Customer Churn Analysis

May 22, 2024

1 Customer Churn Analysis

This is a dataset of an ecommerce company and we have some customers who are churning (leaving).

1.1 Goals

1. Perform exploratory analysis of the provided customer data to share insights of the behavior and characteristics of the customers. Make suggestions to help the company with customer retention
2. Build a predictive model to identify customers who are at risk of leaving the company (churn) based on the provided variables. This can help the company take proactive steps to retain these customers and reduce the rate of churn

1.2 Data description

1. CustomerID
2. Churn: Churn Flag
3. Tenure: in months
4. PreferredLoginDevice
5. CityTier
6. WarehouseToHome: Distance in between warehouse to home of customer
7. PreferredPaymentMode
8. Gender
9. HourSpendOnApp
10. NumberOfDeviceRegistered
11. PreferedOrderCat
12. SatisfactionScore
13. MaritalStatus
14. NumberOfAddress
15. OrderAmountHikeFromlastYear: Percentage increases in order from last year
16. CouponUsed: Total number of coupon has been used in last month

17. OrderCount: Total number of orders has been places in last month
18. DaySinceLastOrder
19. CashbackAmount: Average cashback in last month
20. Complain: Complain flag - if the customer ever had a complain

1.3 Tips

1. Sharing your thoughts and reasoning as you go will help!
2. Feel free to use any libraries like scikit-learn, use stackoverflow. Don't use ChatGPT and similar.
3. If you are unable to complete any step I can provide help towards the answer. Demonstrating understanding of the solution and result will earn some points!

1.4 Import the libraries

[1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

2 1. Data overview

Question: Read the sheet named 'E Comm' from file 'E Commerce Dataset.xlsx' saved in current directory into df variable. Print first 5 rows of the dataframe

[2]:
```
df = pd.read_excel('E Commerce Dataset.xlsx')
df.head(5)
```

[2]:
```
   CustomerID  Churn  Tenure PreferredLoginDevice  CityTier  WarehouseToHome  \
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

  PreferredPaymentMode  Gender  HourSpendOnApp  NumberOfDeviceRegistered  \
0           Debit Card  Female             3.0                         3
1                  UPI    Male             3.0                         4
2           Debit Card    Male             2.0                         4
3           Debit Card    Male             2.0                         4
4                   CC    Male             NaN                         3

     PreferedOrderCat  SatisfactionScore MaritalStatus  NumberOfAddress  \
0  Laptop & Accessory                  2        Single                9
1              Mobile                  3        Single                7
2              Mobile                  3        Single                6
3  Laptop & Accessory                  5        Single                8
```

```
4             Mobile                  5        Single              3

   Complain  OrderAmountHikeFromlastYear  CouponUsed  OrderCount  \
0         1                         11.0         1.0         1.0
1         1                         15.0         0.0         1.0
2         1                         14.0         0.0         1.0
3         0                         23.0         0.0         1.0
4         0                         11.0         1.0         1.0

   DaySinceLastOrder  CashbackAmount
0                5.0          159.93
1                0.0          120.90
2                3.0          120.28
3                3.0          134.07
4                3.0          129.60
```

[3]:
```
df.shape
```

[3]: (5630, 20)

[4]:
```
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
```

Question: How many unique values are in each column?

[5]:
```
for columns in df:
  print(columns,df[columns].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
```

Question: Calculate average churn rate Note: Churn = 1 means customer has churned

[6]:
```
df[df['Churn'] == 1].count()
```

[6]:
```
CustomerID                  948
Churn                       948
Tenure                      867
PreferredLoginDevice        948
CityTier                    948
WarehouseToHome             864
PreferredPaymentMode        948
Gender                      948
HourSpendOnApp              890
NumberOfDeviceRegistered    948
PreferedOrderCat            948
SatisfactionScore           948
MaritalStatus               948
NumberOfAddress             948
Complain                    948
```

```
OrderAmountHikeFromlastYear    934
CouponUsed                     940
OrderCount                     930
DaySinceLastOrder              894
CashbackAmount                 948
dtype: int64
```

[7]:
```
#check if there is any n/a
df['Churn'].isna().nunique()
```

[7]:
```
1
```

[8]:
```
#churn rate
df[df['Churn'] == 1].shape[0]/df.shape[0]*100
```

[8]:
```
16.838365896980463
```

Question: How many missing values / nulls are there in each column?

