TELECOM CUSTOMER CHURN PREDICTION 📈

1. Introduction

What is Customer Churn? Customer churn is defined as when customers or subscribers discontinue doing business with a firm or service.

Customers in the telecom industry can choose from a variety of service providers and actively switch from one to the next. The telecommunications business has an annual churn rate of 15-25 percent in this highly competitive market.

Individualized customer retention is tough because most firms have a large number of customers and can't afford to devote much time to each of them. The costs would be too great, outweighing the additional revenue. However, if a corporation could forecast which customers are likely to leave ahead of time, it could focus customer retention efforts only on these "high risk" clients. The ultimate goal is to expand its coverage area and retrieve more customers loyalty. The core to succeed in this market lies in the customer itself.

Customer churn is a critical metric because it is much less expensive to retain existing customers than it is to acquire new customers.

To reduce customer churn, telecom companies need to predict which customers are at high risk of churn.

To detect early signs of potential churn, one must first develop a holistic view of the customers and their interactions across numerous channels, including store/branch visits, product purchase histories, customer service calls, Web-based transactions, and social media interactions, to mention a few.

As a result, by addressing churn, these businesses may not only preserve their market position, but also grow and thrive. More customers they have in their network, the lower the cost of initiation and the larger the profit. As a result, the company's key focus for success is reducing client attrition and implementing effective retention strategy.

2. Loading libraries and data

In [5]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
import missingno as msno
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')
```

In [6]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier
from catboost import CatBoostClassifier
from sklearn import metrics
from sklearn.metrics import roc_curve
from sklearn.metrics import recall_score, confusion_matrix, precision_score, f1_
```

In [7]:
```
## Loading data
df = pd.read_csv(r"C:\Users\chitt\Downloads\WA_Fn-UseC_-Telco-Customer-Churn.csv
df
```

Out[7]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService
0	7590-VHVEG	Female	0	Yes	No	1	No
1	5575-GNVDE	Male	0	No	No	34	Yes
2	3668-QPYBK	Male	0	No	No	2	Yes
3	7795-CFOCW	Male	0	No	No	45	No
4	9237-HQITU	Female	0	No	No	2	Yes
...	...	...	...	...	...	...	...
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes
7040	4801-JZAZL	Female	0	Yes	Yes	11	No
7041	8361-LTMKD	Male	1	Yes	No	4	Yes
7042	3186-AJIEK	Male	0	No	No	66	Yes

7043 rows × 21 columns

3. Understanding the data

Each row represents a customer, each column contains customer's attributes described on the column Metadata.

In [10]:

```
df.head(4)
```

Out[10]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Mul
0	7590-VHVEG	Female	0	Yes	No	1	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	
3	7795-CFOCW	Male	0	No	No	45	No	

4 rows × 21 columns

In [11]:

```
df.tail(4)
```

Out[11]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes
7040	4801-JZAZL	Female	0	Yes	Yes	11	No
7041	8361-LTMKD	Male	1	Yes	No	4	Yes
7042	3186-AJIEK	Male	0	No	No	66	Yes

4 rows × 21 columns

The data set includes information about:

Customers who left within the last month – the column is called Churn

Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies

Customer account information - how long they’ve been a customer, contract, payment method, paperless billing, monthly charges, and total charges

Demographic info about customers – gender, age range, and if they have partners and dependents

In [13]:

```
df.shape
```

Out[13]: (7043, 21)

In [14]:
```
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
```

In [15]:
```
df.columns.values
```

Out[15]:
```
array(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
       'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges',
       'TotalCharges', 'Churn'], dtype=object)
```

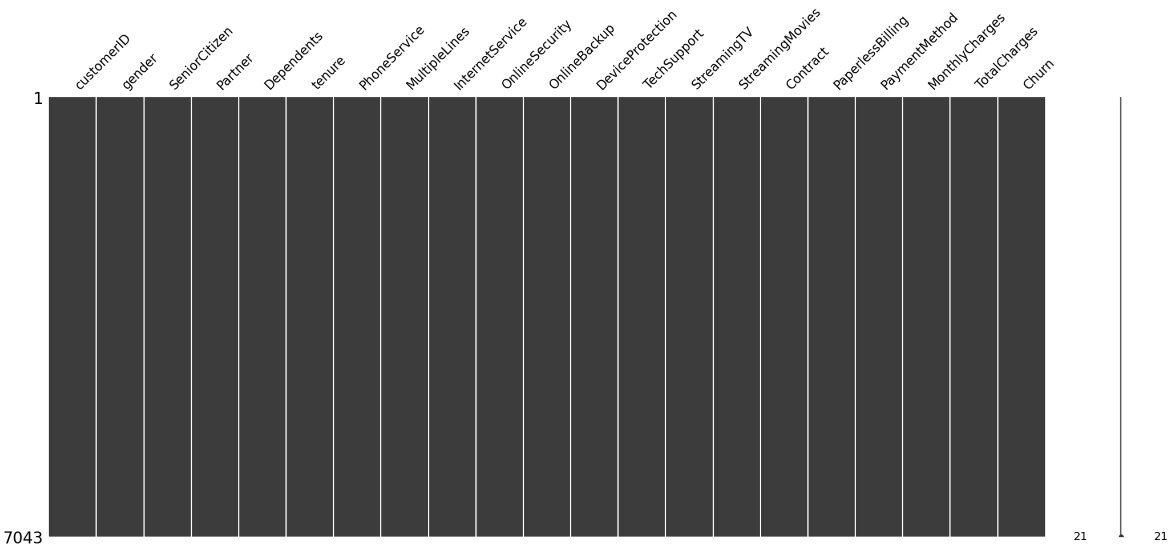
In [16]:
```
df.dtypes
```

Out[16]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

. The target the we will use to guide the exploration is Churn

4. Visualize missing values

In [19]:
```
# Visualize missing values as a matrix
msno.matrix(df);
```



Using this matrix we can very quickly find the pattern of missingness in the dataset.

From the above visualisation we can observe that it has no peculiar pattern that stands out. In fact there is no missing data.

5. Data Manipulation

In [22]:
```
df = df.drop(['customerID'],axis=1)
```

```
df.head()
```

Out[22]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	In
0	Female	0	Yes	No	1	No	No phone service	
1	Male	0	No	No	34	Yes	No	
2	Male	0	No	No	2	Yes	No	
3	Male	0	No	No	45	No	No phone service	
4	Female	0	No	No	2	Yes	No	

. On deep analysis, we can find some indirect missingness in our data(which can be in from of blankspaces). Lets see that!

In [24]:
```
df['TotalCharges'] = pd.to_numeric(df.TotalCharges, errors='coerce')
df.isnull().sum()
```

Out[24]:
```
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        11
Churn                0
dtype: int64
```

Here we see that the TotalCharges has 11 missing values. Let's check this data.

In [26]:
```
df[np.isnan(df['TotalCharges'])]
```

Out[26]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
488	Female	0	Yes	Yes	0	No	No phone service
753	Male	0	No	Yes	0	Yes	No
936	Female	0	Yes	Yes	0	Yes	No
1082	Male	0	Yes	Yes	0	Yes	Yes
1340	Female	0	Yes	Yes	0	No	No phone service
3331	Male	0	Yes	Yes	0	Yes	No
3826	Male	0	Yes	Yes	0	Yes	Yes
4380	Female	0	Yes	Yes	0	Yes	No
5218	Male	0	Yes	Yes	0	Yes	No
6670	Female	0	Yes	Yes	0	Yes	Yes
6754	Male	0	No	Yes	0	Yes	Yes

It can also be noted that the Tenure column is 0 for these entries even though the MonthlyCharges column is not empty. Let's see if there are any other 0 values in the tenure column.

In [28]:

```
df[df['tenure'] == 0].index
```

Out[28]:

```
Index([488, 753, 936, 1082, 1340, 3331, 3826, 4380, 5218, 6670, 6754], dtype='i
nt64')
```

There are no additional missing values in the Tenure column. Let's delete the rows with missing values in Tenure columns since there are only 11 rows and deleting them will not affect the data.

In [30]:

```
df.drop(labels=df[df['tenure'] == 0].index, axis=0, inplace=True)
df[df['tenure'] == 0].index
```

Out[30]:

```
Index([], dtype='int64')
```

To solve the problem of missing values in TotalCharges column, I decided to fill it with the mean of TotalCharges values.

In [32]:

```
df.fillna(df["TotalCharges"].mean())
```

Out[32]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	Female	0	Yes	No	1	No	No phone service
1	Male	0	No	No	34	Yes	No
2	Male	0	No	No	2	Yes	No
3	Male	0	No	No	45	No	No phone service
4	Female	0	No	No	2	Yes	No
...	...	...	...	...	...	...	...
7038	Male	0	Yes	Yes	24	Yes	Yes
7039	Female	0	Yes	Yes	72	Yes	Yes
7040	Female	0	Yes	Yes	11	No	No phone service
7041	Male	1	Yes	No	4	Yes	Yes
7042	Male	0	No	No	66	Yes	No

7032 rows × 20 columns

In [33]:

```
df.isnull().sum()
```

Out[33]:
```
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
```

In [34]:
```
df["SeniorCitizen"]= df["SeniorCitizen"].map({0: "No", 1: "Yes"})
df.head()
```

Out[34]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	In
0	Female	No	Yes	No	1	No	No phone service	
1	Male	No	No	No	34	Yes	No	
2	Male	No	No	No	2	Yes	No	
3	Male	No	No	No	45	No	No phone service	
4	Female	No	No	No	2	Yes	No	

In [35]:
```
df["InternetService"].describe(include=['object', 'bool'])
```

Out[35]:
```
count            7032
unique              3
top       Fiber optic
freq             3096
Name: InternetService, dtype: object
```

In [36]:
```
numerical_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
df[numerical_cols].describe()
```

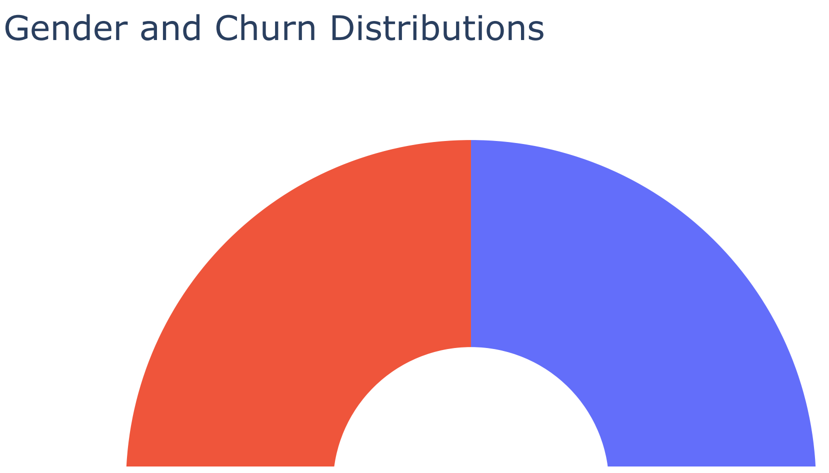
Out[36]:

	tenure	MonthlyCharges	TotalCharges
count	7032.000000	7032.000000	7032.000000
mean	32.421786	64.798208	2283.300441
std	24.545260	30.085974	2266.771362
min	1.000000	18.250000	18.800000
25%	9.000000	35.587500	401.450000
50%	29.000000	70.350000	1397.475000
75%	55.000000	89.862500	3794.737500
max	72.000000	118.750000	8684.800000

6. Data Visualization

In [38]:

```
g_labels = ['Male', 'Female']
c_labels = ['No', 'Yes']
# Create subplots: use 'domain' type for Pie subplot
fig = make_subplots(rows=1, cols=2, specs=[[{'type':'domain'}, {'type':'domain'}
fig.add_trace(go.Pie(labels=g_labels, values=df['gender'].value_counts(), name="
              1, 1)
fig.add_trace(go.Pie(labels=c_labels, values=df['Churn'].value_counts(), name="C
              1, 2)

# Use `hole` to create a donut-like pie chart
fig.update_traces(hole=.4, hoverinfo="label+percent+name", textfont_size=16)

fig.update_layout(
    title_text="Gender and Churn Distributions",
    # Add annotations in the center of the donut pies.
    annotations=[dict(text='Gender', x=0.16, y=0.5, font_size=20, showarrow=Fals
                 dict(text='Churn', x=0.84, y=0.5, font_size=20, showarrow=False
fig.show()
```



.26.6 % of customers switched to another firm. .Customers are 49.5 % female and 50.5 % male.

