
12.0                  15
13.0                   9
15.0                   8
16.0                   4
Mobile Phone
2.0                 1452
1.0                 1265
3.0                 239
7.0                 147
4.0                 143
5.0                 133
8.0                 128
```

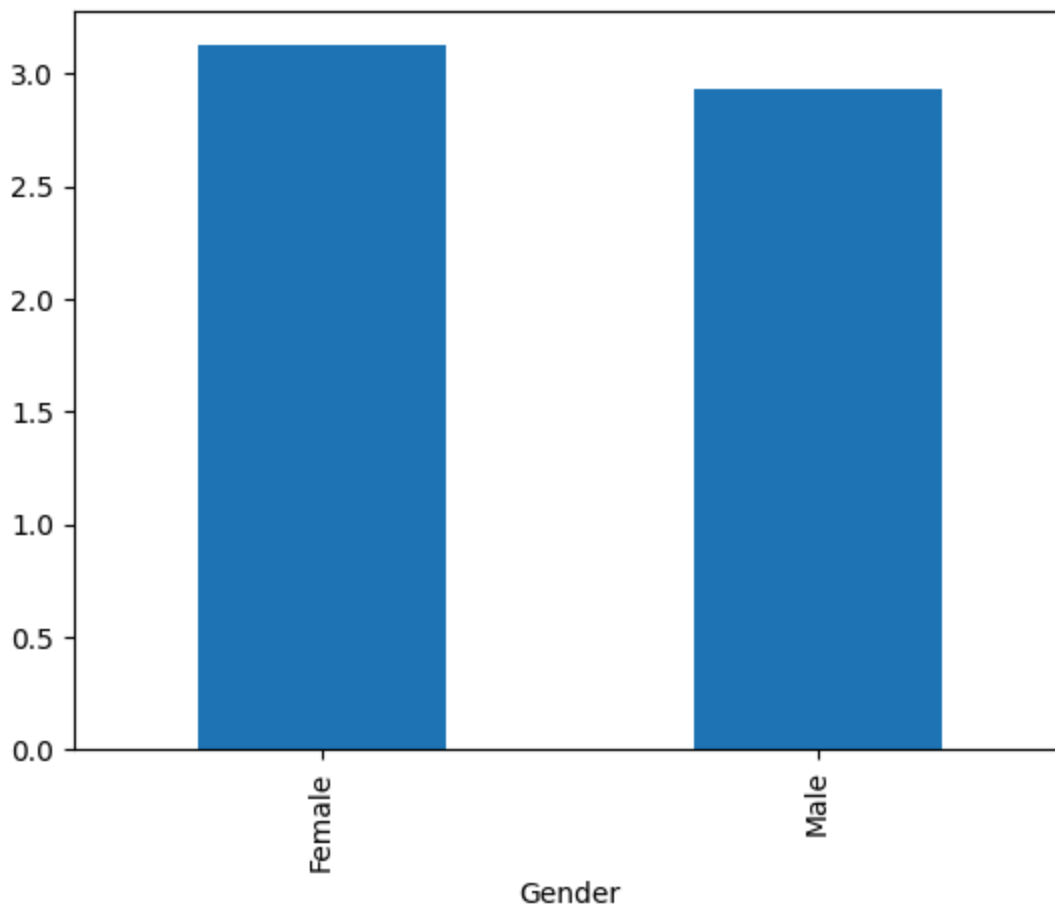
6.0	97
9.0	43
12.0	39
11.0	35
15.0	25
13.0	21
10.0	21
16.0	19
14.0	16

Name: count, dtype: int64

```
gender_orders = df.groupby('Gender')['OrderCount'].mean().plot(kind='bar')
```

gender_orders

<Axes: xlabel='Gender'>