[9]:
```
for col in df.columns:
  print(col, df[col].isna().sum())
```

```
CustomerID 0
Churn 0
Tenure 264
PreferredLoginDevice 0
CityTier 0
WarehouseToHome 251
PreferredPaymentMode 0
Gender 0
HourSpendOnApp 255
NumberOfDeviceRegistered 0
PreferedOrderCat 0
SatisfactionScore 0
MaritalStatus 0
NumberOfAddress 0
Complain 0
OrderAmountHikeFromlastYear 265
CouponUsed 256
OrderCount 258
DaySinceLastOrder 307
CashbackAmount 0
```

3 2. Exploratory Data Analysis

3.1 Univariate analysis

Here we will understand select variables

3.1.1 1. Numeric variables

Question: Histogram Show histograms for all numeric columns. Describe the each variable's distribution briefly to a business stakeholder

[10]:
```
numerical_df =␣
↪df[['CustomerID','Churn','Tenure','CityTier','WarehouseToHome','HourSpendOnApp','NumberOfDe
↪'OrderAmountHikeFromlastYear',        'CouponUsed',        'OrderCount',        'DaySinceLa
numerical_df.head(5)
```

[10]:

	CustomerID	Churn	Tenure	CityTier	WarehouseToHome	HourSpendOnApp	\
0	50001	1	4.0	3	6.0	3.0	
1	50002	1	NaN	1	8.0	3.0	
2	50003	1	NaN	1	30.0	2.0	
3	50004	1	0.0	3	15.0	2.0	
4	50005	1	0.0	1	12.0	NaN	

	NumberOfDeviceRegistered	SatisfactionScore	NumberOfAddress	Complain	\
0	3	2	9	1	
1	4	3	7	1	
2	4	3	6	1	
3	4	5	8	0	
4	3	5	3	0	

	OrderAmountHikeFromlastYear	CouponUsed	OrderCount	DaySinceLastOrder	\
0	11.0	1.0	1.0	5.0	
1	15.0	0.0	1.0	0.0	
2	14.0	0.0	1.0	3.0	
3	23.0	0.0	1.0	3.0	
4	11.0	1.0	1.0	3.0	

	CashbackAmount
0	159.93
1	120.90
2	120.28
3	134.07
4	129.60

[11]:
```
categorical_df =␣
↪df[['PreferredLoginDevice','PreferredPaymentMode','Gender','PreferedOrderCat','MaritalStatu
categorical_df.head(5)
```

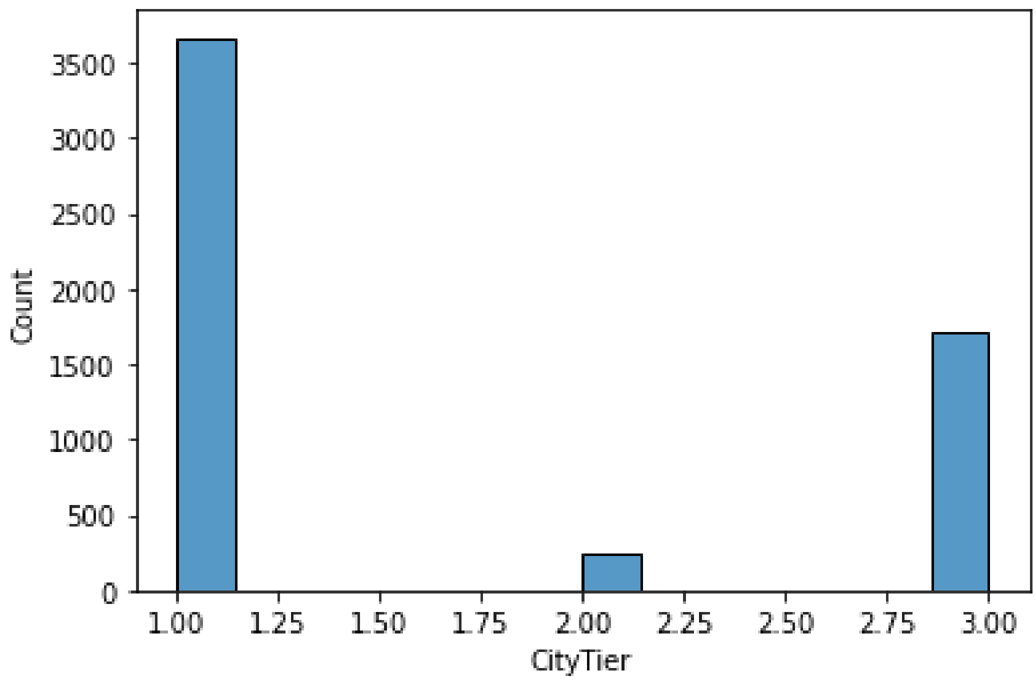
[11]:

	PreferredLoginDevice	PreferredPaymentMode	Gender	PreferedOrderCat	\
0	Mobile Phone	Debit Card	Female	Laptop & Accessory	
1	Phone	UPI	Male	Mobile	
2	Phone	Debit Card	Male	Mobile	
3	Phone	Debit Card	Male	Laptop & Accessory	
4	Phone	CC	Male	Mobile	

```
  MaritalStatus
0        Single
1        Single
2        Single
3        Single
4        Single
```