In [40]:
```
df["Churn"][df["Churn"]=="No"].groupby(by=df["gender"]).count()
```

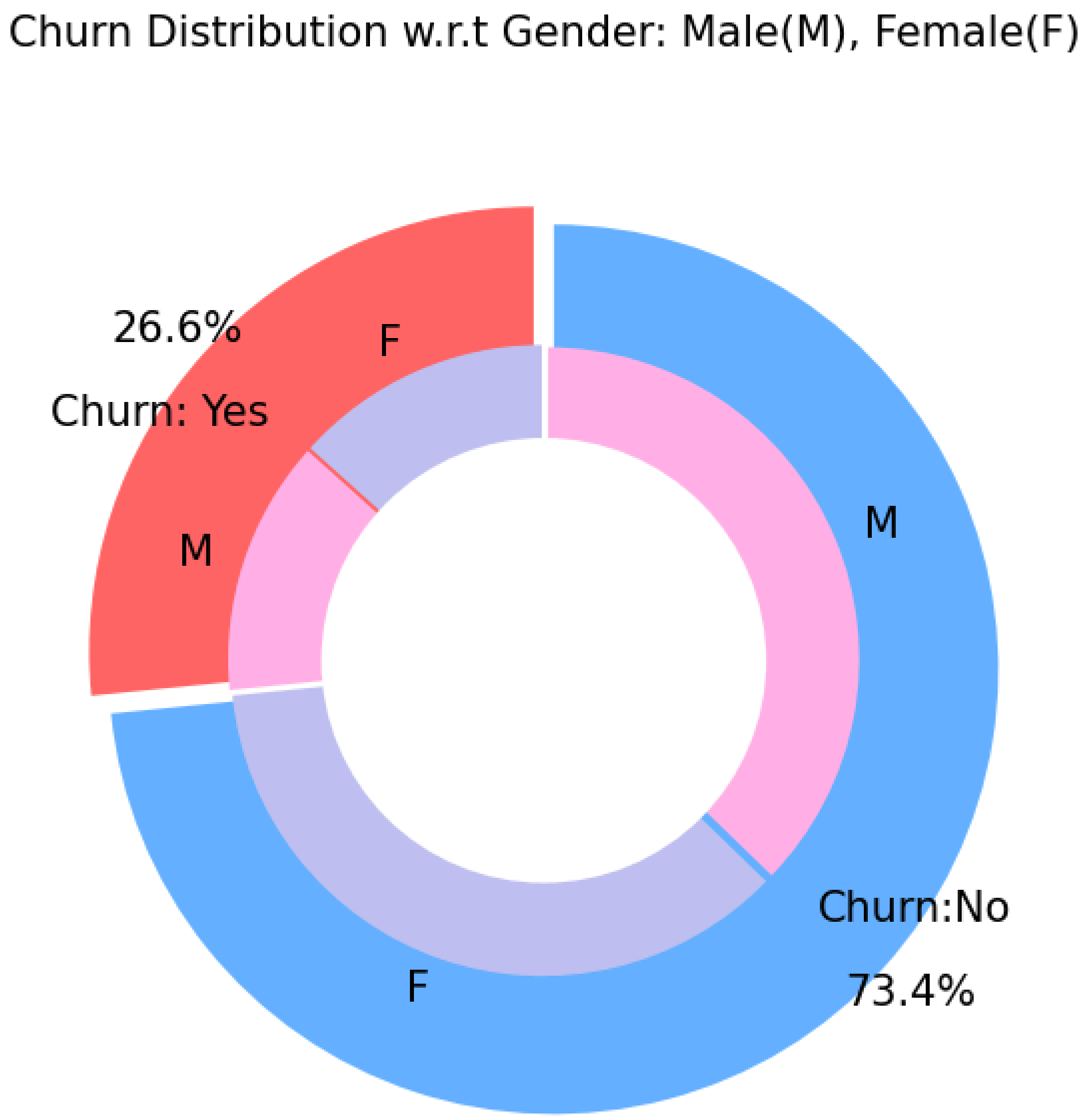
Out[40]:
```
gender
Female    2544
Male      2619
Name: Churn, dtype: int64
```

In [41]:
```
df["Churn"][df["Churn"]=="Yes"].groupby(by=df["gender"]).count()
```

Out[41]:
```
gender
Female    939
Male      930
Name: Churn, dtype: int64
```

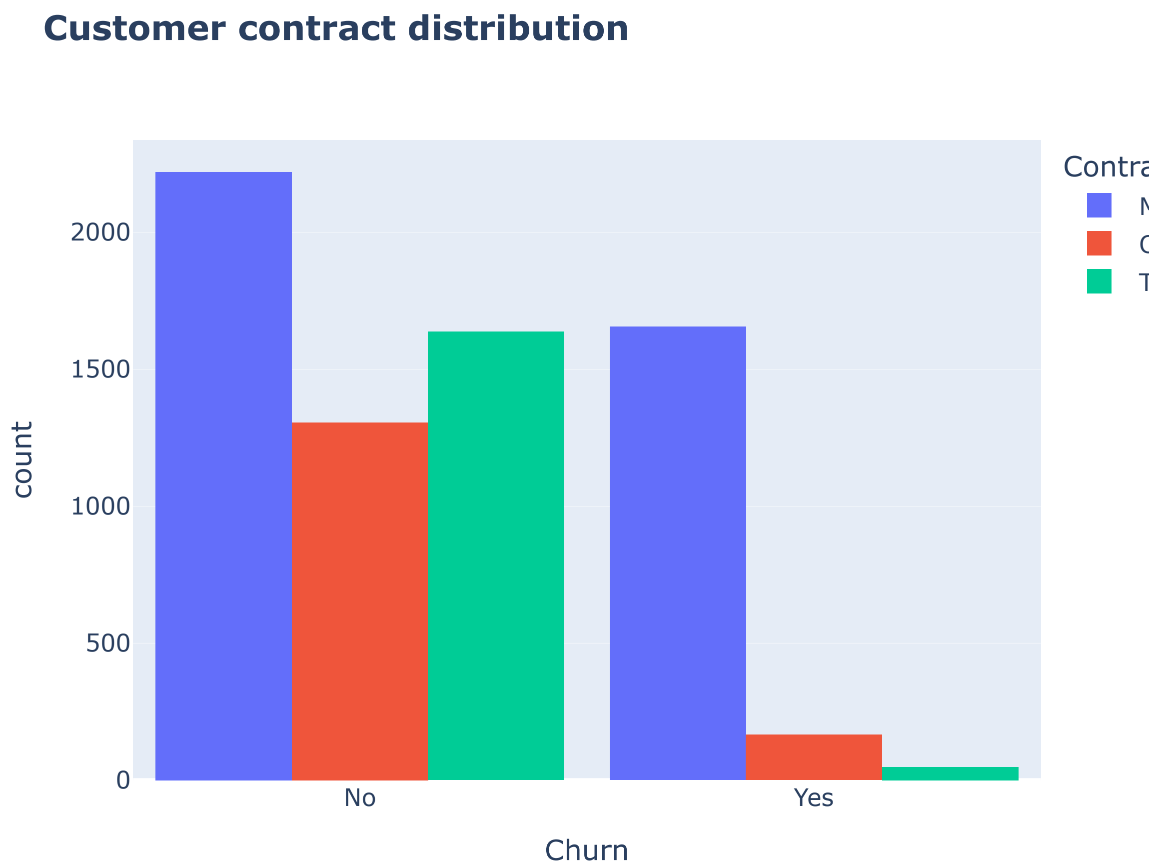
In [42]:
```
plt.figure(figsize=(6, 6))
labels =["Churn: Yes","Churn:No"]
values = [1869,5163]
labels_gender = ["F","M","F","M"]
sizes_gender = [939,930 , 2544,2619]
colors = ['#ff6666', '#66b3ff']
colors_gender = ['#c2c2f0','#ffb3e6', '#c2c2f0','#ffb3e6']
explode = (0.3,0.3)
explode_gender = (0.1,0.1,0.1,0.1)
textprops = {"fontsize":15}
```

```
#Plot
plt.pie(values, labels=labels,autopct='%1.1f%%',pctdistance=1.08, labeldistance=
plt.pie(sizes_gender,labels=labels_gender,colors=colors_gender,startangle=90, ex
#Draw circle
centre_circle = plt.Circle((0,0),5,color='black', fc='white',linewidth=0)
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.title('Churn Distribution w.r.t Gender: Male(M), Female(F)', fontsize=15, y=

# show plot

plt.axis('equal')
plt.tight_layout()
plt.show()
```



There is negligible difference in customer percentage/ count who chnaged the service provider. Both genders behaved in similar fashion when it comes to migrating to another service provider/firm.

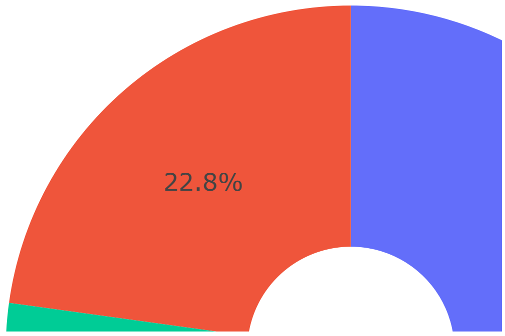
In [44]:
```
fig = px.histogram(df, x="Churn", color="Contract", barmode="group", title="<b>C
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



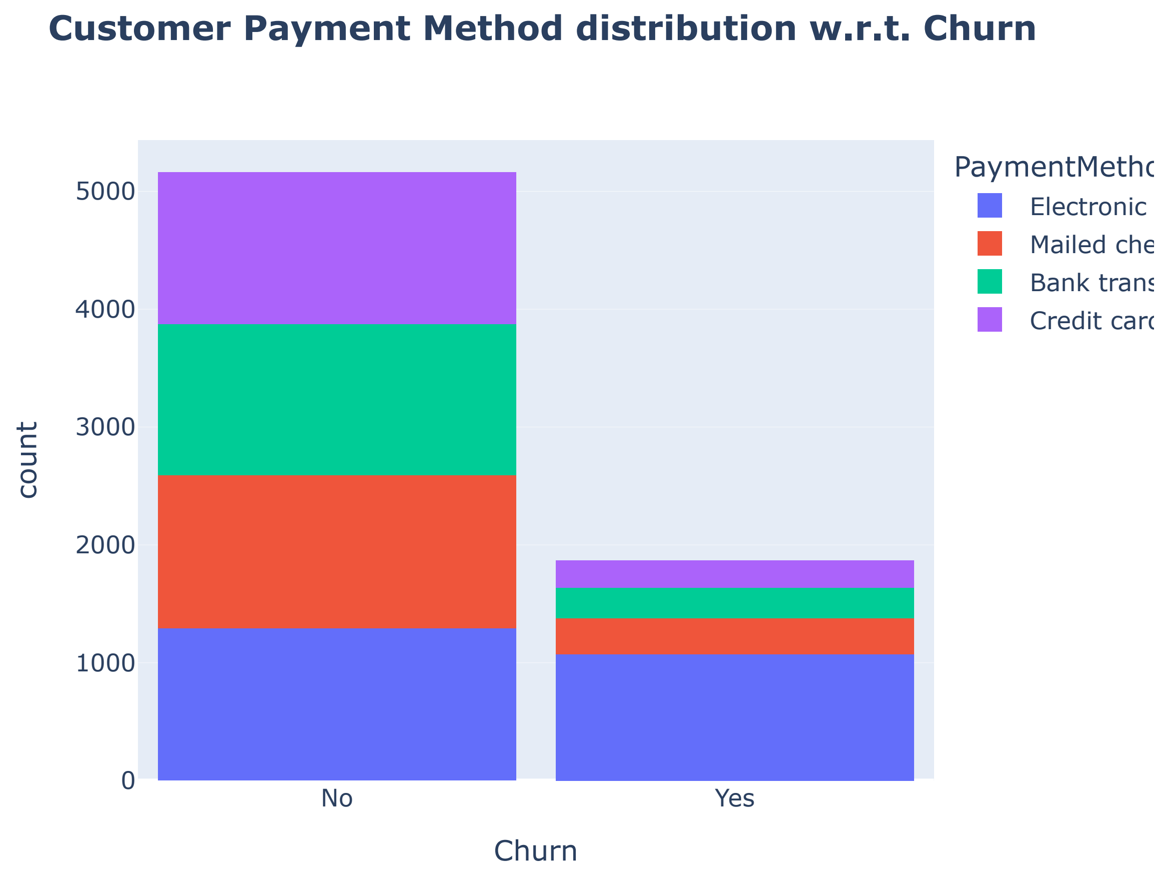
About 75% of customer with Month-to-Month Contract opted to move out as compared to 13% of customrs with One Year Contract and 3% with Two Year Contract

In [46]:
```
labels = df['PaymentMethod'].unique()
values = df['PaymentMethod'].value_counts()

fig = go.Figure(data=[go.Pie(labels=labels, values=values, hole=.3)])
fig.update_layout(title_text="<b>Payment Method Distribution</b>")
fig.show()
```

Payment Method Distribution



In [47]:
```
fig = px.histogram(df, x="Churn", color="PaymentMethod", title="<b>Customer Paym
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



Major customers who moved out were having Electronic Check as Payment Method. Customers who opted for Credit-Card automatic transfer or Bank Automatic Transfer and Mailed Check as Payment Method were less likely to move out.