```
percentageM = 600/3384 * 100
```

```
#the percentage of the leaving males out of the males
```

```
percentageM
```

17.73049645390071

```
percentageF = 348/2246 * 100
```

```
percentageF #the percentage of the leaving females out of the female
```

```
15.49421193232413
```

```
import pandas as pd
```

```
import plotly.express as px
```

```
# Create figure
```

```
fig = px.pie(df, values='Churn', names='Gender')
```

```
fig.update_traces(marker=dict(colors=['pink ', 'baby blue']))
```

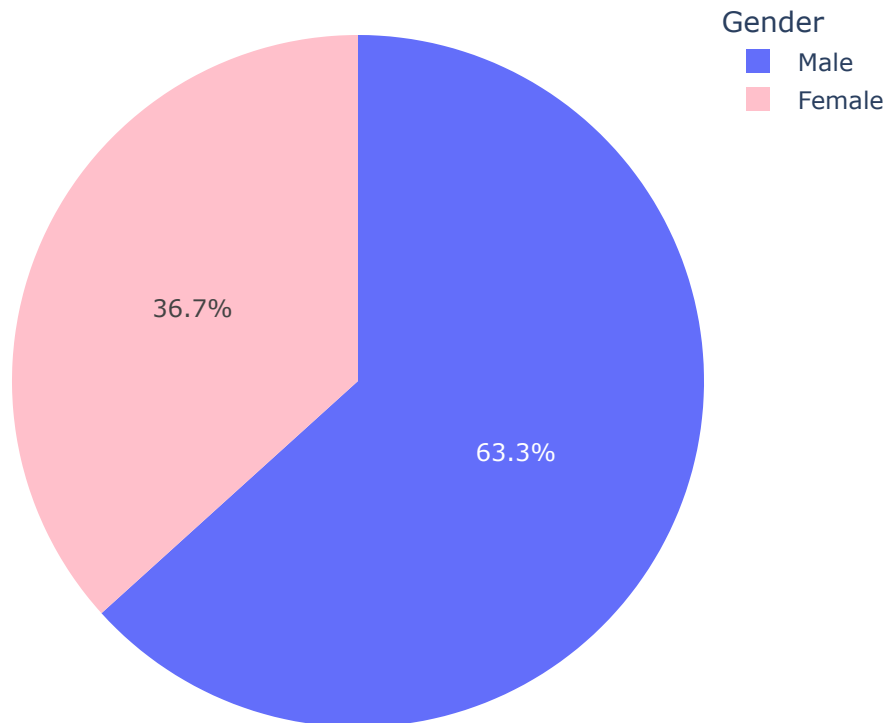
```
# Update layout
```

```
fig.update_layout(  
    title='Churn Rate by Gender',  
    legend_title='Gender'  
)
```

```
# Show plot
```

```
fig.show()
```

Churn Rate by Gender



as we see the males are more likely to churn as we have 63.3 % churned males from the app may be the company should consider increasing the products that grab the males interest and so on.. we are going to see if there is another factors that makes the highest segment of churned customers are males

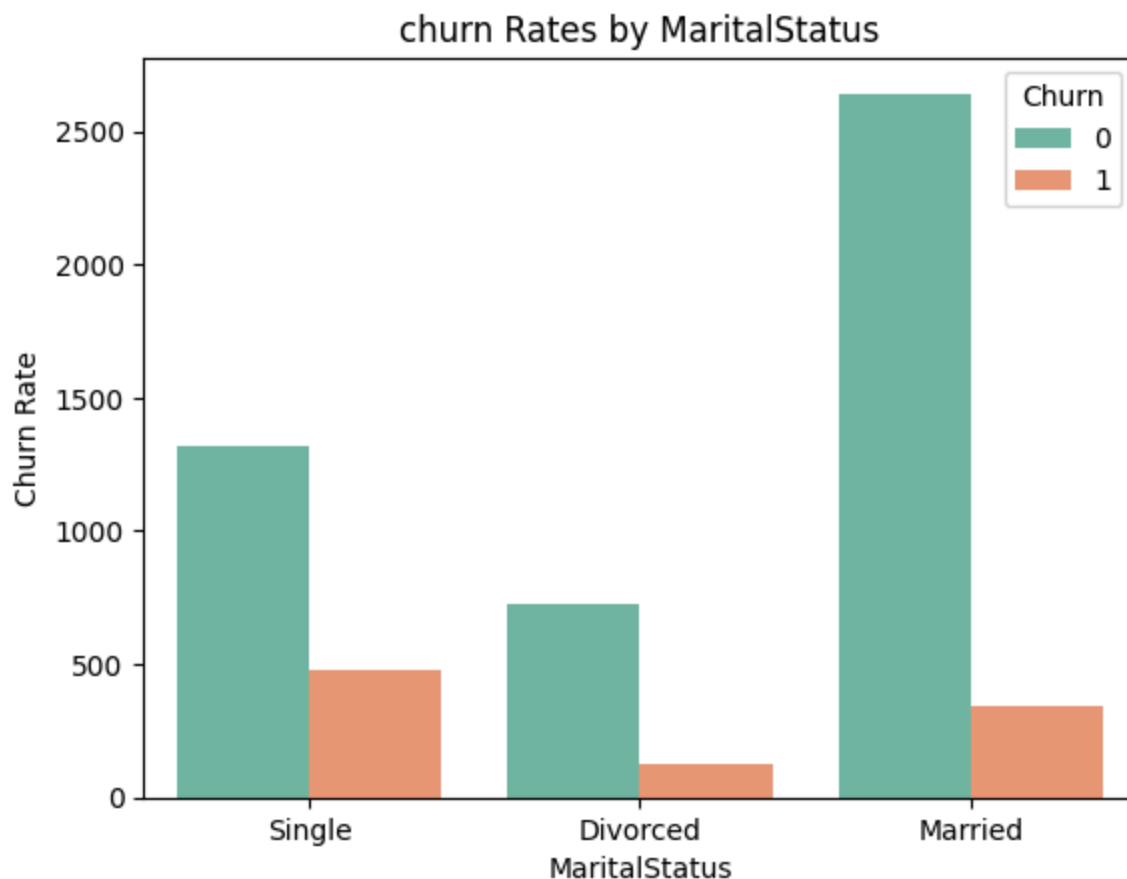
2-Which MaritalStatus has the highest Churn rate?