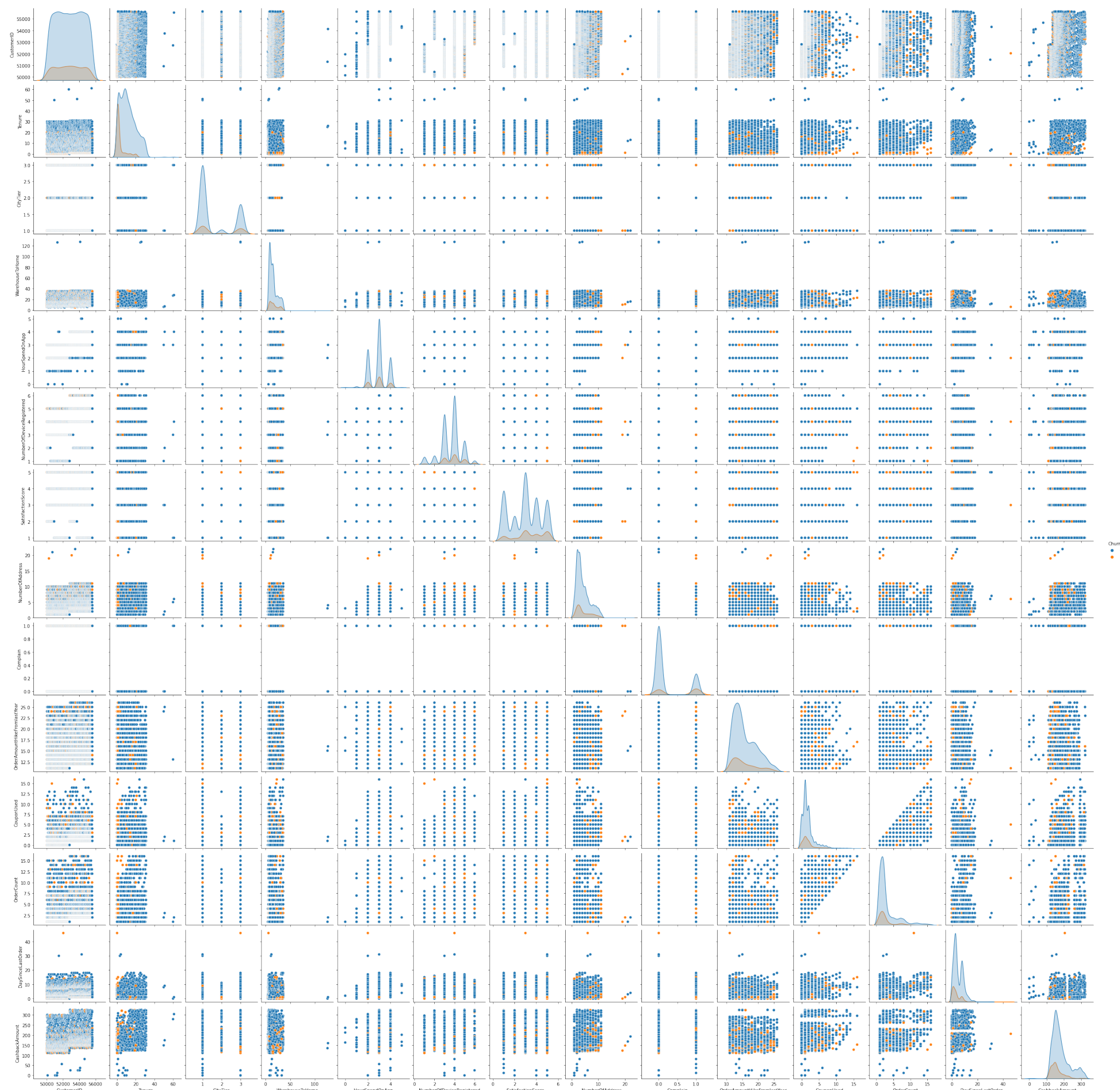
[12]:
```
sns.histplot(data=numerical_df, x="CityTier")
```

[12]: `<AxesSubplot:xlabel='CityTier', ylabel='Count'>`



[13]:
```
sns.pairplot(numerical_df,hue="Churn")
```

[13]: `<seaborn.axisgrid.PairGrid at 0x7f83c83fb4c0>`



3.1.2 2. Non numeric columns

Cleaning

[14]:
```
#As mobile phone and phone are both same so we have merged them
df.loc[df['PreferredLoginDevice'] == 'Phone', 'PreferredLoginDevice' ] = 'Mobile Phone'
df.loc[df['PreferedOrderCat'] == 'Mobile', 'PreferedOrderCat' ] = 'Mobile Phone'
#as cod is also cash on delievery
#as cc is also credit card so i merged them
df.loc[df['PreferredPaymentMode'] == 'COD', 'PreferredPaymentMode' ] = 'Cash on Delivery'   # uses loc function
df.loc[df['PreferredPaymentMode'] == 'CC', 'PreferredPaymentMode' ] = 'Credit Card'
```

Question: Show the unique values of each variable and print the number of occurences of each value Describe these results briefly