In [97]:
```
df["InternetService"].unique()
```

Out[97]:
```
array(['DSL', 'Fiber optic', 'No'], dtype=object)
```

In [99]:
```
df[df["gender"]=="Male"][["InternetService", "Churn"]].value_counts()
```

Out[99]:
```
InternetService  Churn
DSL              No       992
Fiber optic      No       910
No               No       717
Fiber optic      Yes      633
DSL              Yes      240
No               Yes       57
Name: count, dtype: int64
```

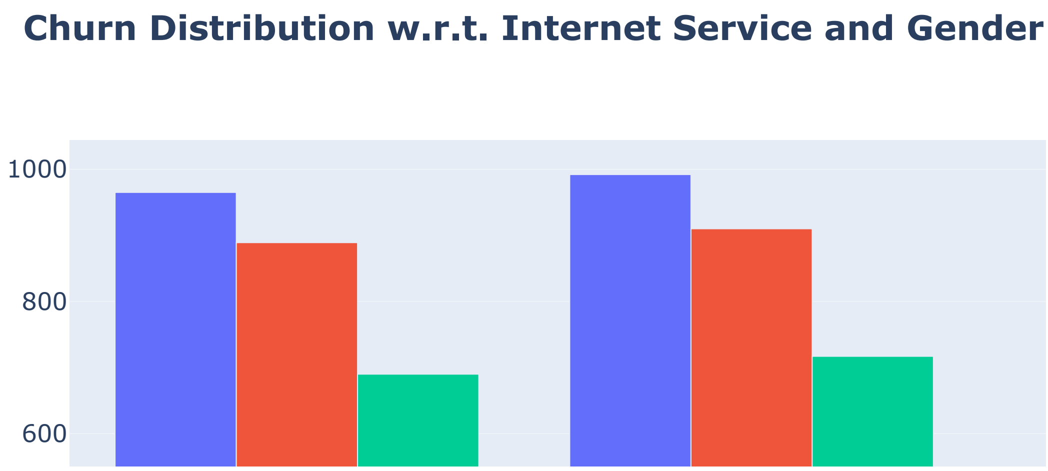
In [101…
```
df[df["gender"]=="Female"][["InternetService", "Churn"]].value_counts()
```

Out[101…

```
InternetService  Churn
DSL              No       965
Fiber optic      No       889
No               No       690
Fiber optic      Yes      664
DSL              Yes      219
No               Yes       56
Name: count, dtype: int64
```

In [103…

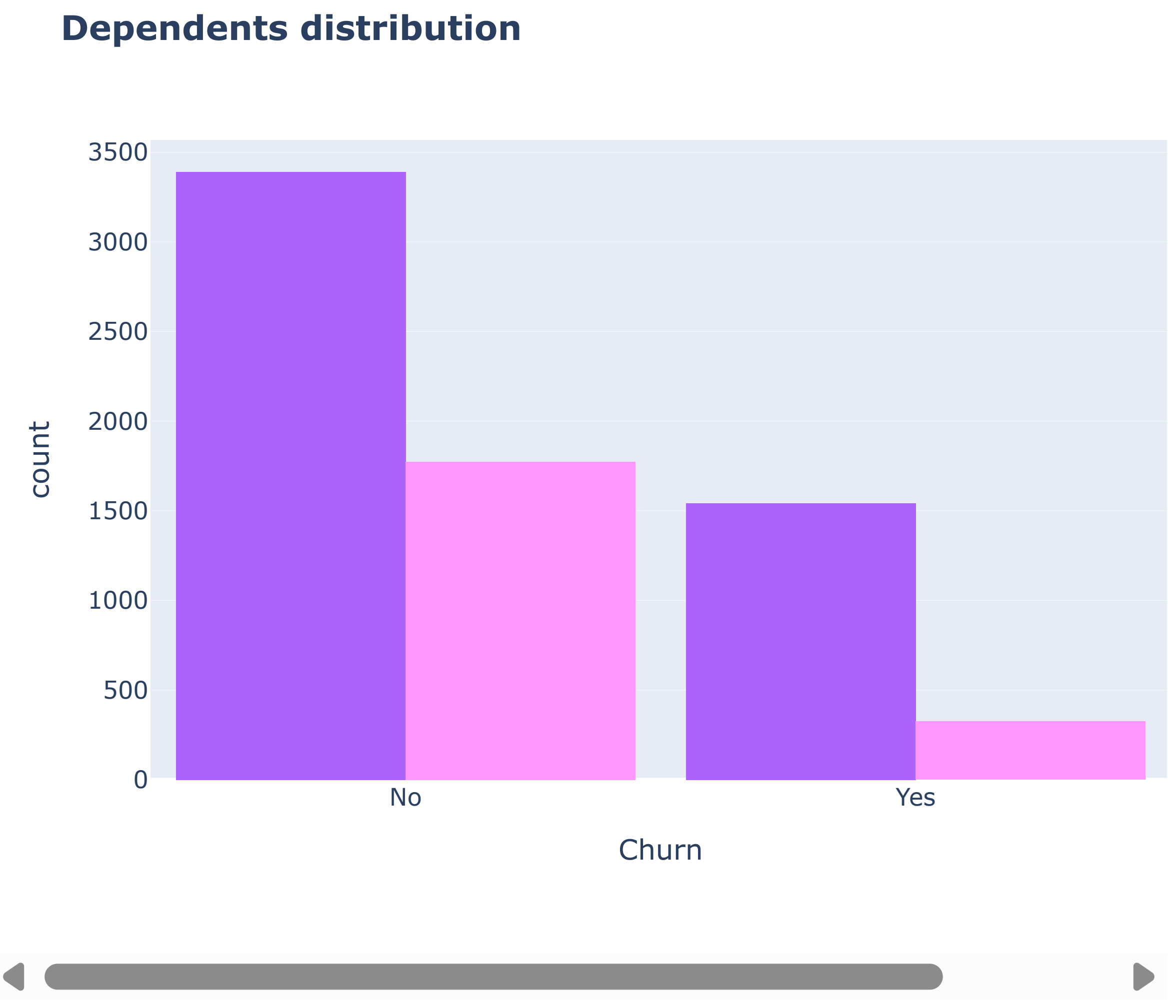
```
fig = go.Figure()

fig.add_trace(go.Bar(
  x = [['Churn:No', 'Churn:No', 'Churn:Yes', 'Churn:Yes'],
       ["Female", "Male", "Female", "Male"]],
  y = [965, 992, 219, 240],
  name = 'DSL',
))

fig.add_trace(go.Bar(
  x = [['Churn:No', 'Churn:No', 'Churn:Yes', 'Churn:Yes'],
       ["Female", "Male", "Female", "Male"]],
  y = [889, 910, 664, 633],
  name = 'Fiber optic',
))

fig.add_trace(go.Bar(
  x = [['Churn:No', 'Churn:No', 'Churn:Yes', 'Churn:Yes'],
       ["Female", "Male", "Female", "Male"]],
  y = [690, 717, 56, 57],
  name = 'No Internet',
))

fig.update_layout(title_text="<b>Churn Distribution w.r.t. Internet Service and

fig.show()
```



- A lot of customers choose the Fiber optic service and it's also evident that the customers who use Fiber optic have high churn rate, this might suggest a dissatisfaction with this type of internet service.
-

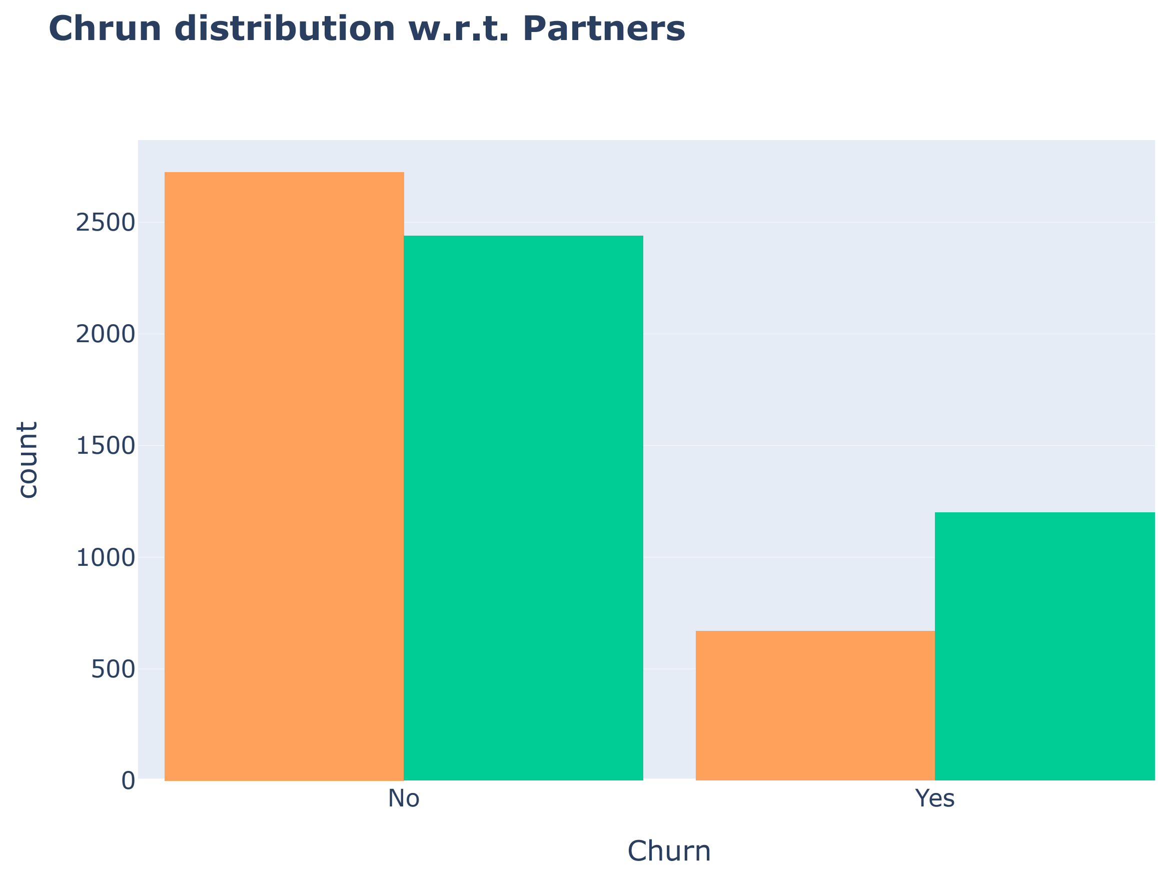
Customers having DSL service are majority in number and have less churn rate compared to Fibre optic service.

In [50]:
```
color_map = {"Yes": "#FF97FF", "No": "#AB63FA"}
fig = px.histogram(df, x="Churn", color="Dependents", barmode="group", title="<b
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



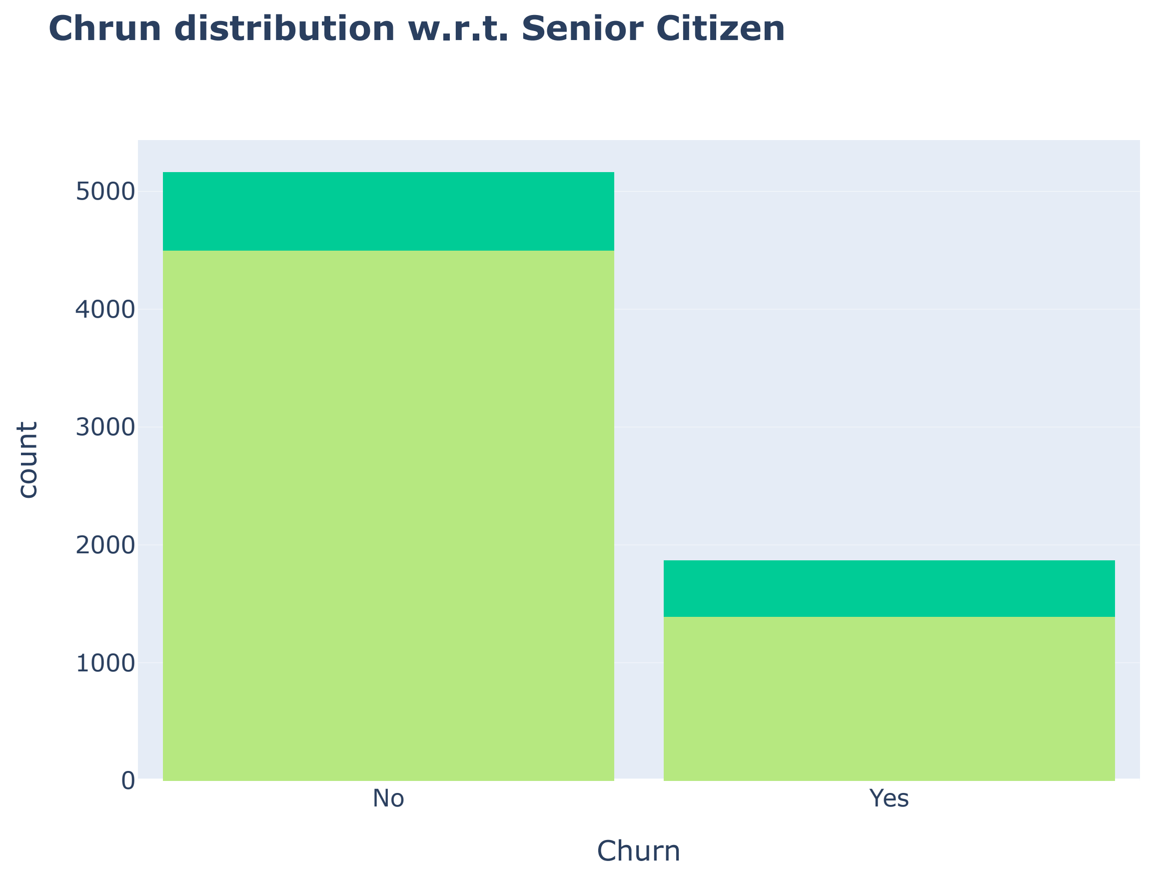
Customers without dependents are more likely to churn

In [52]:
```
color_map = {"Yes": '#FFA15A', "No": '#00CC96'}
fig = px.histogram(df, x="Churn", color="Partner", barmode="group", title="<b>Ch
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



