Loading libraries and data

In [1]:
```
import pandas as pd
import numpy as np
import missingno as msno
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
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_score, accuracy_score, classi
fication_report
```

In [3]:
```
#Loading data
df = pd.read_csv("C:\\Users\\Admin\\Downloads\\Telecom_Customer_Churn.csv")
```

Undertanding the data

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

In [4]:
```
df.head()
```

Out[4]:

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

5 rows × 21 columns

The data set includes information about:

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

2. 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

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

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

In [5]:
```
df.shape
```

Out[5]:
```
(7043, 21)
```

In [6]:
```
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 [7]:
```
df.columns.values
```

Out[7]:
```
array(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
       'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges',
       'TotalCharges', 'Churn'], dtype=object)
```

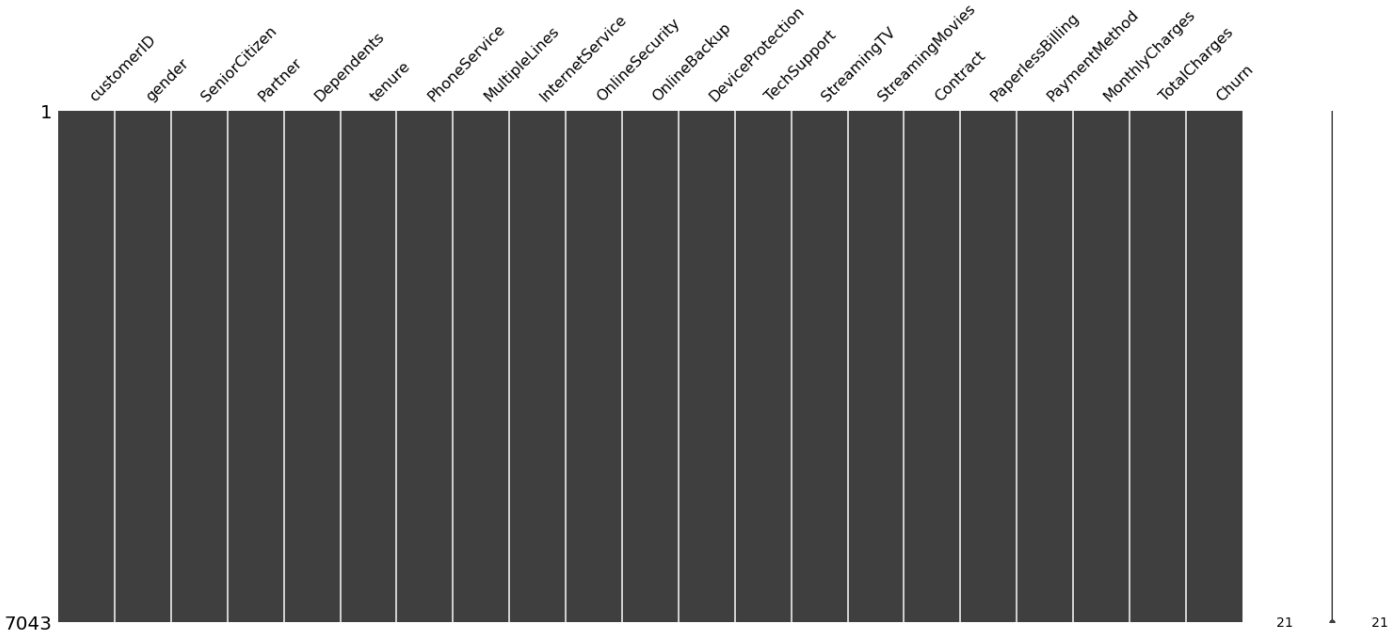
In [8]:
```
df.dtypes
```

Out[8]:
```
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

Visualize missing values

In [9]:
```
# 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.

Data Manipulation

In [10]:
```
df = df.drop(['customerID'], axis = 1)
df.head()
```

Out[10]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	Devic
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No	

On deep analysis, we can find some indirect missingness in our data (which can be in form of blankspaces). Let's see that!

In [11]:
```
df['TotalCharges'] = pd.to_numeric(df.TotalCharges, errors='coerce')
df.isnull().sum()
```

Out[11]:
```
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 [12]:
```
df[np.isnan(df['TotalCharges'])]
```

Out[12]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	D
488	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	No	
753	Male	0	No	Yes	0	Yes	No	No	No internet service	No internet service	
936	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	Yes	
1082	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	
1340	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	Yes	
3331	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	
3826	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	
4380	Female	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	
5218	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	
6670	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	Yes	
6754	Male	0	No	Yes	0	Yes	Yes	DSL	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 [13]:
```
df[df['tenure'] == 0].index
```

Out[13]:
```
Int64Index([488, 753, 936, 1082, 1340, 3331, 3826, 4380, 5218, 6670, 6754], dtype='int64')
```

-- 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 [14]:
```
df.drop(labels=df[df['tenure'] == 0].index, axis=0, inplace=True)
df[df['tenure'] == 0].index
```

Out[14]:
```
Int64Index([], dtype='int64')
```

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

In [15]:
```
df.fillna(df["TotalCharges"].mean())
```

Out[15]:

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

7032 rows × 20 columns

In [16]:
```
df.isnull().sum()
```

Out[16]:
```
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 [17]:
```
df["SeniorCitizen"]= df["SeniorCitizen"].map({0: "No", 1: "Yes"})
df.head()
```

Out[17]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	Devic
0	Female	No	Yes	No	1	No	No phone service	DSL	No	Yes	
1	Male	No	No	No	34	Yes	No	DSL	Yes	No	
2	Male	No	No	No	2	Yes	No	DSL	Yes	Yes	
3	Male	No	No	No	45	No	No phone service	DSL	Yes	No	
4	Female	No	No	No	2	Yes	No	Fiber optic	No	No	

In [18]:
```
df["InternetService"].describe(include=['object', 'bool'])
```

Out[18]:
```
count            7032
unique              3
top       Fiber optic
freq             3096
Name: InternetService, dtype: object
```

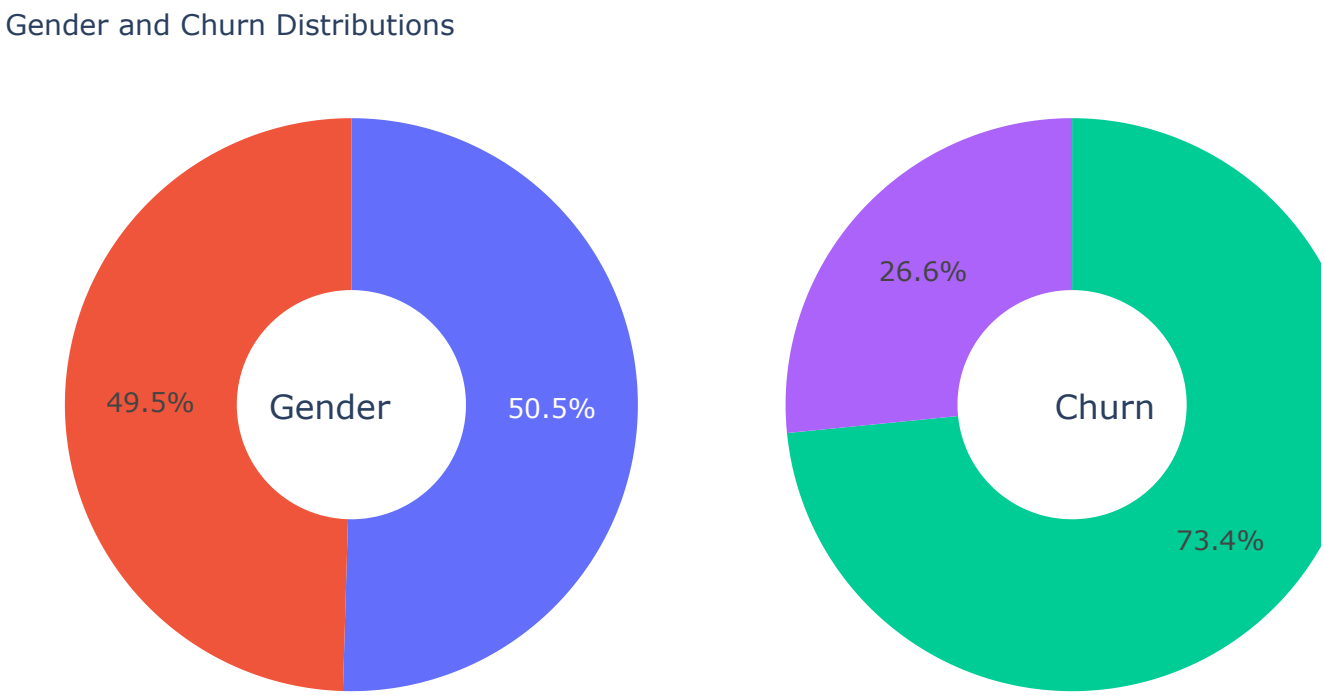
In [19]:
```
numerical_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
df[numerical_cols].describe()
```

Out[19]:

	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

Data Visualization

In [20]:
```
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="Gender"),
              1, 1)
fig.add_trace(go.Pie(labels=c_labels, values=df['Churn'].value_counts(), name="Churn"),
              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=False),
                 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.

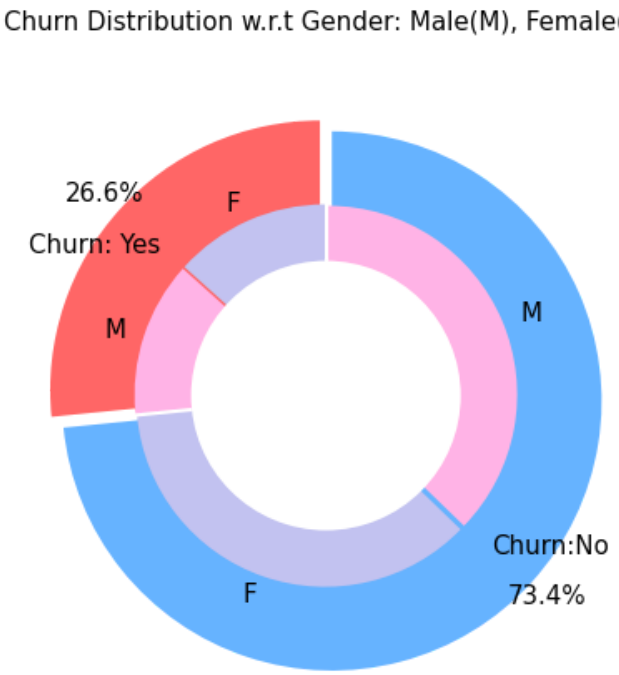
In [21]:
```
df["Churn"][df["Churn"]=="No"].groupby(by=df["gender"]).count()
```

Out[21]:
```
gender
Female    2544
Male      2619
Name: Churn, dtype: int64
```

In [22]:
```
df["Churn"][df["Churn"]=="Yes"].groupby(by=df["gender"]).count()
```