[15]:
```
for col in df.columns:
    if df[col].dtype == object:
      print(df[col].unique(), df[col].value_counts())
```

```
['Mobile Phone' 'Computer'] Mobile Phone    3996
Computer        1634
Name: PreferredLoginDevice, dtype: int64
['Debit Card' 'UPI' 'Credit Card' 'Cash on Delivery' 'E wallet'] Debit Card
2314
Credit Card         1774
E wallet             614
Cash on Delivery     514
UPI                  414
Name: PreferredPaymentMode, dtype: int64
['Female' 'Male'] Male      3384
Female    2246
Name: Gender, dtype: int64
['Laptop & Accessory' 'Mobile Phone' 'Others' 'Fashion' 'Grocery'] Mobile Phone
2080
Laptop & Accessory    2050
Fashion                826
Grocery                410
Others                 264
Name: PreferedOrderCat, dtype: int64
['Single' 'Divorced' 'Married'] Married     2986
Single      1796
Divorced     848
Name: MaritalStatus, dtype: int64
```

3.2 Analysing the Churn by select variables

Provide business recommendation for each of the below

Question: Relation between complains and churn

[16]:
```
df['Churn'].corr(df['Complain'])
```

[16]:
```
0.25018825469703104
```

[17]:
```
churn_rate_complain = df[df['Complain'] == 1]['Churn'].mean()
churn_rate_no_complain = df[df['Complain'] == 0]['Churn'].mean()
```

[18]:
```
print("Churn rate for Complain =", churn_rate_complain)
print("Churn rate for No Complain =",churn_rate_no_complain)
```

```
Churn rate for Complain = 0.3167082294264339
Churn rate for No Complain = 0.1092896174863388
```

3.3 Correlation matrix

Visualize the correlation between all variables

Question: Do we need to do any preprocessing on categorical variables before calculating correlation?

[19]:
```
#Onc hot coding for categorical dataset
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder()
new_df = enc.fit_transform(categorical_df)
df_ohc = pd.DataFrame(new_df.toarray(), columns=enc.get_feature_names_out(),␣
↪dtype=int)
```

[20]:
```
df_ohc.head(5)
```

[20]:
```
   PreferredLoginDevice_Computer  PreferredLoginDevice_Mobile Phone  \
0                              0                                  1
1                              0                                  0
2                              0                                  0
3                              0                                  0
4                              0                                  0

   PreferredLoginDevice_Phone  PreferredPaymentMode_CC  \
0                           0                        0
1                           1                        0
2                           1                        0
3                           1                        0
4                           1                        1

   PreferredPaymentMode_COD  PreferredPaymentMode_Cash on Delivery  \
0                         0                                      0
1                         0                                      0
2                         0                                      0
3                         0                                      0
4                         0                                      0

   PreferredPaymentMode_Credit Card  PreferredPaymentMode_Debit Card  \
0                                 0                                1
1                                 0                                0
2                                 0                                1
3                                 0                                1
4                                 0                                0

   PreferredPaymentMode_E wallet  PreferredPaymentMode_UPI  …  Gender_Male  \
```

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

   PreferedOrderCat_Fashion  PreferedOrderCat_Grocery  \
0                         0                         0
1                         0                         0
2                         0                         0
3                         0                         0
4                         0                         0

   PreferedOrderCat_Laptop & Accessory  PreferedOrderCat_Mobile  \
0                                    1                        0
1                                    0                        1
2                                    0                        1
3                                    1                        0
4                                    0                        1

   PreferedOrderCat_Mobile Phone  PreferedOrderCat_Others  \
0                              0                        0
1                              0                        0
2                              0                        0
3                              0                        0
4                              0                        0

   MaritalStatus_Divorced  MaritalStatus_Married  MaritalStatus_Single
0                       0                      0                     1
1                       0                      0                     1
2                       0                      0                     1
3                       0                      0                     1
4                       0                      0                     1

[5 rows x 21 columns]
```

[21]:

```
df_final = pd.concat([numerical_df, df_ohc], axis=1)
df_final.head(5)
```

[21]:

```
   CustomerID  Churn  Tenure  CityTier  WarehouseToHome  HourSpendOnApp  \
0       50001      1     4.0         3              6.0             3.0
1       50002      1     NaN         1              8.0             3.0
2       50003      1     NaN         1             30.0             2.0
3       50004      1     0.0         3             15.0             2.0
4       50005      1     0.0         1             12.0             NaN

   NumberOfDeviceRegistered  SatisfactionScore  NumberOfAddress  Complain  \
```

```
0                        3                  2                9          1
1                        4                  3                7          1
2                        4                  3                6          1
3                        4                  5                8          0
4                        3                  5                3          0

   …  Gender_Male  PreferedOrderCat_Fashion  PreferedOrderCat_Grocery  \
0  …            0                         0                         0
1  …            1                         0                         0
2  …            1                         0                         0
3  …            1                         0                         0
4  …            1                         0                         0

   PreferedOrderCat_Laptop & Accessory  PreferedOrderCat_Mobile  \
0                                    1                        0
1                                    0                        1
2                                    0                        1
3                                    1                        0
4                                    0                        1

   PreferedOrderCat_Mobile Phone  PreferedOrderCat_Others  \
0                              0                        0
1                              0                        0
2                              0                        0
3                              0                        0
4                              0                        0