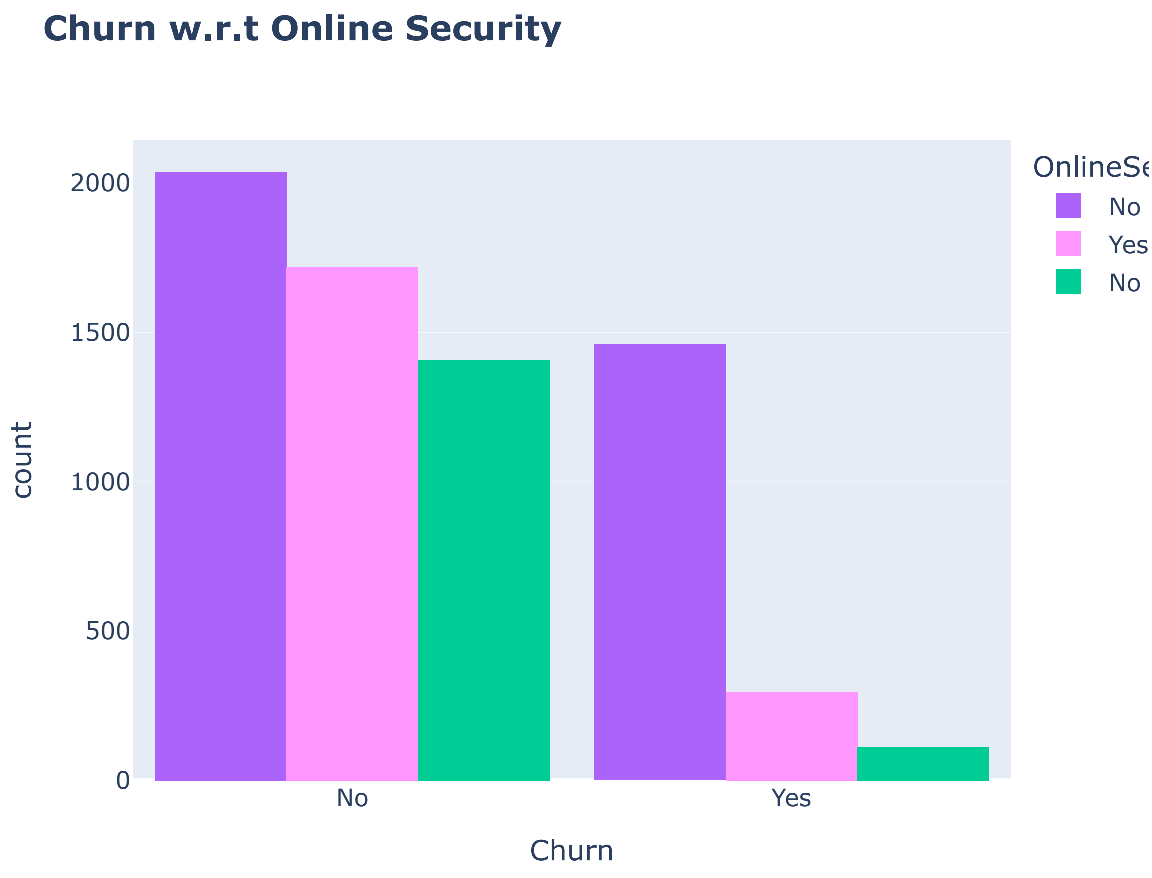
Customers that doesn't have partners are more likely to churn

In [54]:
```
color_map = {"Yes": '#00CC96', "No": '#B6E880'}
fig = px.histogram(df, x="Churn", color="SeniorCitizen", title="<b>Chrun distrib
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



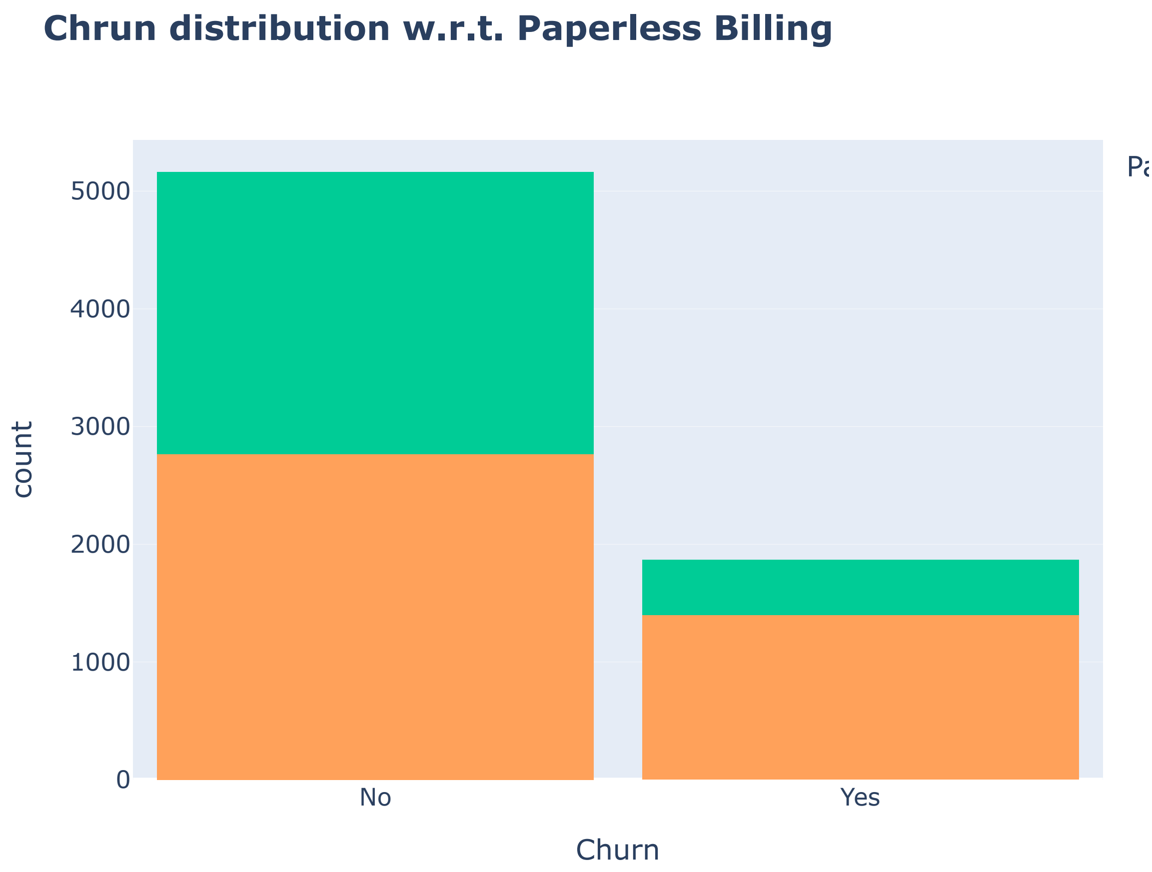
It can be observed that the fraction of senior citizen is very less. Most of the senior citizens churn.

In [56]:
```
color_map = {"Yes": "#FF97FF", "No": "#AB63FA"}
fig = px.histogram(df, x="Churn", color="OnlineSecurity", barmode="group", title
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



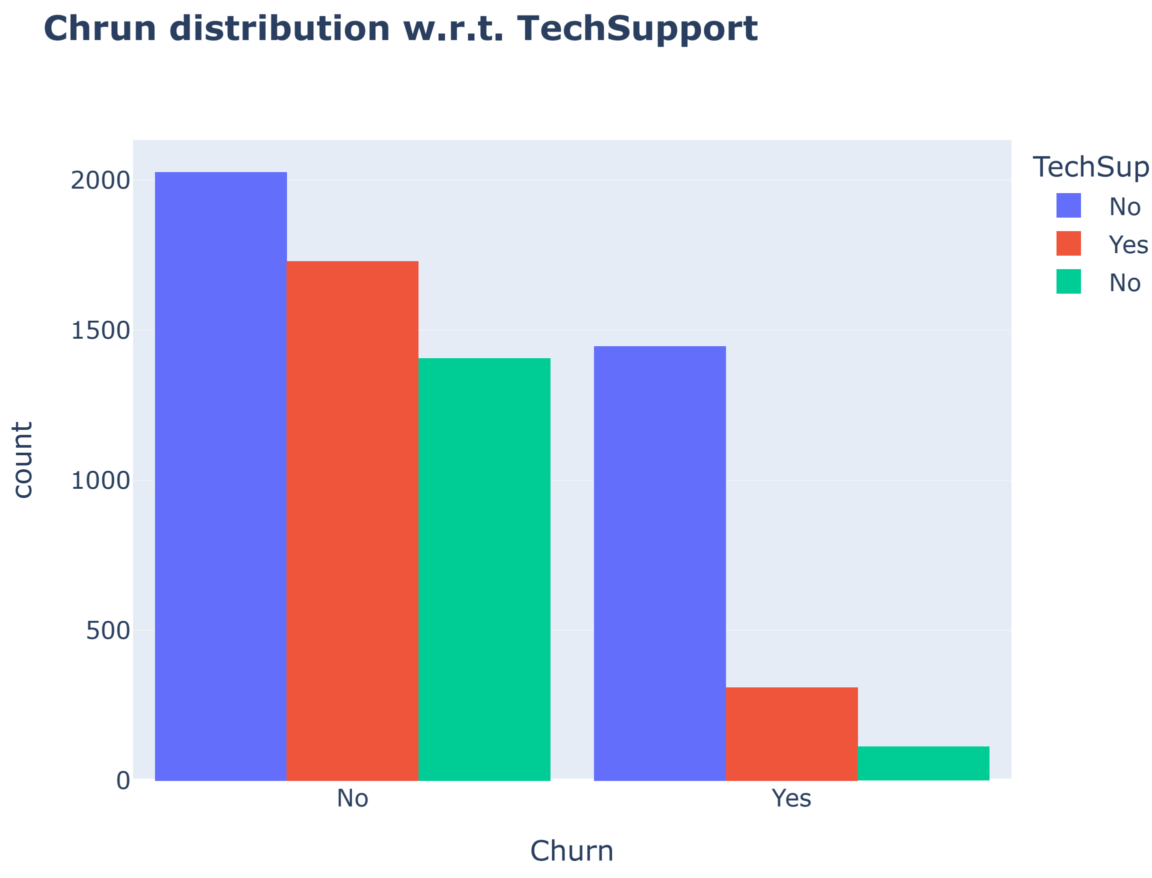
Most customers churn in the absence of online security,

In [58]:
```
color_map = {"Yes": '#FFA15A', "No": '#00CC96'}
fig = px.histogram(df, x="Churn", color="PaperlessBilling",  title="<b>Chrun dis
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



Customers with Paperless Billing are most likely to churn.

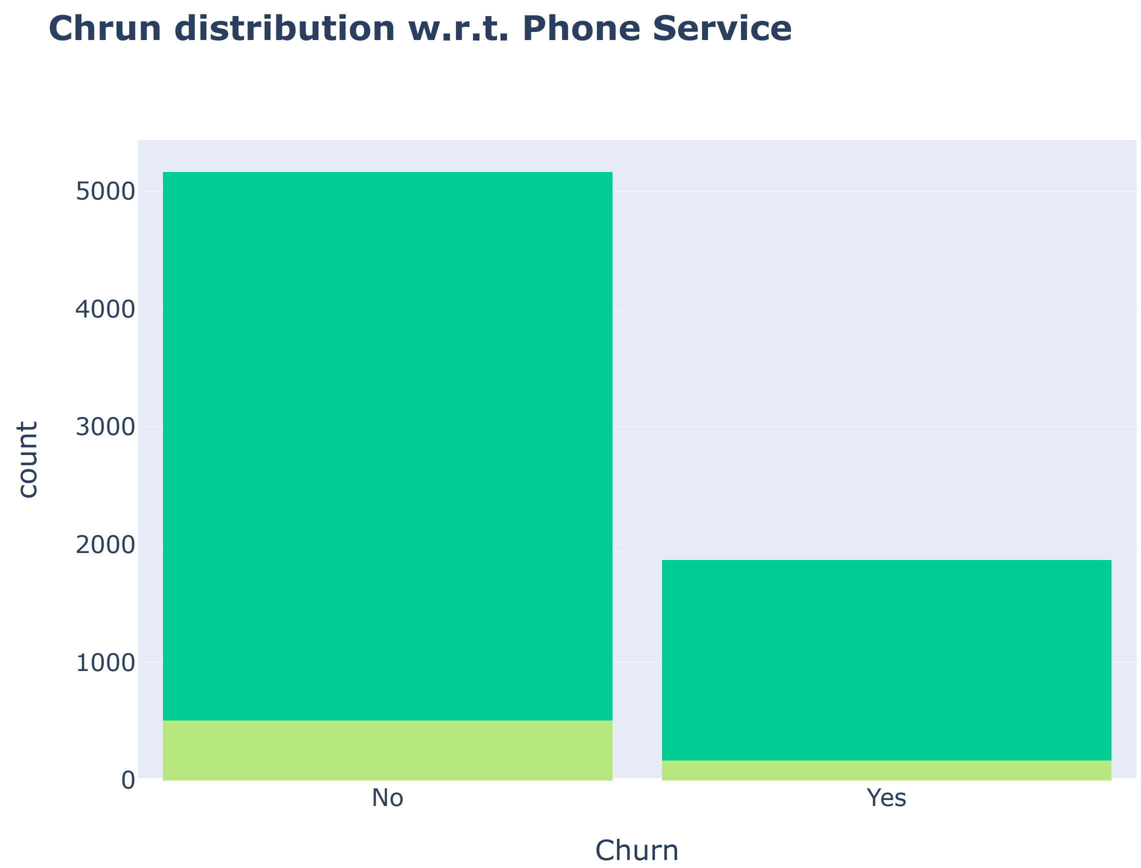
In [60]:
```
fig = px.histogram(df, x="Churn", color="TechSupport",barmode="group",  title="<
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



Customers with no TechSupport are most likely to migrate to another service provider.