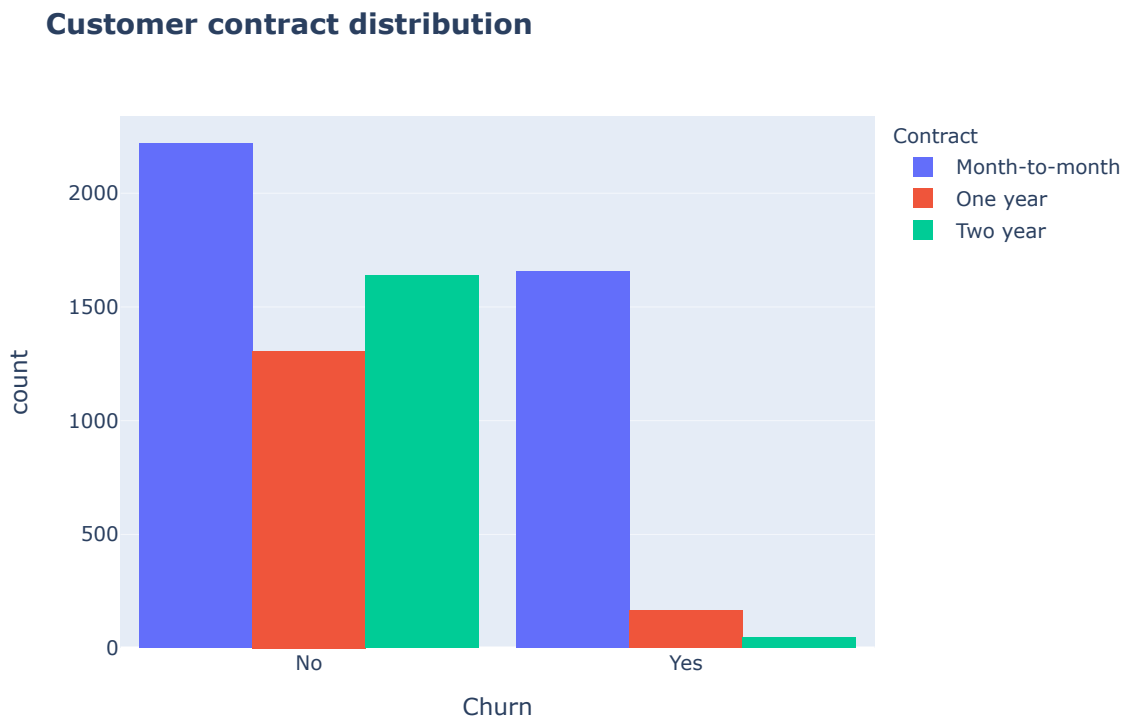
Out[22]:
```
gender
Female    939
Male      930
Name: Churn, dtype: int64
```

In [23]:
```
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=0.8,colors=colors, startangle
=90,frame=True, explode=explode,radius=10, textprops =textprops, counterclock = True, )
plt.pie(sizes_gender,labels=labels_gender,colors=colors_gender,startangle=90, explode=explode_gender,radius=
7, textprops =textprops, counterclock = True, )
#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=1.1)

# show plot

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



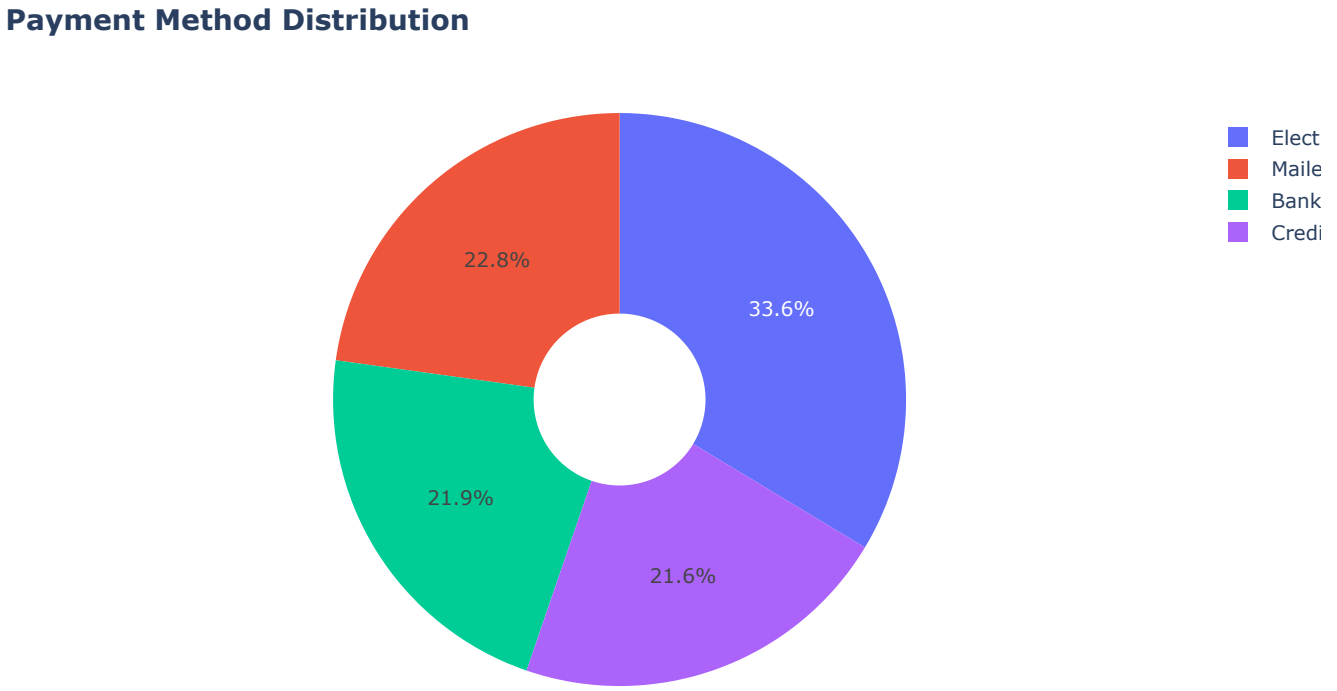
There is negligible difference in customer percentage/ count who chnaged the service provider. Both genders behaved in similar fashion when it comes to migrating to another service provider/firm.

In [24]:
```
fig = px.histogram(df, x="Churn", color="Contract", barmode="group", title="<b>Customer contract distribution<b>")
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```