   MaritalStatus_Divorced  MaritalStatus_Married  MaritalStatus_Single
0                       0                      0                     1
1                       0                      0                     1
2                       0                      0                     1
3                       0                      0                     1
4                       0                      0                     1

[5 rows x 36 columns]
```

[22]:
```
df_final = df_final.dropna()
df_final.head(5)
```

[22]:
```
    CustomerID  Churn  Tenure  CityTier  WarehouseToHome  HourSpendOnApp  \
0        50001      1     4.0         3              6.0             3.0
3        50004      1     0.0         3             15.0             2.0
5        50006      1     0.0         1             22.0             3.0
11       50012      1    11.0         1              6.0             3.0
12       50013      1     0.0         1             11.0             2.0

    NumberOfDeviceRegistered  SatisfactionScore  NumberOfAddress  Complain  \
```

```
0                            3                   2                  9          1
3                            4                   5                  8          0
5                            5                   5                  2          1
11                           4                   3                 10          1
12                           3                   3                  2          1

    …  Gender_Male  PreferedOrderCat_Fashion  PreferedOrderCat_Grocery  \
0   …            0                         0                         0
3   …            1                         0                         0
5   …            0                         0                         0
11  …            1                         1                         0
12  …            1                         0                         0

    PreferedOrderCat_Laptop & Accessory  PreferedOrderCat_Mobile  \
0                                     1                        0
3                                     1                        0
5                                     0                        0
11                                    0                        0
12                                    0                        1

    PreferedOrderCat_Mobile Phone  PreferedOrderCat_Others  \
0                               0                        0
3                               0                        0
5                               1                        0
11                              0                        0
12                              0                        0

    MaritalStatus_Divorced  MaritalStatus_Married  MaritalStatus_Single
0                        0                      0                     1
3                        0                      0                     1
5                        0                      0                     1
11                       0                      0                     1
12                       0                      0                     1

[5 rows x 36 columns]
```

Question: Plot correlation matrix Discuss a few significant correlations

[23]:
```
#CustomerID column as it's not relevant for correlation
df_final = df_final.drop(columns=['CustomerID'])
df_final.head(5)
```

[23]:
```
    Churn  Tenure  CityTier  WarehouseToHome  HourSpendOnApp  \
0       1     4.0         3              6.0             3.0
3       1     0.0         3             15.0             2.0
5       1     0.0         1             22.0             3.0
11      1    11.0         1              6.0             3.0
```

```
12      1     0.0         1             11.0             2.0

   NumberOfDeviceRegistered  SatisfactionScore  NumberOfAddress  Complain  \
0                         3                  2                9         1
3                         4                  5                8         0
5                         5                  5                2         1
11                        4                  3               10         1
12                        3                  3                2         1

   OrderAmountHikeFromlastYear  …  Gender_Male  PreferedOrderCat_Fashion  \
0                         11.0  …            0                         0
3                         23.0  …            1                         0
5                         22.0  …            0                         0
11                        13.0  …            1                         1
12                        13.0  …            1                         0

   PreferedOrderCat_Grocery  PreferedOrderCat_Laptop & Accessory  \
0                         0                                    1
3                         0                                    1
5                         0                                    0
11                        0                                    0
12                        0                                    0

   PreferedOrderCat_Mobile  PreferedOrderCat_Mobile Phone  \
0                        0                              0
3                        0                              0
5                        0                              1
11                       0                              0
12                       1                              0

   PreferedOrderCat_Others  MaritalStatus_Divorced  MaritalStatus_Married  \
0                        0                       0                      0
3                        0                       0                      0
5                        0                       0                      0
11                       0                       0                      0
12                       0                       0                      0

   MaritalStatus_Single
0                     1
3                     1
5                     1
11                    1
12                    1