In [106…

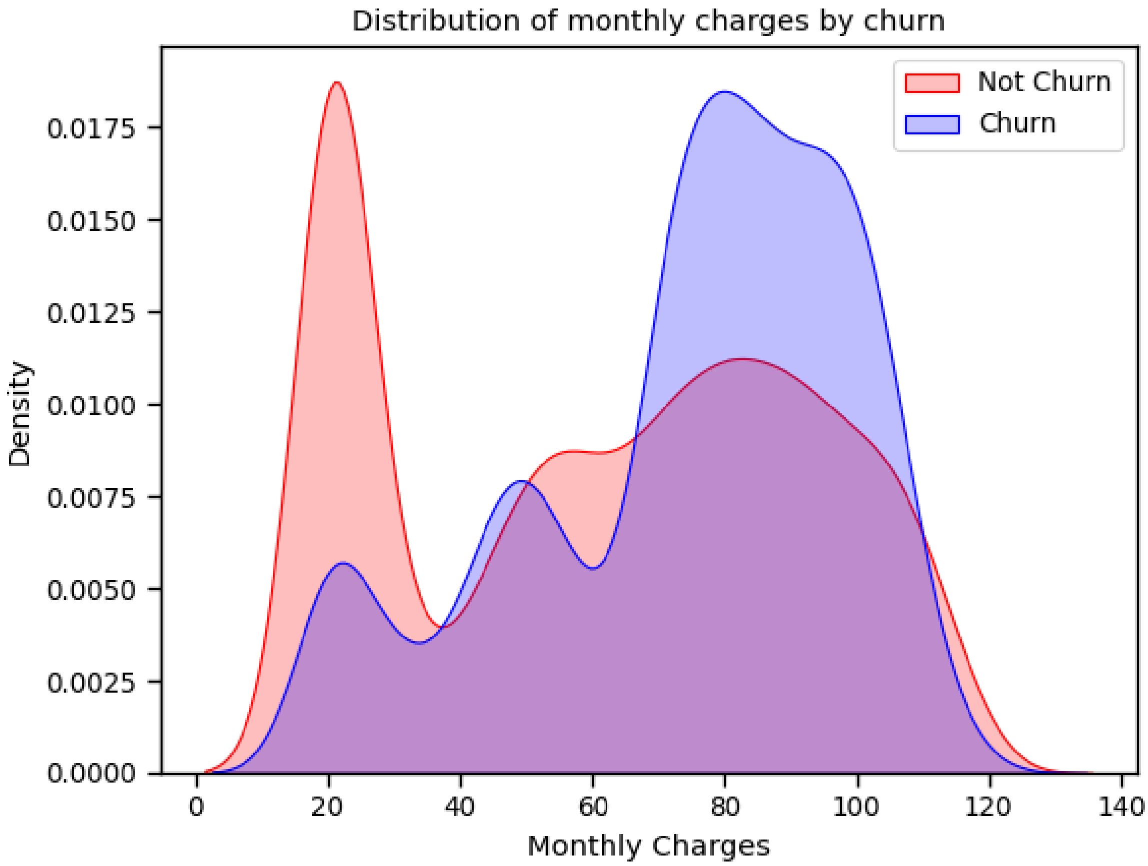
```
color_map = {"Yes": '#00CC96', "No": '#B6E880'}
fig = px.histogram(df, x="Churn", color="PhoneService", title="<b>Chrun distribu
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



- Very small fraction of customers don't have a phone service and out of that, 1/3rd Customers are more likely to churn.

In [109…

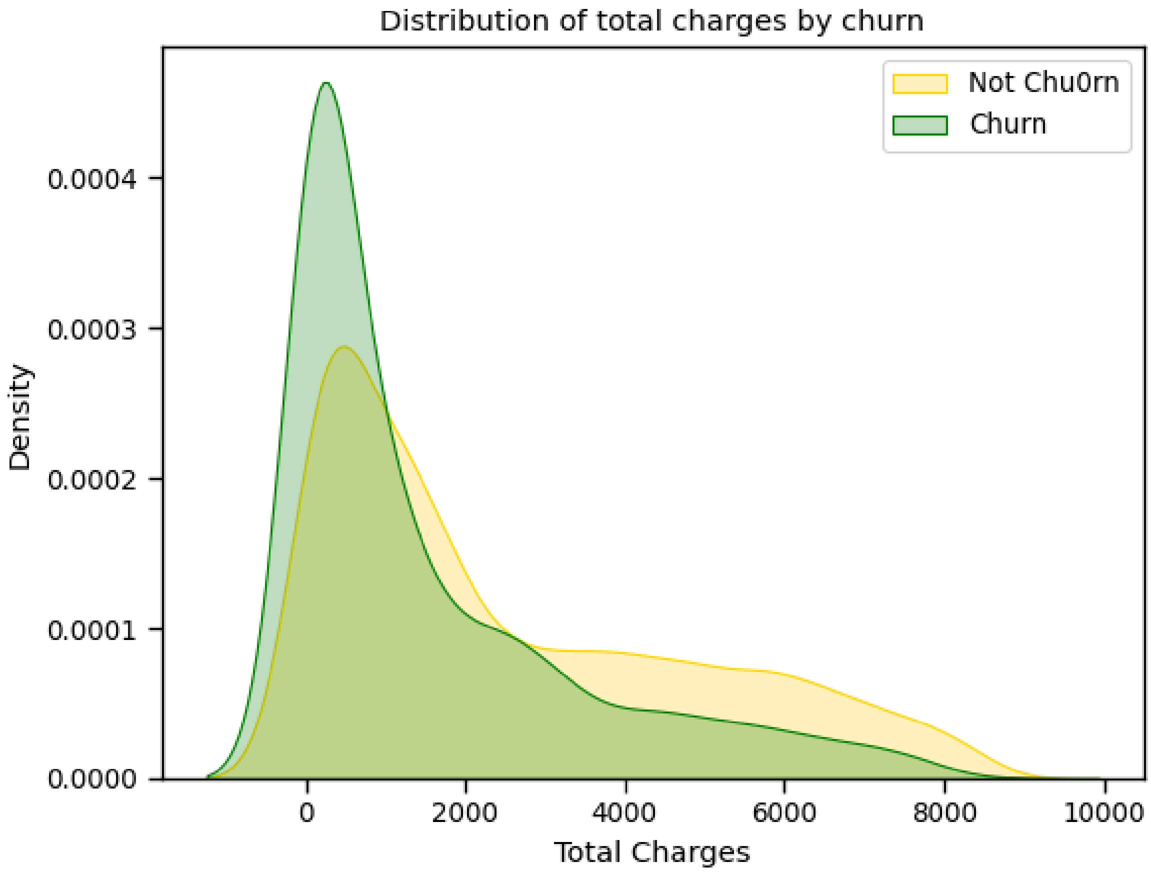
```
sns.set_context("paper",font_scale=1.1)
ax = sns.kdeplot(df.MonthlyCharges[(df["Churn"] == 'No') ],
                 color="Red", shade = True);
ax = sns.kdeplot(df.MonthlyCharges[(df["Churn"] == 'Yes') ],
                 ax =ax, color="Blue", shade= True);
ax.legend(["Not Churn","Churn"],loc='upper right');
ax.set_ylabel('Density');
ax.set_xlabel('Monthly Charges');
ax.set_title('Distribution of monthly charges by churn');
```



- Customers with higher Monthly Charges are also more likely to churn

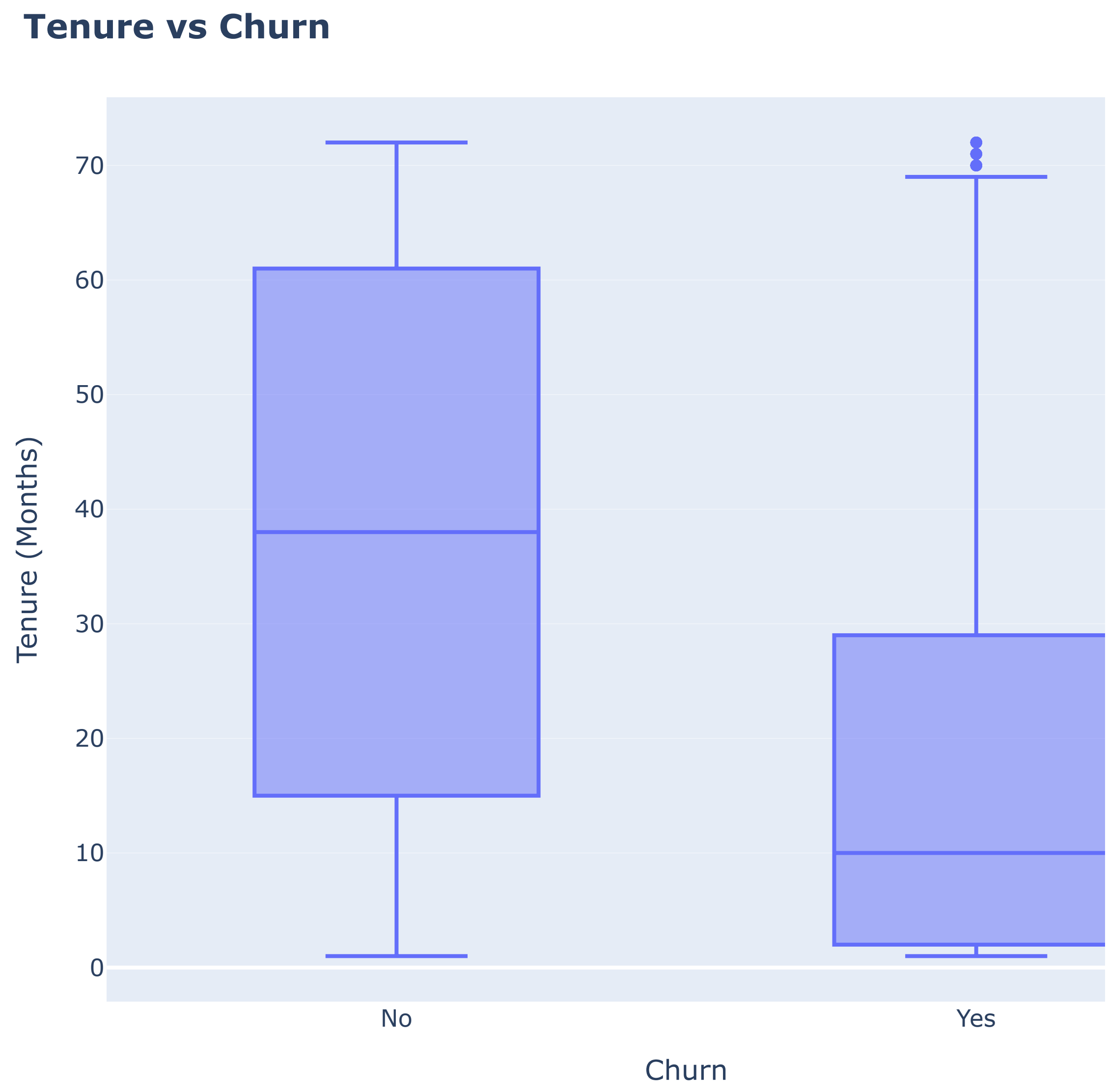
In [112…

```
ax = sns.kdeplot(df.TotalCharges[(df["Churn"] == 'No') ],
                 color="Gold", shade = True);
ax = sns.kdeplot(df.TotalCharges[(df["Churn"] == 'Yes') ],
                 ax =ax, color="Green", shade= True);
ax.legend(["Not Chu0rn","Churn"],loc='upper right');
ax.set_ylabel('Density');
ax.set_xlabel('Total Charges');
ax.set_title('Distribution of total charges by churn');
```



In [114…

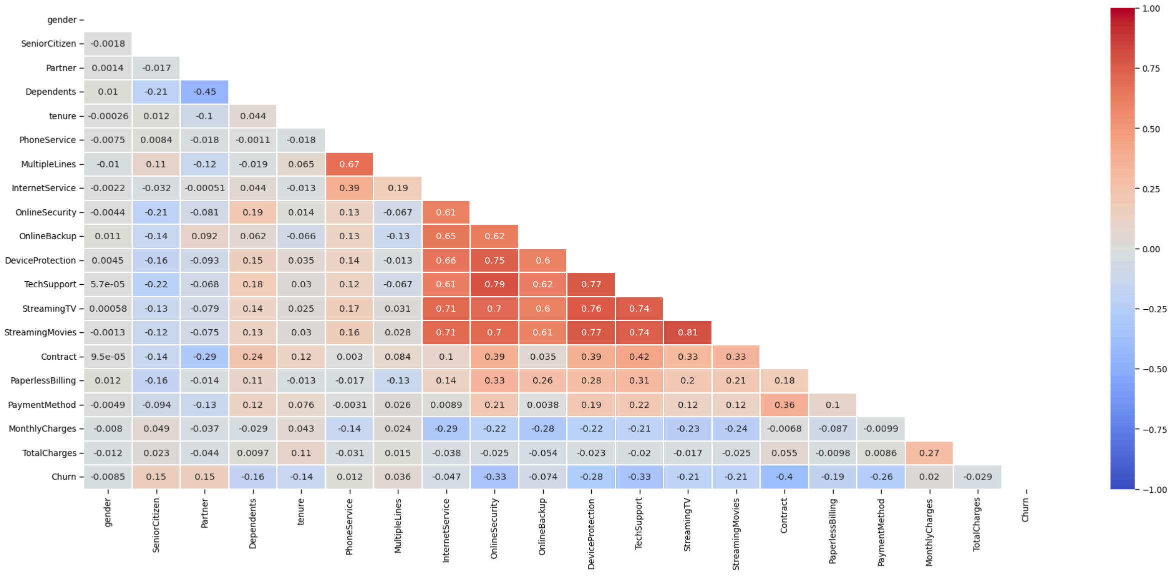
```
fig = px.box(df, x='Churn', y = 'tenure')