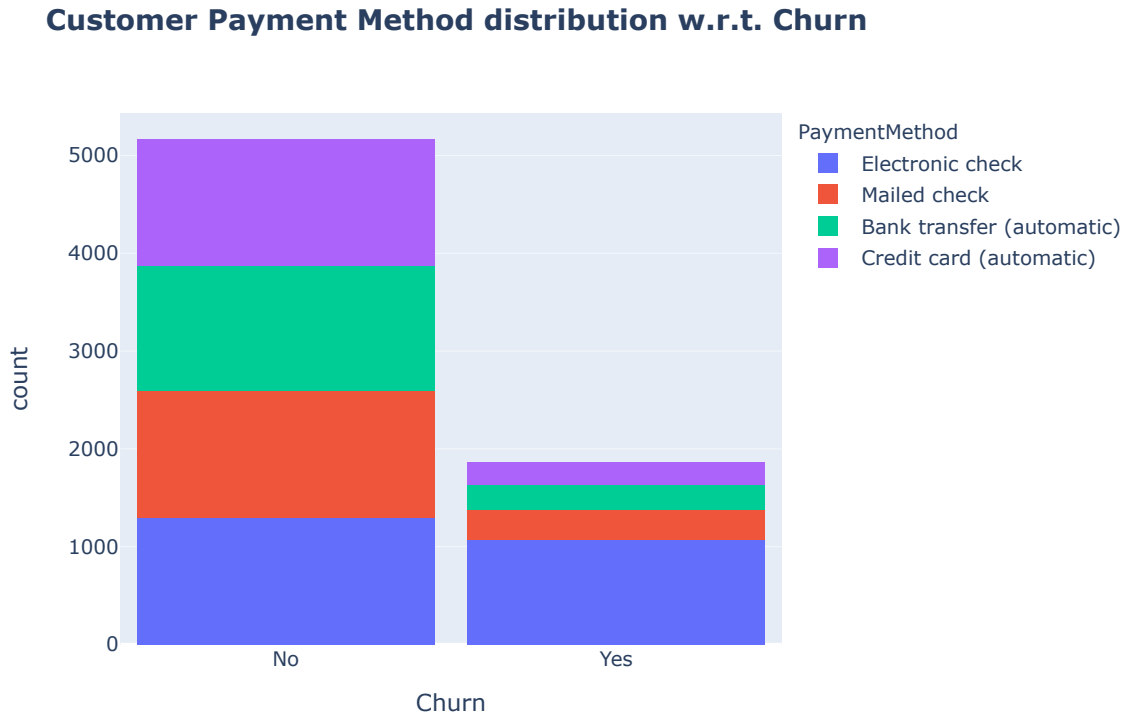


About 75% of customer with Month-to-Month Contract opted to move out as compared to 13% of customrs with One Year Contract and 3% with Two Year Contract

In [25]:
```
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()
```



In [26]:
```
fig = px.histogram(df, x="Churn", color="PaymentMethod", title="<b>Customer Payment Method distribution w.r.t. Churn</b>")
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```

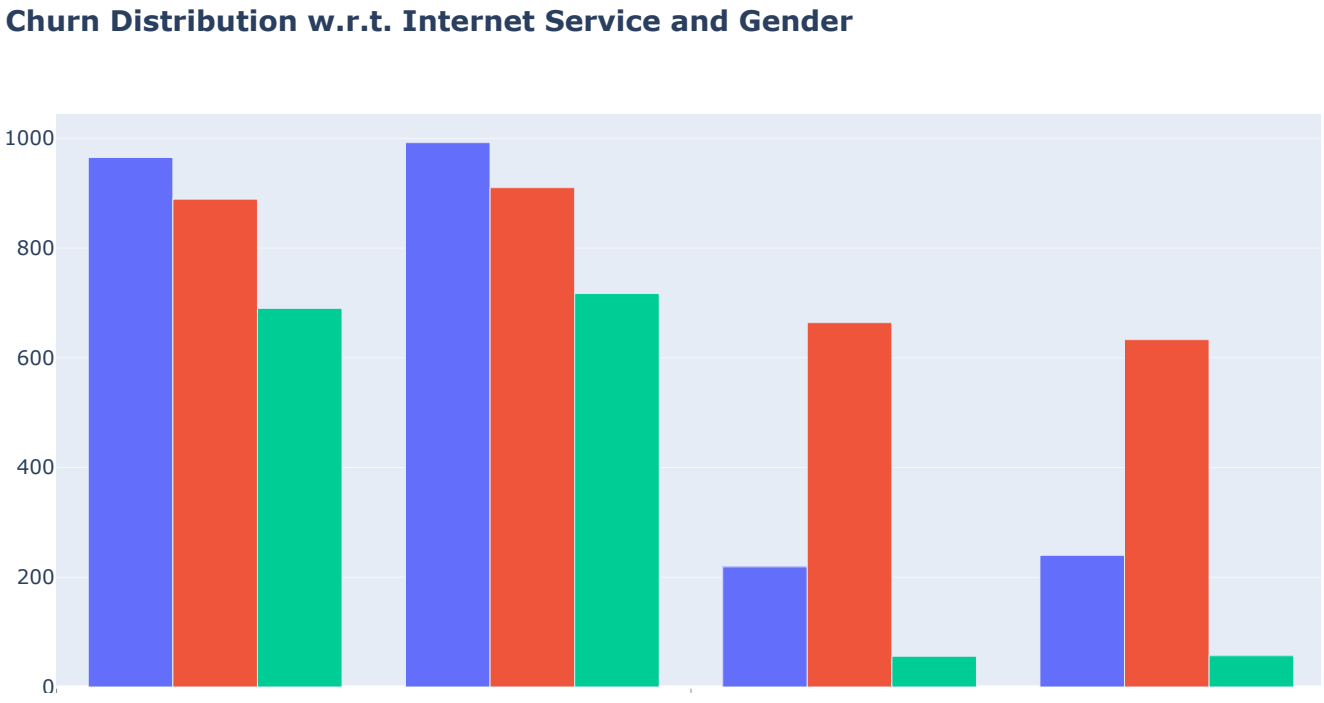


-- Major customers who moved out were having Electronic Check as Payment Method. -- Customers who opted for Credit-Card automatic transfer or Bank Automatic Transfer and Mailed Check as Payment Method were less likely to move out.

In [27]:
```
df["InternetService"].unique()
```

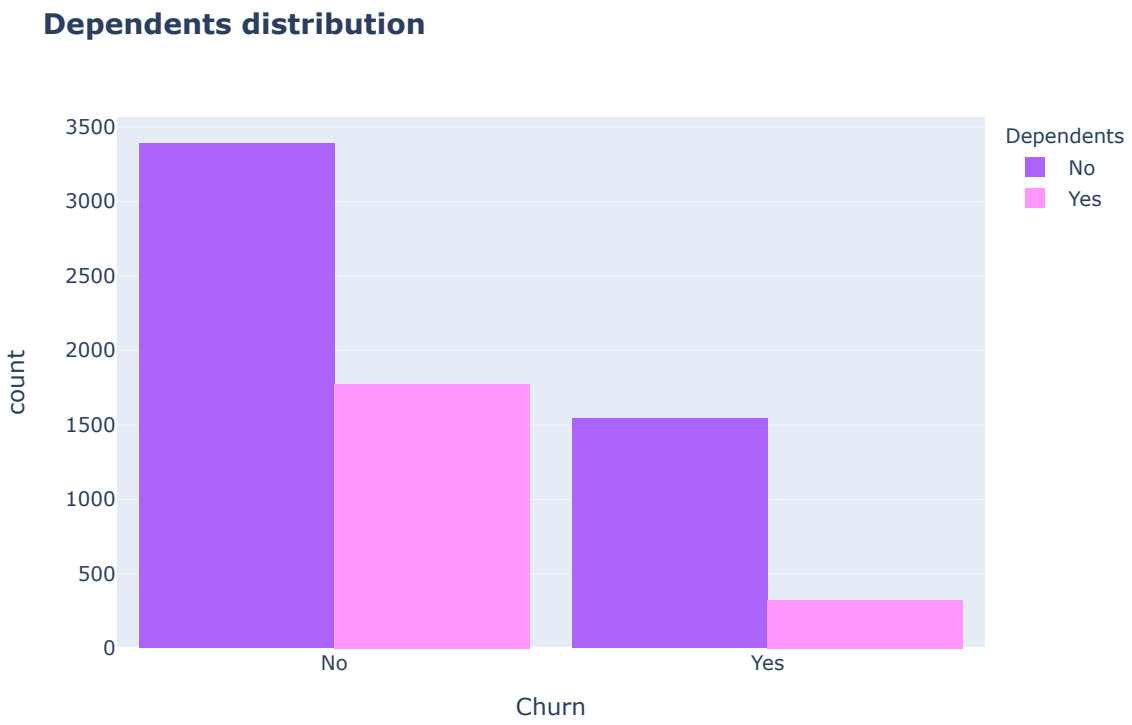
Out[27]:
```
array(['DSL', 'Fiber optic', 'No'], dtype=object)
```

In [28]:
```
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 Gender</b>")