[5 rows x 35 columns]
```

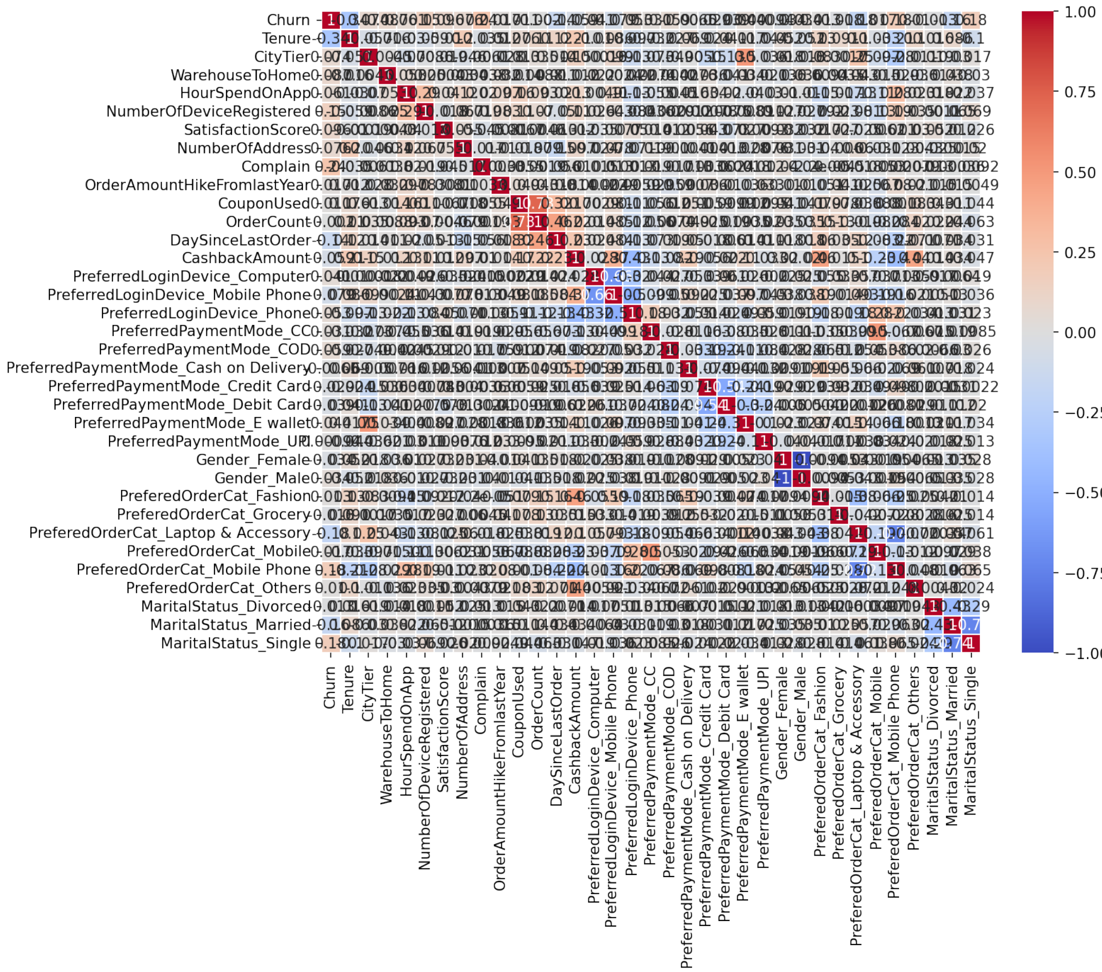
[24]:
```
corr_matrix = df_final.corr()
corr_matrix.head(5)
```

[24]:
```
                    Churn    Tenure  CityTier  WarehouseToHome  \
Churn            1.000000 -0.340013  0.073858         0.087318
Tenure          -0.340013  1.000000 -0.057414        -0.016353
CityTier         0.073858 -0.057414  1.000000         0.004457
WarehouseToHome  0.087318 -0.016353  0.004457         1.000000
HourSpendOnApp   0.060845 -0.029818 -0.070035         0.052731

                 HourSpendOnApp  NumberOfDeviceRegistered  SatisfactionScore  \
Churn                  0.060845                  0.149041           0.095759
Tenure                -0.029818                 -0.058752          -0.009972
CityTier              -0.070035                 -0.008616          -0.019494
WarehouseToHome        0.052731                  0.024582           0.000434
HourSpendOnApp         1.000000                  0.293021           0.039879

                 NumberOfAddress  Complain  OrderAmountHikeFromlastYear  …  \
Churn                   0.076336  0.238137                     0.017193  …
Tenure                  0.196547 -0.035228                     0.012197  …
CityTier               -0.046406 -0.006122                    -0.027628  …
WarehouseToHome         0.003422  0.003829                     0.031975  …
HourSpendOnApp          0.124962  0.020413                     0.096827  …

                 Gender_Male  PreferedOrderCat_Fashion  \
Churn               0.033792                  0.013086
Tenure             -0.052123                  0.130259
CityTier           -0.018072                  0.083035
WarehouseToHome     0.035581                 -0.009435
HourSpendOnApp     -0.009952                 -0.147830

                 PreferedOrderCat_Grocery  \
Churn                           -0.017880
Tenure                           0.091251
CityTier                        -0.001750
WarehouseToHome                  0.003512
HourSpendOnApp                  -0.017382

                 PreferedOrderCat_Laptop & Accessory  PreferedOrderCat_Mobile  \
Churn                                      -0.184584                 0.016675
Tenure                                      0.104482                -0.033466
CityTier                                    0.245824                -0.097493
WarehouseToHome                             0.043231                -0.015441
HourSpendOnApp                             -0.130819                -0.112896

                 PreferedOrderCat_Mobile Phone  PreferedOrderCat_Others  \
Churn                                 0.181683                 0.010208
```

```
Tenure                                     -0.211477                  0.103702
CityTier                                   -0.281079                 -0.011248
WarehouseToHome                            -0.028939                 -0.035530
HourSpendOnApp                              0.281309                  0.023109

                  MaritalStatus_Divorced  MaritalStatus_Married  \
Churn                          -0.013023              -0.159808
Tenure                          0.015788               0.085990
CityTier                        0.019181              -0.029876
WarehouseToHome                -0.013650               0.038336
HourSpendOnApp                  0.018024               0.022257