# Update yaxis properties
fig.update_yaxes(title_text='Tenure (Months)', row=1, col=1)
# Update xaxis properties
fig.update_xaxes(title_text='Churn', row=1, col=1)

# Update size and title
fig.update_layout(autosize=True, width=750, height=600,
    title_font=dict(size=25, family='Courier'),
    title='<b>Tenure vs Churn</b>',
)

fig.show()
```



- New customers are more likely to churn

In [119…

```
plt.figure(figsize=(25, 10))

corr = df.apply(lambda x: pd.factorize(x)[0]).corr()

mask = np.triu(np.ones_like(corr, dtype=bool))

ax = sns.heatmap(corr, mask=mask, xticklabels=corr.columns, yticklabels=corr.col
```



7. Data Preprocessing

- Splitting the data into train and test sets

In [123…

```
def object_to_int(dataframe_series):
    if dataframe_series.dtype=='object':
        dataframe_series = LabelEncoder().fit_transform(dataframe_series)
    return dataframe_series
```

In [125…

```
df = df.apply(lambda x: object_to_int(x))
df.head()
```

Out[125…

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	In
0	0	0	1	0	1	0	1	
1	1	0	0	0	34	1	0	
2	1	0	0	0	2	1	0	
3	1	0	0	0	45	0	1	
4	0	0	0	0	2	1	0	

In [127…

```
plt.figure(figsize=(14,7))
df.corr()['Churn'].sort_values(ascending = False)
```

Out[127...

```
Churn               1.000000
MonthlyCharges      0.192858
PaperlessBilling    0.191454
SeniorCitizen       0.150541
PaymentMethod       0.107852
MultipleLines       0.038043
PhoneService        0.011691
gender             -0.008545
StreamingTV        -0.036303
StreamingMovies    -0.038802
InternetService    -0.047097
Partner            -0.149982
Dependents         -0.163128
DeviceProtection   -0.177883
OnlineBackup       -0.195290
TotalCharges       -0.199484
TechSupport        -0.282232
OnlineSecurity     -0.289050
tenure             -0.354049
Contract           -0.396150
Name: Churn, dtype: float64
<Figure size 1400x700 with 0 Axes>
```

In [129...

```
X = df.drop(columns = ['Churn'])
y = df['Churn'].values
```

In [131...

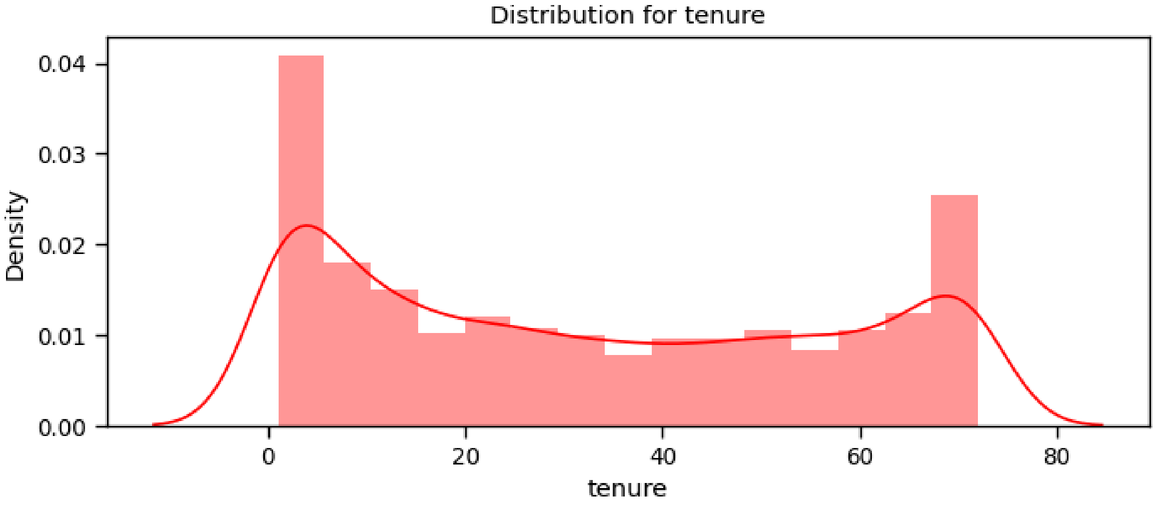
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.30, random
```

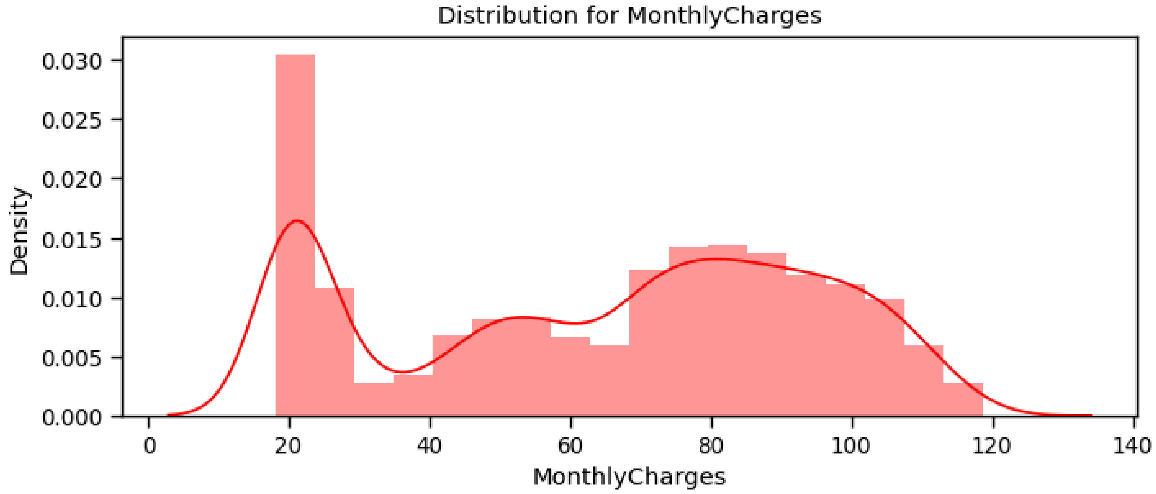
In [133...

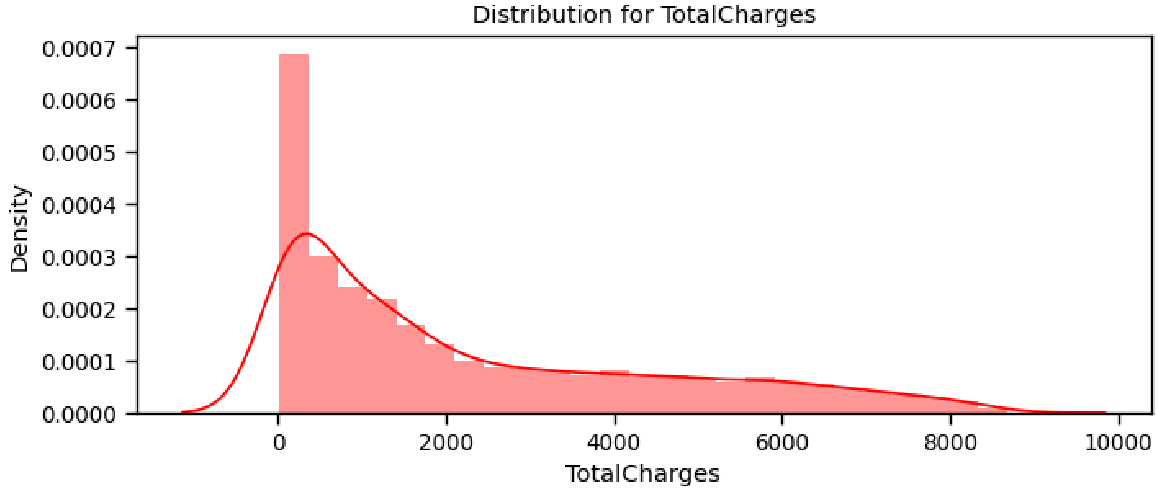
```
def distplot(feature, frame, color='r'):
    plt.figure(figsize=(8,3))
    plt.title("Distribution for {}".format(feature))
    ax = sns.distplot(frame[feature], color= color)
```

In [135...

```
num_cols = ["tenure", 'MonthlyCharges', 'TotalCharges']
for feat in num_cols: distplot(feat, df)
```





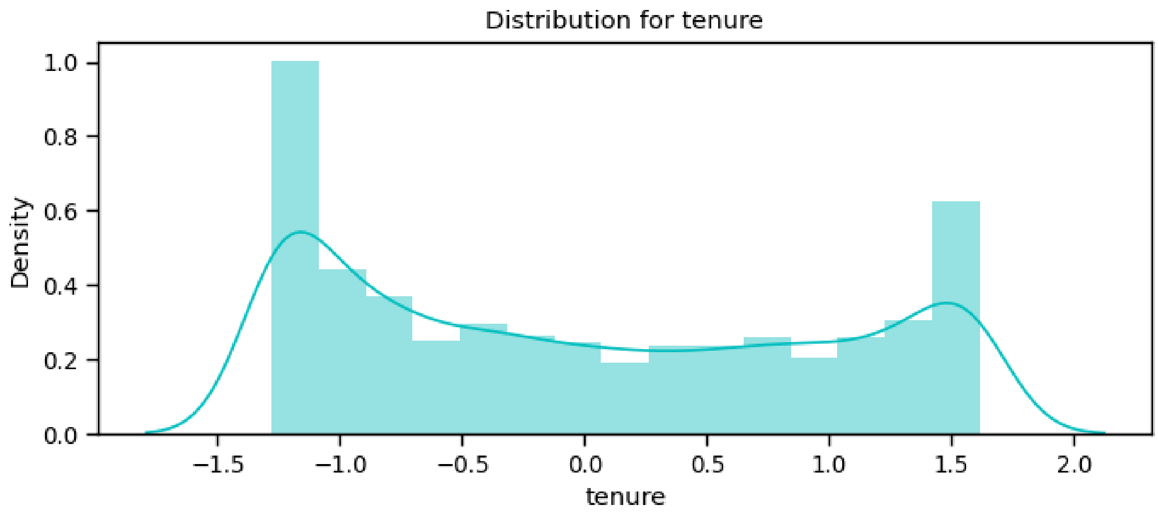


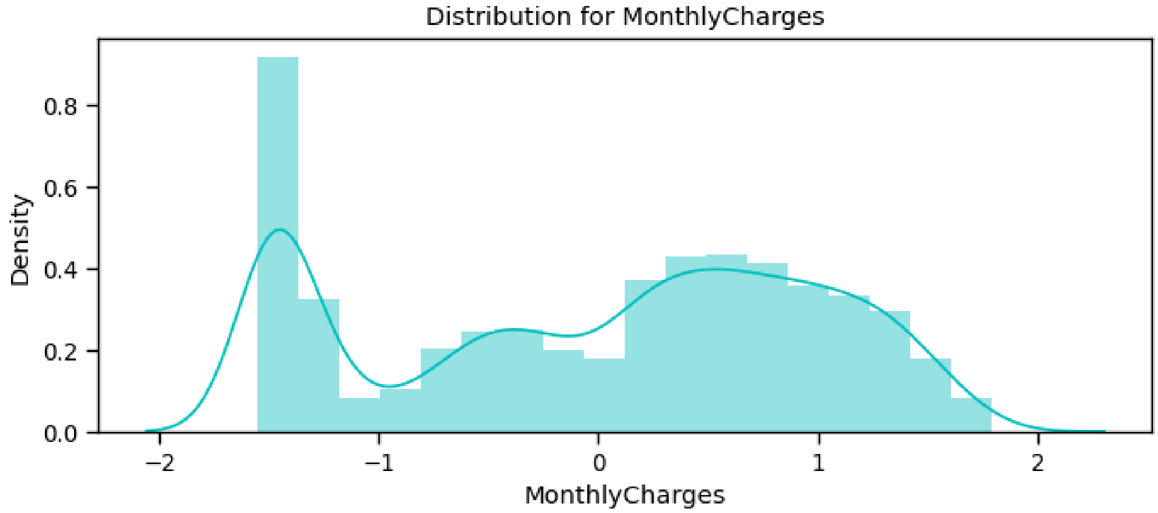
- Since the numerical features are distributed over different value ranges, i will use standar scalar to scale them down to the same range.