fig.show()
```



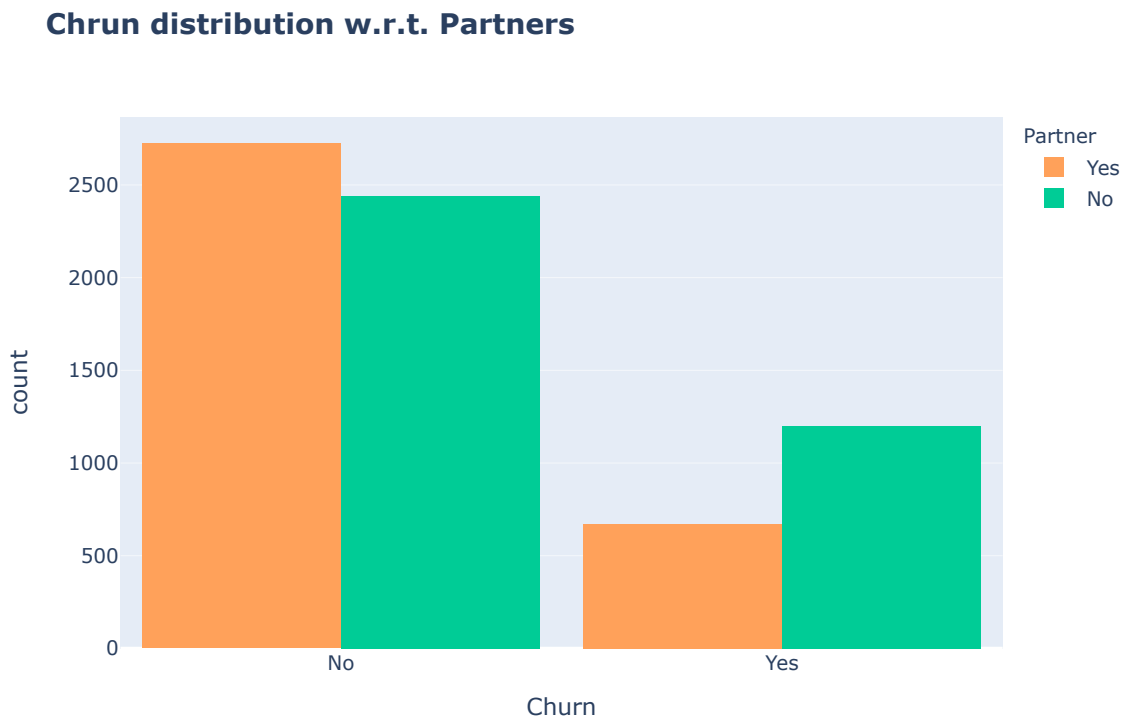
-- A lot of customers choose the Fiber optic service and it's also evident that the customers who use Fiber optic have high churn rate, this might suggest a dissatisfaction with this type of internet service. -- Customers having DSL service are majority in number and have less churn rate compared to Fibre optic service.

In [29]:
```
color_map = {"Yes": "#FF97FF", "No": "#AB63FA"}
fig = px.histogram(df, x="Churn", color="Dependents", barmode="group", title="<b>Dependents distribution</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