                  MaritalStatus_Single
Churn                         0.179481
Tenure                       -0.103150
CityTier                      0.017370
WarehouseToHome              -0.030496
HourSpendOnApp               -0.037134

[5 rows x 35 columns]
```

[25]:

```python
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
figure(figsize=(10, 8), dpi=150)
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.8)
plt.show()
```



Optional: What is the correlation of each feature with target Sort the correlation in descending order and show the top 5

[44]:
```
corr_matrix.sort_values(by = 'Churn', ascending=False).head(5)
```

[44]:

	Churn	Tenure	CityTier	WarehouseToHome	\
Churn	1.000000	-0.340013	0.073858	0.087318	
Complain	0.238137	-0.035228	-0.006122	0.003829	
PreferedOrderCat_Mobile Phone	0.181683	-0.211477	-0.281079	-0.028939	
MaritalStatus_Single	0.179481	-0.103150	0.017370	-0.030496	
NumberOfDeviceRegistered	0.149041	-0.058752	-0.008616	0.024582	

	HourSpendOnApp	NumberOfDeviceRegistered	\
Churn	0.060845	0.149041	
Complain	0.020413	0.018881	
PreferedOrderCat_Mobile Phone	0.281309	0.188563	

```
MaritalStatus_Single                  -0.037134                 0.069345
NumberOfDeviceRegistered               0.293021                 1.000000

                               SatisfactionScore  NumberOfAddress  Complain  \
Churn                                   0.095759         0.076336  0.238137
Complain                               -0.044533        -0.017363  1.000000
PreferedOrderCat_Mobile Phone           0.011297        -0.023102  0.019793
MaritalStatus_Single                   -0.025659         0.020125 -0.009180
NumberOfDeviceRegistered               -0.017788         0.066684  0.018881

                               OrderAmountHikeFromlastYear  …  Gender_Male  \
Churn                                             0.017193  …     0.033792
Complain                                          0.003260  …    -0.039522
PreferedOrderCat_Mobile Phone                     0.080301  …     0.053910
MaritalStatus_Single                             -0.004949  …    -0.027833
NumberOfDeviceRegistered                          0.083342  …    -0.026706

                               PreferedOrderCat_Fashion  \
Churn                                          0.013086
Complain                                      -0.000022
PreferedOrderCat_Mobile Phone                 -0.253118
MaritalStatus_Single                          -0.014253
NumberOfDeviceRegistered                      -0.091604

                               PreferedOrderCat_Grocery  \
Churn                                         -0.017880
Complain                                       0.004534
PreferedOrderCat_Mobile Phone                 -0.027697
MaritalStatus_Single                          -0.013853
NumberOfDeviceRegistered                       0.022548

                               PreferedOrderCat_Laptop & Accessory  \
Churn                                                    -0.184584
Complain                                                 -0.018126
PreferedOrderCat_Mobile Phone                            -0.721851
MaritalStatus_Single                                     -0.060812
NumberOfDeviceRegistered                                 -0.080608

                               PreferedOrderCat_Mobile  \
Churn                                         0.016675
Complain                                     -0.005327
PreferedOrderCat_Mobile Phone                -0.125238
MaritalStatus_Single                          0.037872
NumberOfDeviceRegistered                     -0.125343

                               PreferedOrderCat_Mobile Phone  \
Churn                                               0.181683
```

```
Complain                                          0.019793
PreferedOrderCat_Mobile Phone                     1.000000
MaritalStatus_Single                              0.065241
NumberOfDeviceRegistered                          0.188563

                               PreferedOrderCat_Others  \
Churn                                         0.010208
Complain                                      0.007866
PreferedOrderCat_Mobile Phone                -0.048049
MaritalStatus_Single                         -0.024032
NumberOfDeviceRegistered                      0.035364

                               MaritalStatus_Divorced  MaritalStatus_Married  \
Churn                                       -0.013023              -0.159808
Complain                                     0.012777              -0.000364
PreferedOrderCat_Mobile Phone                0.001864              -0.062740
MaritalStatus_Single                        -0.288871              -0.737892
NumberOfDeviceRegistered                    -0.001099              -0.064517

                               MaritalStatus_Single
Churn                                      0.179481
Complain                                  -0.009180
PreferedOrderCat_Mobile Phone              0.065241
MaritalStatus_Single                       1.000000
NumberOfDeviceRegistered                   0.069345

[5 rows x 35 columns]
```

4 3. Modelling

4.1 Prepare data

Fill nulls in each column

[27]:
```python
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=2)
```

[28]:
```python
for col in df.columns:
    nullCount = df[col].isnull().sum()
    if nullCount > 0:
        df[col]=imputer.fit_transform(df[[col]])
        print("Filled", nullCount, "nulls in", col)
```

```
Filled 264 nulls in Tenure
Filled 251 nulls in WarehouseToHome
Filled 255 nulls in HourSpendOnApp
Filled 265 nulls in OrderAmountHikeFromlastYear
```