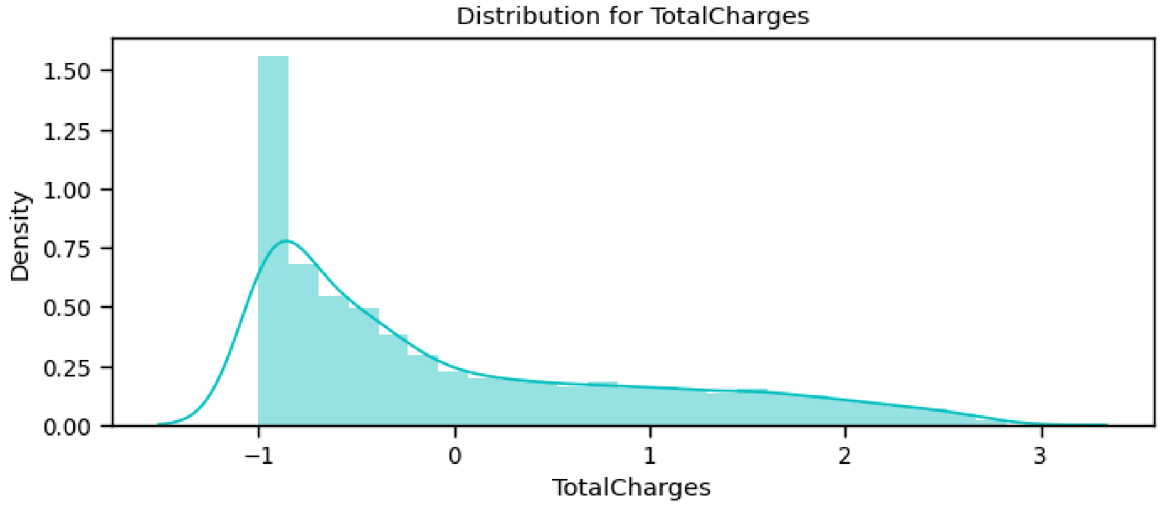
Standarddizing numeric attributes

In [139…

```
df_std = pd.DataFrame(StandardScaler().fit_transform(df[num_cols].astype('float6
                            columns=num_cols)
for feat in numerical_cols: distplot(feat, df_std, color='c')
```







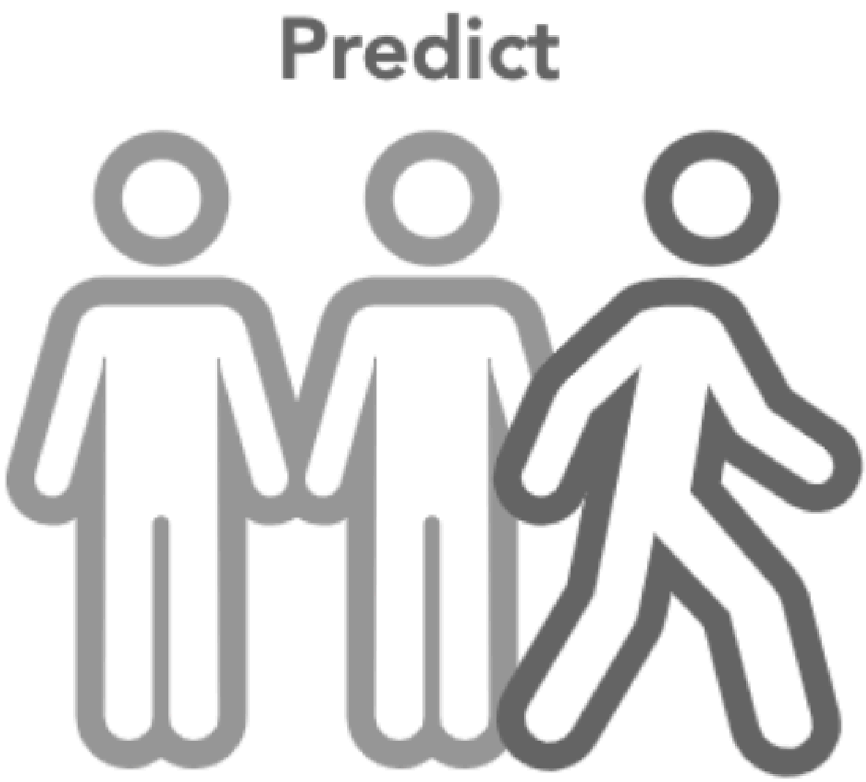
In [141…

```
# Divide the columns into 3 categories, one ofor standardisation, one for label

cat_cols_ohe =['PaymentMethod', 'Contract', 'InternetService'] # those that need
cat_cols_le = list(set(X_train.columns)- set(num_cols) - set(cat_cols_ohe)) #tho
```

In [143…

```
scaler= StandardScaler()

X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.transform(X_test[num_cols])
```

8. Machine Learning Model Evaluation and Predictions



KNN

In [149…

```
knn_model = KNeighborsClassifier(n_neighbors = 11)
knn_model.fit(X_train,y_train)
predicted_y = knn_model.predict(X_test)
accuracy_knn = knn_model.score(X_test,y_test)
print("KNN accuracy:",accuracy_knn)
```

```
KNN accuracy: 0.776303317535545
```

In [151…

```
print(classification_report(y_test, predicted_y))
```

```
              precision    recall  f1-score   support

           0       0.83      0.87      0.85      1549
           1       0.59      0.52      0.55       561

    accuracy                           0.78      2110
   macro avg       0.71      0.69      0.70      2110
weighted avg       0.77      0.78      0.77      2110
```

Random Forest

In [156…

```
model_rf = RandomForestClassifier(n_estimators=500 , oob_score = True, n_jobs =
                                  random_state =50, max_features = "sqrt",
                                  max_leaf_nodes = 30)
model_rf.fit(X_train, y_train)

# Make predictions
```

```
prediction_test = model_rf.predict(X_test)
print (metrics.accuracy_score(y_test, prediction_test))
```

```
0.8137440758293839
```

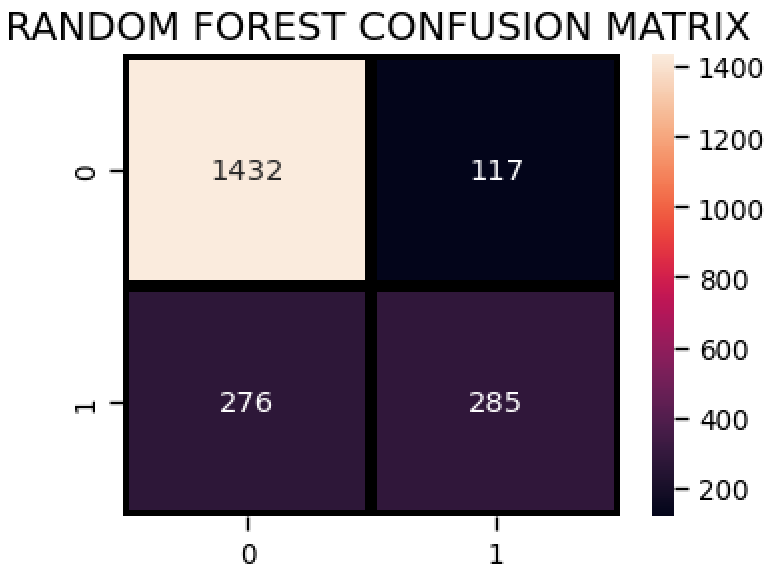
In [158…

```
print(classification_report(y_test, prediction_test))
```

```
              precision    recall  f1-score   support

           0       0.84      0.92      0.88      1549
           1       0.71      0.51      0.59       561

    accuracy                           0.81      2110
   macro avg       0.77      0.72      0.74      2110
weighted avg       0.80      0.81      0.80      2110
```

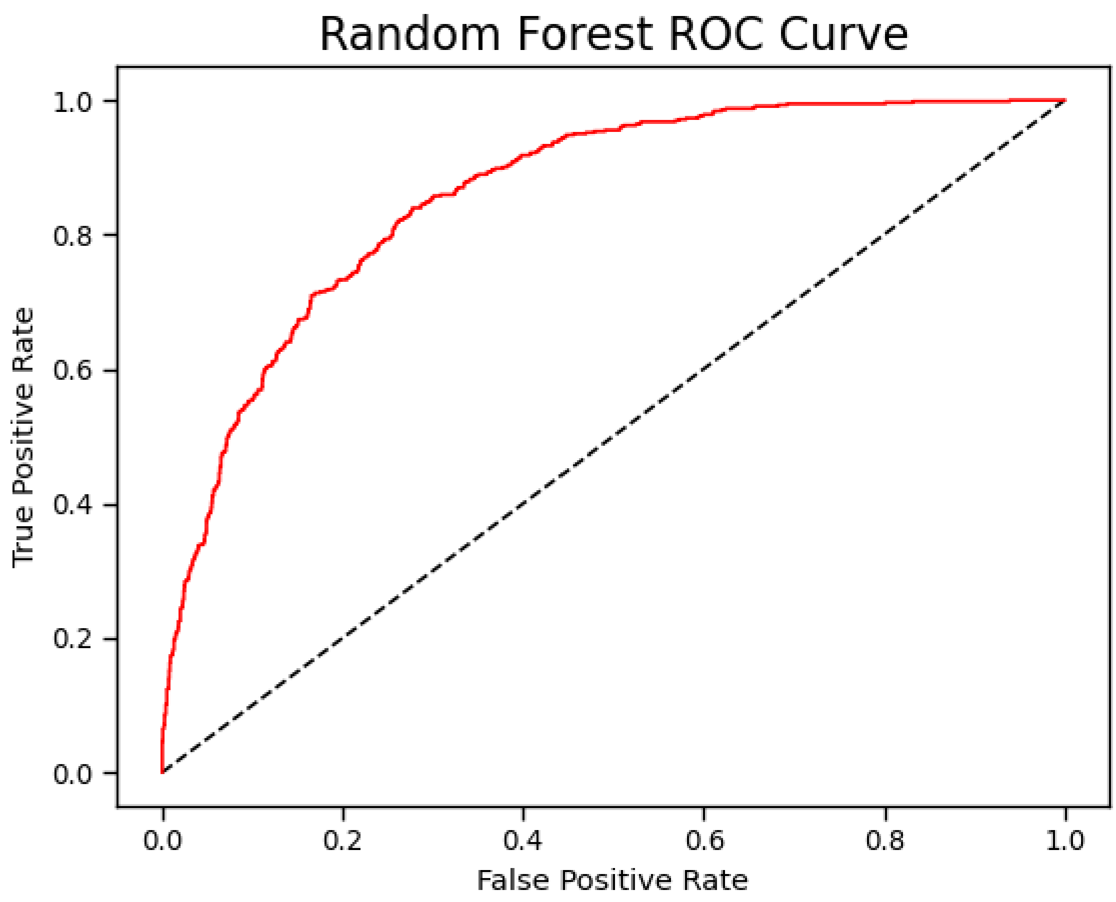
In [160…

```
plt.figure(figsize=(4,3))
sns.heatmap(confusion_matrix(y_test, prediction_test),
                annot=True,fmt = "d",linecolor="k",linewidths=3)

plt.title(" RANDOM FOREST CONFUSION MATRIX",fontsize=14)
plt.show()
```



In [162…

```
y_rfpred_prob = model_rf.predict_proba(X_test)[:,1]
fpr_rf, tpr_rf, thresholds = roc_curve(y_test, y_rfpred_prob)
plt.plot([0, 1], [0, 1], 'k--' )
plt.plot(fpr_rf, tpr_rf, label='Random Forest',color = "r")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Random Forest ROC Curve',fontsize=16)
plt.show();
```



Logistic Regression

In [165…

```
lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)
accuracy=lr_model.score(X_test, y_test)
print("Logestic Regression accuracy:", accuracy)
```

```
Logestic Regression accuracy: 0.8090047393364929
```

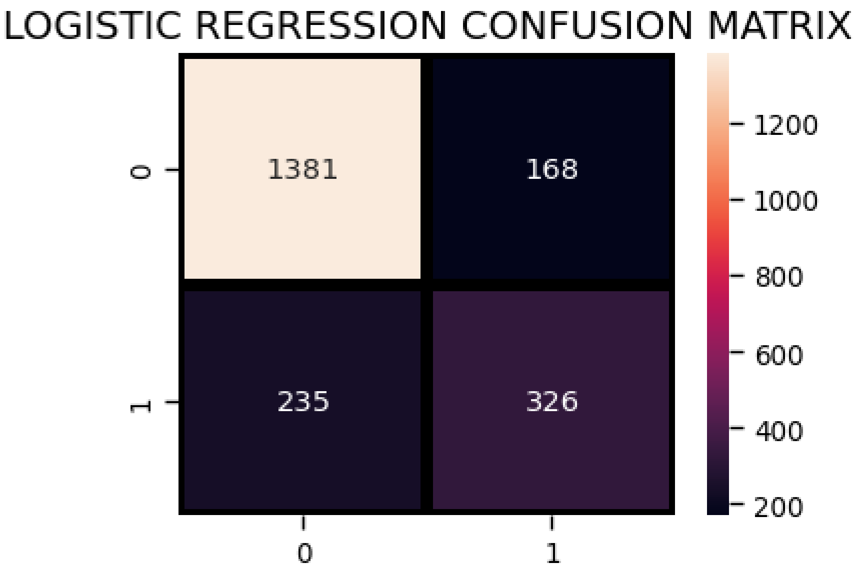
In [167…

```
lr_pred = lr_model.predict(X_test)
report = classification_report(y_test, lr_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.85      0.89      0.87      1549
           1       0.66      0.58      0.62       561

    accuracy                           0.81      2110
   macro avg       0.76      0.74      0.75      2110
weighted avg       0.80      0.81      0.80      2110
```