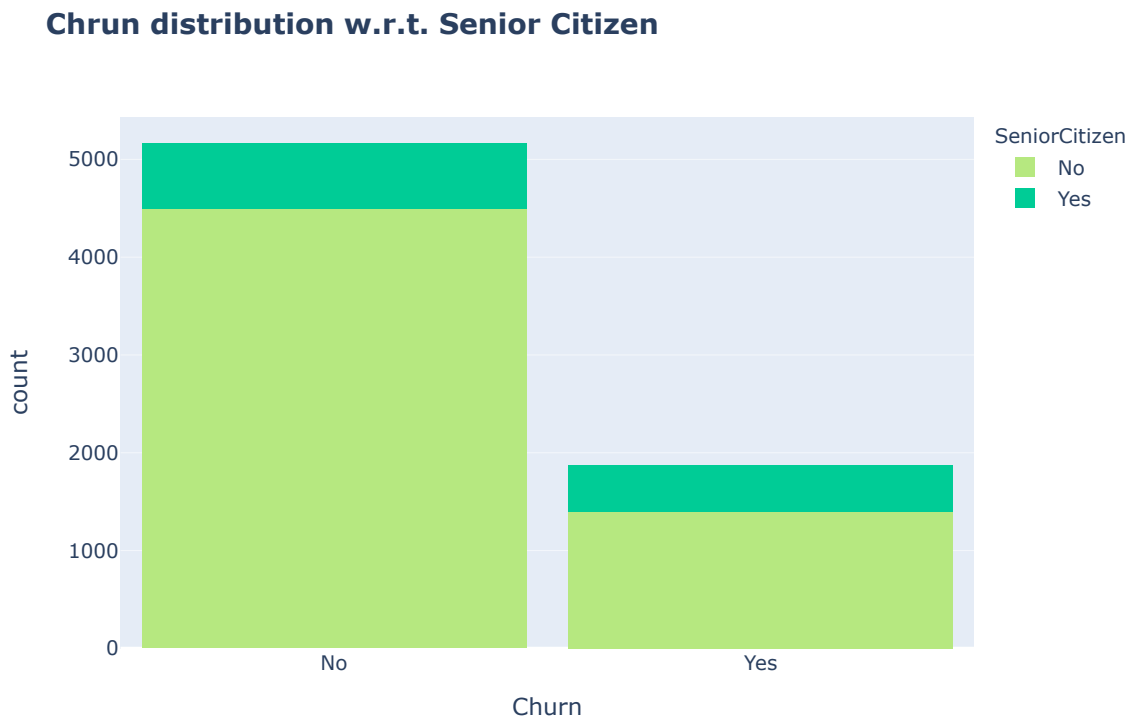
Customers without dependents are more likely to churn

In [30]:
```
color_map = {"Yes": '#FFA15A', "No": '#00CC96'}
fig = px.histogram(df, x="Churn", color="Partner", barmode="group", title="<b>Chrun distribution w.r.t. Partners</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



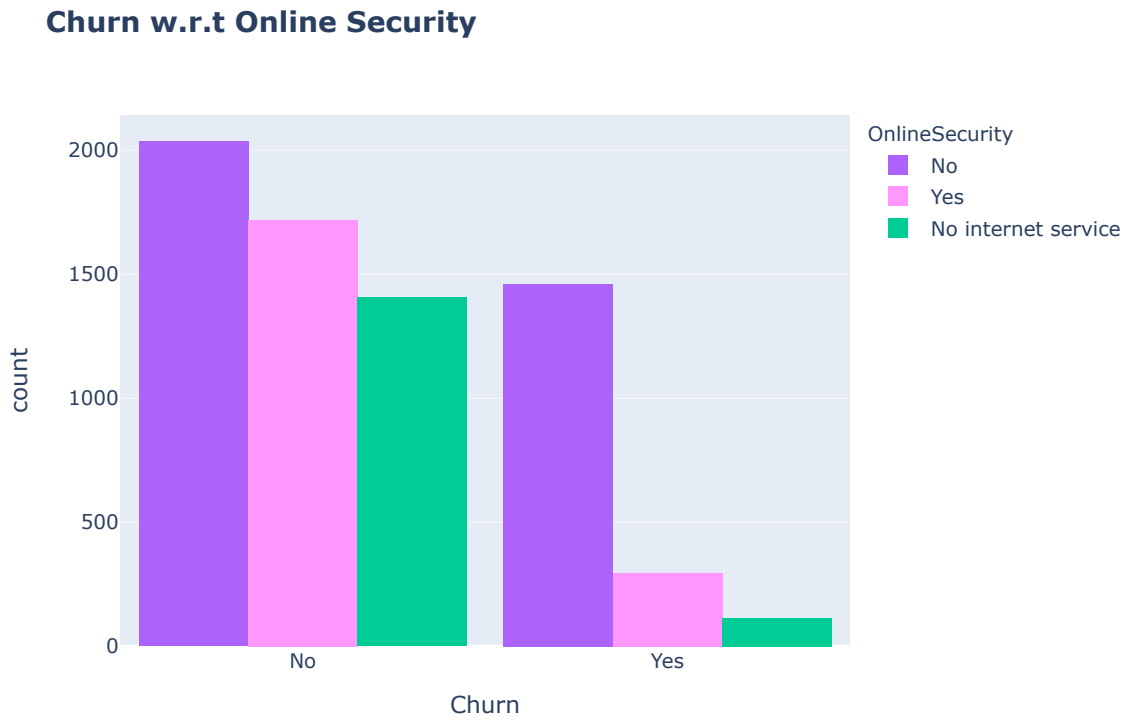
Customers that doesn't have partners are more likely to churn

In [31]:
```
color_map = {"Yes": '#00CC96', "No": '#B6E880'}
fig = px.histogram(df, x="Churn", color="SeniorCitizen", title="<b>Chrun distribution w.r.t. Senior Citizen</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