```
df.groupby("Churn")["MaritalStatus"].value_counts()
```

```
Churn  MaritalStatus
0      Married      2642
      Single      1316
      Divorced      724
1      Single      480
      Married      344
      Divorced      124
Name: count, dtype: int64
```

```
sns.countplot(x='MaritalStatus',hue='Churn',data=df,palette='Set2')
plt.title("churn Rates by MaritalStatus")
plt.ylabel("Churn Rate")
```



```
Text(0, 0.5, 'Churn Rate')
```



the married are the highest customer segment in the company may be the company should consider taking care of the products that suits the single and the married customers as the singles are the most likely to churn from the app

3-Which CityTier has higher Tenure and OrderCount?



```
df_grouped_tenure = df.groupby('CityTier')['Tenure'].agg(['mean', 'max'])
df_grouped_tenure
```

	mean	max	
CityTier			
1	10.528818	51.0	
2	11.169725	31.0	
3	9.361740	61.0	

Next steps:

 [View recommended plots](#)

```
df_grouped_OrderCount = df.groupby('CityTier')['OrderCount'].agg(['mean', 'max'])
df_grouped_OrderCount
```

	mean	max	
CityTier			
1	2.953255	16.0	
2	2.584034	13.0	
3	3.185185	16.0	

Next steps:

 [View recommended plots](#)

citytier 2 has the highest tenure rate but the tenure rate does not seem to be a strong factor

```
df.groupby("CityTier")["OrderCount"].mean()
```

```
CityTier
1    2.953255
2    2.584034
3    3.185185
Name: OrderCount, dtype: float64
```


4-Is Customer with High SatisfactionScore have high HourSpendOnApp?

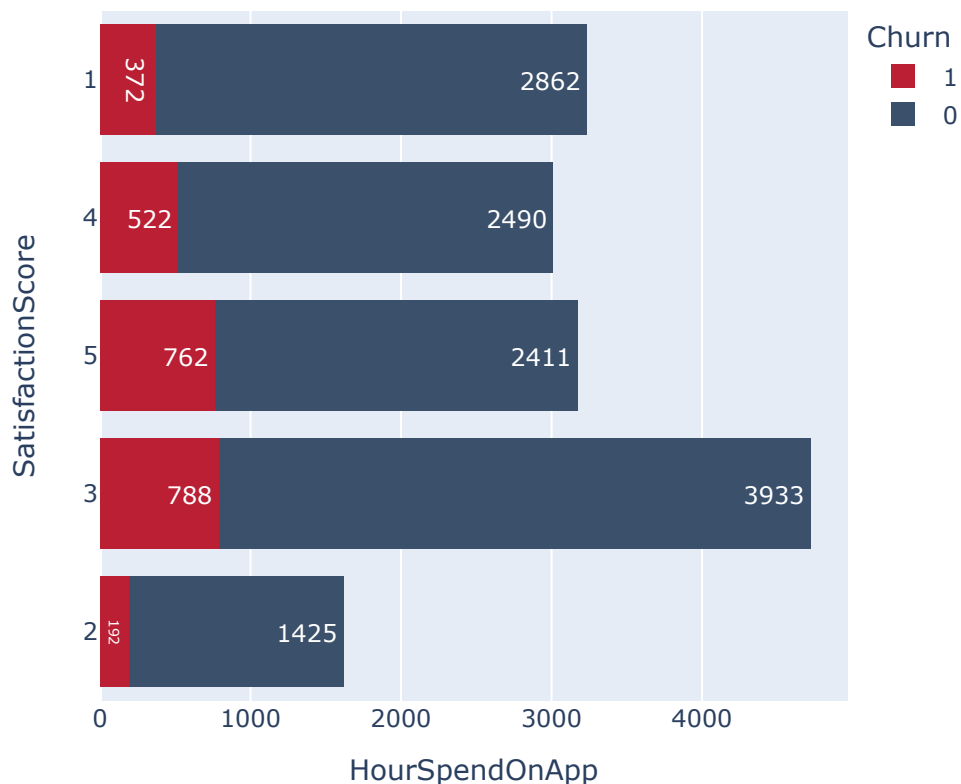
```
df['SatisfactionScore'].dtypes
```

```
dtype('int64')
```

```
fig = px.histogram(df2, x="HourSpendOnApp", y="SatisfactionScore", orientation="h", color="
```

```
# Customize the plot
fig.update_layout(hovermode='x',title_font_size=30)
fig.update_layout(
    title_font_color="black",
    template="plotly",
    title_font_size=30,
    hoverlabel_font_size=20,
    title_x=0.5,
    xaxis_title='HourSpendOnApp',
    yaxis_title='SatisfactionScore',
)
fig.show()
```

irSpendOnApp Vs SatisfactionSc



as we see people with less satisfaction score spend less time on the app than the people of satisfaction score 5 but also i do not think there is any realation between the satisfaction score and people's spent time on the app

5-Which CityTier has the most HourSpendOnApp?

```
g = sns.FacetGrid(df, col='CityTier')
g.map(sns.distplot, 'HourSpendOnApp')
```

/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:854: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:854: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:854: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.