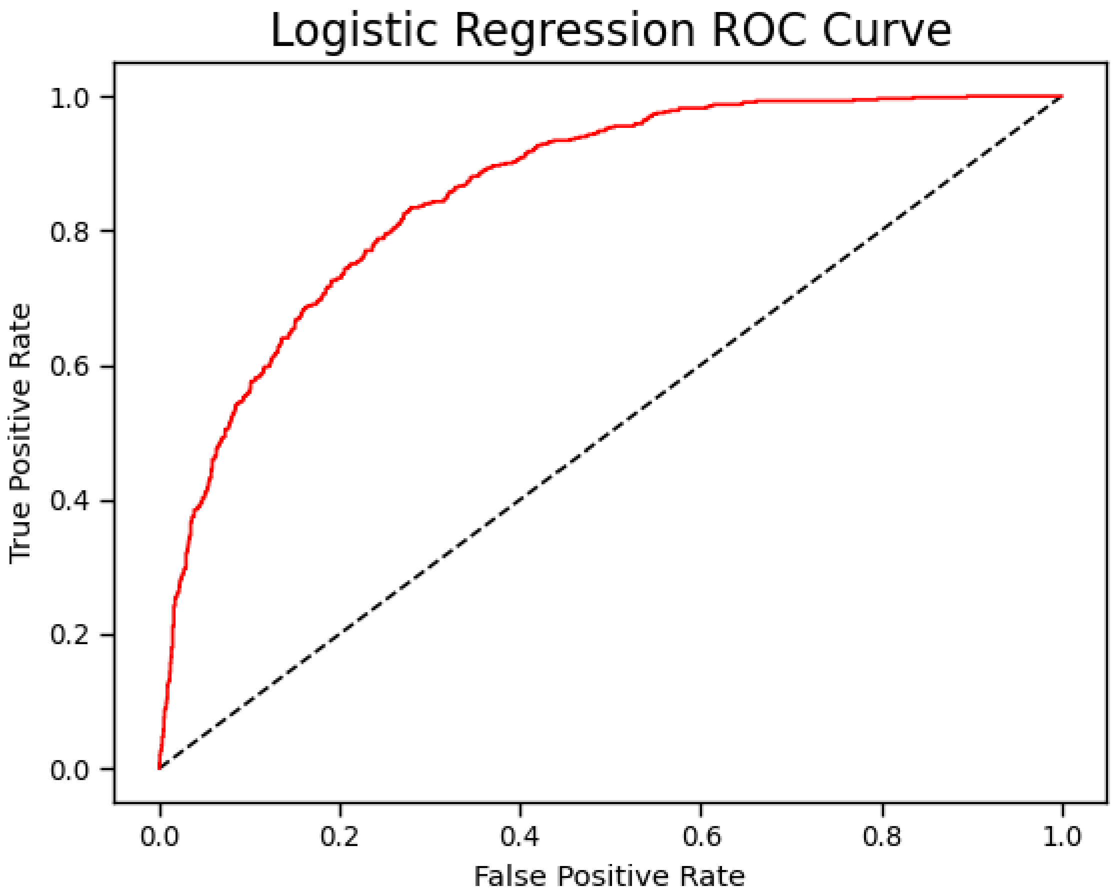
In [169…

```
plt.figure(figsize=(4,3))
sns.heatmap(confusion_matrix(y_test, lr_pred),
                annot=True,fmt = "d",linecolor="k",linewidths=3)

plt.title("LOGISTIC REGRESSION CONFUSION MATRIX",fontsize=14)
plt.show()
```



In [171…

```
y_pred_prob = lr_model.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
plt.plot([0, 1], [0, 1], 'k--' )
plt.plot(fpr, tpr, label='Logistic Regression',color = "r")
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Logistic Regression ROC Curve',fontsize=16)
plt.show();
```



Decision Tree Classifier

In [174...
```
dt_model = DecisionTreeClassifier()
dt_model.fit(X_train,y_train)
predictdt_y = dt_model.predict(X_test)
accuracy_dt = dt_model.score(X_test,y_test)
print("Decision Tree accuracy is :",accuracy_dt)
```

```
Decision Tree accuracy is : 0.7241706161137441
```

- Decision tree gives very low score.

In [179...
```
print(classification_report(y_test, predictdt_y))
```

```
              precision    recall  f1-score   support

           0       0.82      0.80      0.81      1549
           1       0.48      0.52      0.50       561

    accuracy                           0.72      2110
   macro avg       0.65      0.66      0.65      2110
weighted avg       0.73      0.72      0.73      2110
```

AdaBoost Classifier

In [182...
```
a_model = AdaBoostClassifier()
a_model.fit(X_train,y_train)
a_preds = a_model.predict(X_test)
print("AdaBoost Classifier accuracy")
metrics.accuracy_score(y_test, a_preds)
```

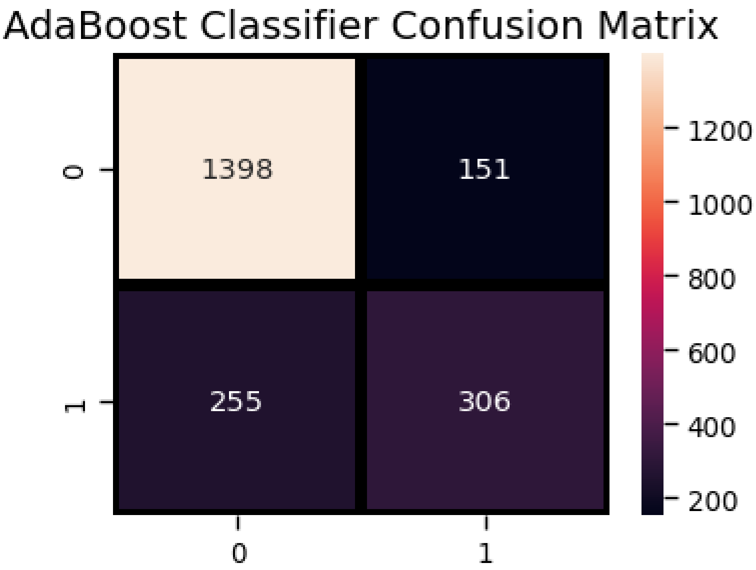
```
AdaBoost Classifier accuracy
```

Out[182...
```
0.8075829383886256
```

In [184...
```
print(classification_report(y_test, a_preds))
```

```
              precision    recall  f1-score   support

           0       0.85      0.90      0.87      1549
           1       0.67      0.55      0.60       561

    accuracy                           0.81      2110
   macro avg       0.76      0.72      0.74      2110
weighted avg       0.80      0.81      0.80      2110
```

In [186...
```
plt.figure(figsize=(4,3))
sns.heatmap(confusion_matrix(y_test, a_preds),
                annot=True,fmt = "d",linecolor="k",linewidths=3)

plt.title("AdaBoost Classifier Confusion Matrix",fontsize=14)
plt.show()
```



Gradient Boosting Classifier

In [189…

```
gb = GradientBoostingClassifier()
gb.fit(X_train, y_train)
gb_pred = gb.predict(X_test)
print("Gradient Boosting Classifier", accuracy_score(y_test, gb_pred))
```

```
Gradient Boosting Classifier 0.8075829383886256
```

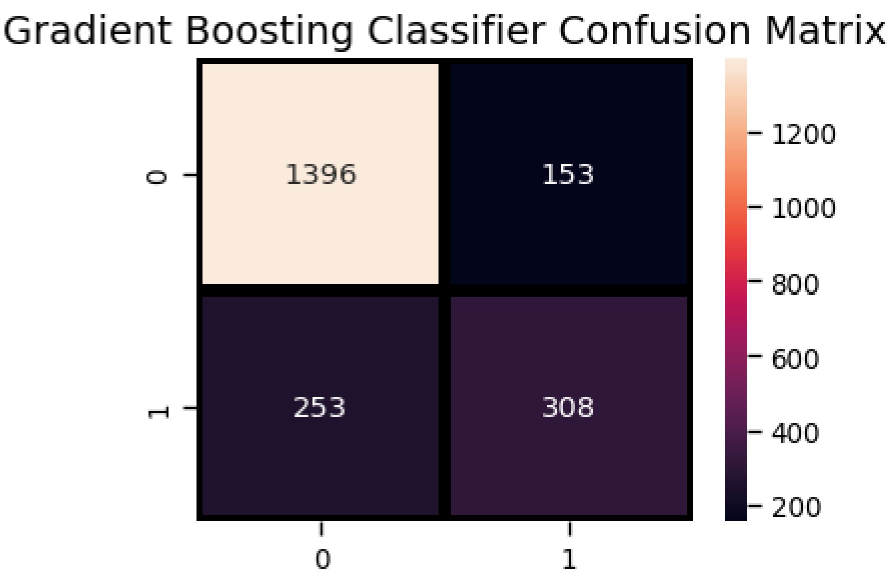
In [191…

```
print(classification_report(y_test, gb_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.90      0.87      1549
           1       0.67      0.55      0.60       561

    accuracy                           0.81      2110
   macro avg       0.76      0.73      0.74      2110
weighted avg       0.80      0.81      0.80      2110
```

In [193…

```
plt.figure(figsize=(4,3))
sns.heatmap(confusion_matrix(y_test, gb_pred),
                annot=True,fmt = "d",linecolor="k",linewidths=3)

plt.title("Gradient Boosting Classifier Confusion Matrix",fontsize=14)
plt.show()
```



Voting Classifier

Leet's now predict the final model based on the highest majority of voting and check it's score.

In [197…

```
from sklearn.ensemble import VotingClassifier
clf1 = GradientBoostingClassifier()
clf2 = LogisticRegression()
clf3 = AdaBoostClassifier()
eclf1 = VotingClassifier(estimators=[('gbc', clf1), ('lr', clf2), ('abc', clf3)]
eclf1.fit(X_train, y_train)
predictions = eclf1.predict(X_test)
print("Final Accuracy Score ")
print(accuracy_score(y_test, predictions))
```

```
Final Accuracy Score
0.8165876777251185
```

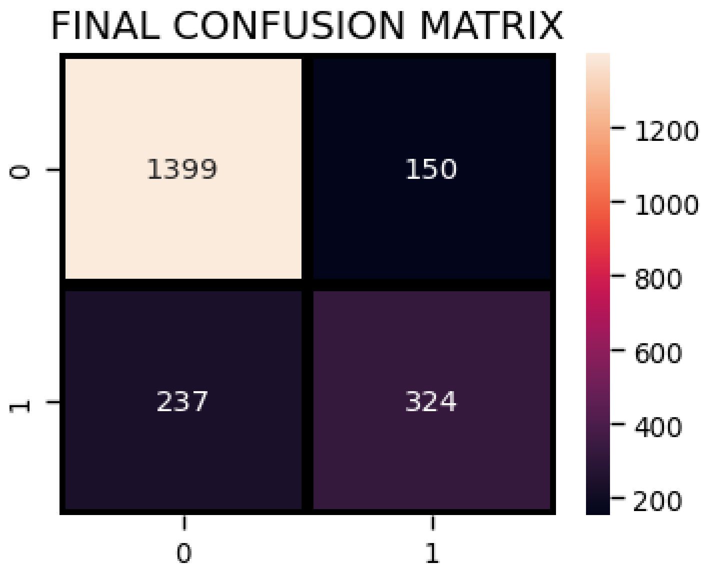
In [199…

```
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.86      0.90      0.88      1549
           1       0.68      0.58      0.63       561

    accuracy                           0.82      2110
   macro avg       0.77      0.74      0.75      2110
weighted avg       0.81      0.82      0.81      2110
```

In [201…

```
plt.figure(figsize=(4,3))
sns.heatmap(confusion_matrix(y_test, predictions),
                annot=True,fmt = "d",linecolor="k",linewidths=3)

plt.title("FINAL CONFUSION MATRIX",fontsize=14)
plt.show()
```



- From the confusion matrix we can see that: There are total 1400+149=1549 actual non-churn values and the algorithm predicts 1400 of them as non churn and 149 of them as churn. While there are 237+324=561 actual churn values and the algorithm predicts 237 of them as non churn values and 324 of them as churn values.

- Customer churn is definitely bad to a firm 's profitability. Various strategies can be implemented to eliminate customer churn. The best way to avoid customer churn is for a company to truly know its customers. This includes identifying customers who are at risk of churning and working to improve their satisfaction. Improving customer service is, of course, at the top of the priority for tackling this issue. Building customer loyalty through relevant experiences and specialized service is another strategy to reduce customer churn. Some firms survey customers who have already churned to understand their reasons for leaving in order to adopt a proactive approach to avoiding future customer churn.

```
In [ ]:
```