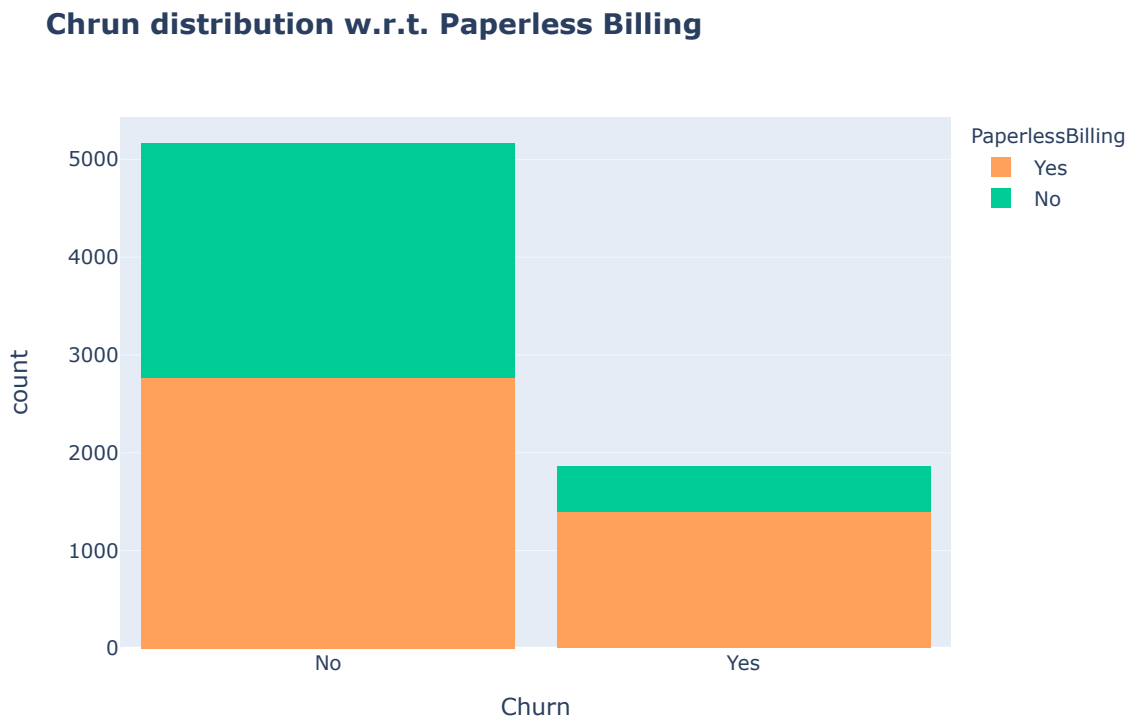
-- It can be observed that the fraction of senior citizen is very less. -- Most of the senior citizens churn.

In [32]:
```
color_map = {"Yes": "#FF97FF", "No": "#AB63FA"}
fig = px.histogram(df, x="Churn", color="OnlineSecurity", barmode="group", title="<b>Churn w.r.t Online Security</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



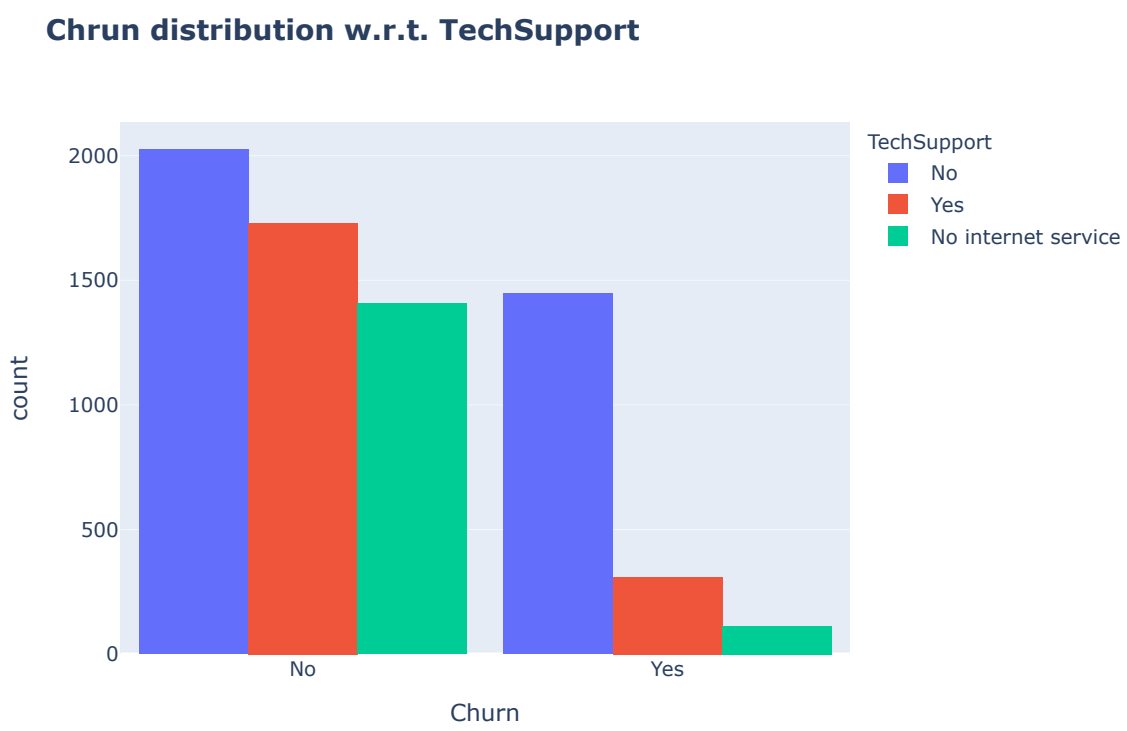
Most customers churn in the absence of online security,

In [33]:
```
color_map = {"Yes": '#FFA15A', "No": '#00CC96'}
fig = px.histogram(df, x="Churn", color="PaperlessBilling",  title="<b>Chrun distribution w.r.t. Paperless Billing</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