```
Filled 256 nulls in CouponUsed
Filled 258 nulls in OrderCount
Filled 307 nulls in DaySinceLastOrder
```

Question: Make the data suitable for model training

[29]:
```
df_final.head(5)
```

[29]:
```
    Churn  Tenure  CityTier  WarehouseToHome  HourSpendOnApp  \
0       1     4.0         3              6.0             3.0
3       1     0.0         3             15.0             2.0
5       1     0.0         1             22.0             3.0
11      1    11.0         1              6.0             3.0
12      1     0.0         1             11.0             2.0

    NumberOfDeviceRegistered  SatisfactionScore  NumberOfAddress  Complain  \
0                          3                  2                9         1
3                          4                  5                8         0
5                          5                  5                2         1
11                         4                  3               10         1
12                         3                  3                2         1

    OrderAmountHikeFromlastYear  …  Gender_Male  PreferedOrderCat_Fashion  \
0                          11.0  …            0                         0
3                          23.0  …            1                         0
5                          22.0  …            0                         0
11                         13.0  …            1                         1
12                         13.0  …            1                         0

    PreferedOrderCat_Grocery  PreferedOrderCat_Laptop & Accessory  \
0                          0                                    1
3                          0                                    1
5                          0                                    0
11                         0                                    0
12                         0                                    0

    PreferedOrderCat_Mobile  PreferedOrderCat_Mobile Phone  \
0                         0                              0
3                         0                              0
5                         0                              1
11                        0                              0
12                        1                              0

    PreferedOrderCat_Others  MaritalStatus_Divorced  MaritalStatus_Married  \
0                         0                       0                      0
3                         0                       0                      0
5                         0                       0                      0
11                        0                       0                      0
```

```
12                          0                        0                       0

    MaritalStatus_Single
0                      1
3                      1
5                      1
11                     1
12                     1

[5 rows x 35 columns]
```

[30]:
```
from sklearn.linear_model import LogisticRegression
x = df_final.drop(['Churn'],axis = 1)
x.head(5)
y = df_final['Churn']
```

[31]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
 ↪random_state=42)
```

[32]:
```
#check the shape of X_train and X_test
x_train.shape, x_test.shape
```

[32]:
```
((3019, 34), (755, 34))
```

[33]:
```
clf = LogisticRegression(random_state=0).fit(x_train,y_train)
```

```
/Users/jacquie/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[34]:
```
clf.fit(x_train, y_train)
```

```
/Users/jacquie/opt/anaconda3/lib/python3.9/site-
packages/sklearn/linear_model/_logistic.py:814: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
```

```
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[34]:
```
LogisticRegression(random_state=0)
```

[35]:
```
#predict result
y_pred = clf.predict(x_test)
```

4.2 Model training

Question: Train one or more models and show their performance on training and test data Train and show train & test accuracy

[36]:
```
from sklearn.metrics import roc_curve, roc_auc_score, classification_report,␣
 ↪accuracy_score, confusion_matrix
train_accuracy = accuracy_score(y_pred, y_test)*100
train_accuracy
```

[36]:
```
89.27152317880794
```

[37]:
```
y_pred_train = clf.predict(x_train)
y_pred_train
```

[37]:
```
array([0, 0, 1, …, 0, 1, 0])
```

[38]:
```
print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train,␣
 ↪y_pred_train)))
```

```
Training-set accuracy score: 0.8917
```

5 4. Evaluation

Feel free to use any libraries / stackoverflow

Question: Show the precision, recall and f1 score for the model with best accuracy

[39]:
```
print(classification_report(y_pred, y_test, digits=6))
```

```
              precision    recall  f1-score   support

           0   0.958333  0.920000  0.938776       675
           1   0.495327  0.662500  0.566845        80

    accuracy                       0.892715       755
   macro avg   0.726830  0.791250  0.752810       755
```

```
weighted avg   0.909273  0.892715  0.899366       755
```

print(classification_report(y_train, y_pred_train, digits=6))

5.1 Confusion matrix

Question: Show the confusion matrix Describe the performance of model and steps you could take to improve it

Bonus: Plot the confusion matrix

[40]:
```
print('Confusion matrix:\n', confusion_matrix(y_pred, y_test))
```

```
Confusion matrix:
 [[621  54]
 [ 27  53]]
```

[41]:
```
print('Confusion matrix:\n', confusion_matrix(y_pred_train, y_train))
```

```
Confusion matrix:
 [[2404  236]
 [  91  288]]
```

6 Discussion

[42]:
```
#check for overfitting and underfitting
print('Training set score: {:.4f}'.format(clf.score(x_train, y_train)))
```

```
Training set score: 0.8917
```

[43]:
```
print('Test set score: {:.4f}'.format(clf.score(x_test, y_test)))
```

```
Test set score: 0.8927
```

The training-set accuracy score is 0.8917 while the test-set accuracy to be 0.8927. These two values are quite comparable. So, there is no question of overfitting.

Next Step, we could perform hyperparameter optimization using gridsearch CV to improve the performance for this particular model

[ ]:
```

```