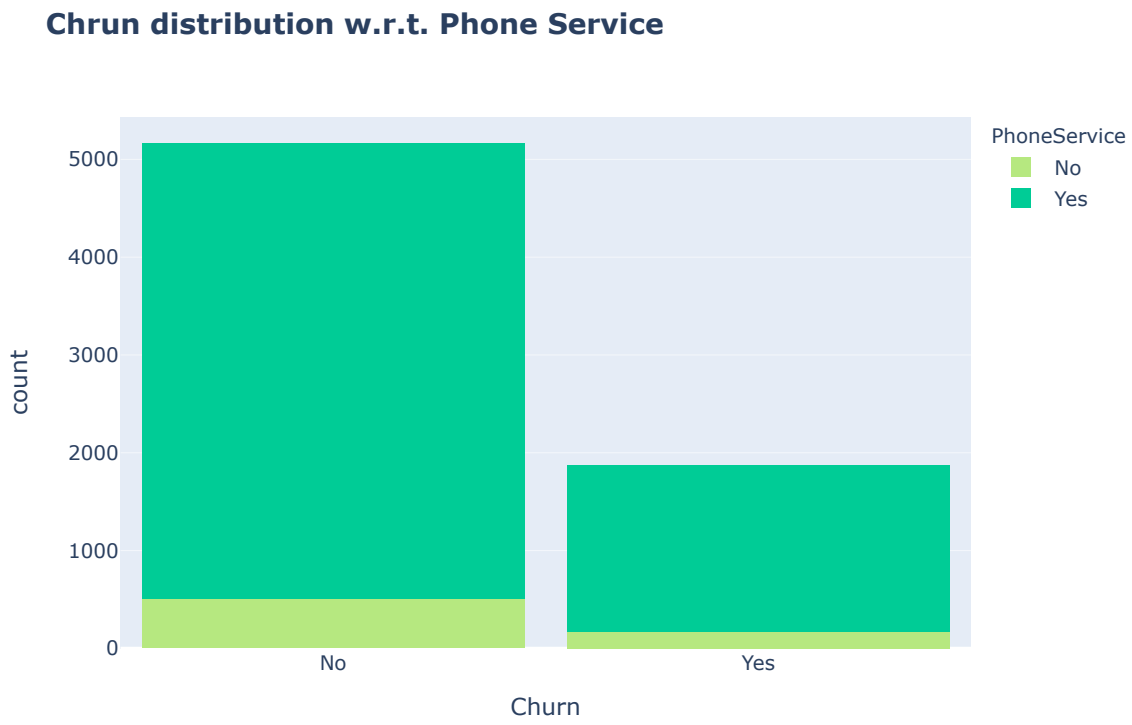
Customers with Paperless Billing are most likely to churn.

In [34]:
```
fig = px.histogram(df, x="Churn", color="TechSupport",barmode="group",  title="<b>Chrun distribution w.r.t. TechSupport</b>")
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



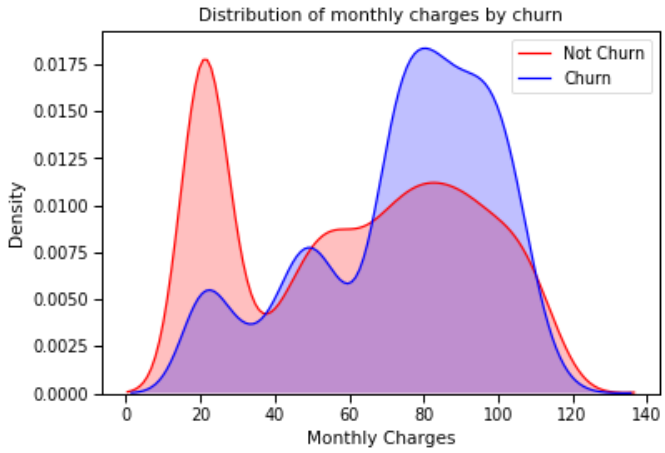
Customers with no TechSupport are most likely to migrate to another service provider.

In [35]:
```
color_map = {"Yes": '#00CC96', "No": '#B6E880'}
fig = px.histogram(df, x="Churn", color="PhoneService", title="<b>Chrun distribution w.r.t. Phone Service</b>", color_discrete_map=color_map)
fig.update_layout(width=700, height=500, bargap=0.1)
fig.show()
```



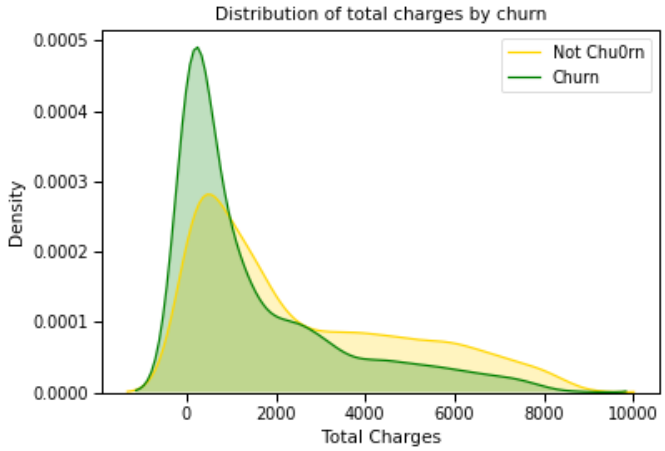
Very small fraction of customers don't have a phone service and out of that, 1/3rd Customers are more likely to churn.

In [36]:
```
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');
```

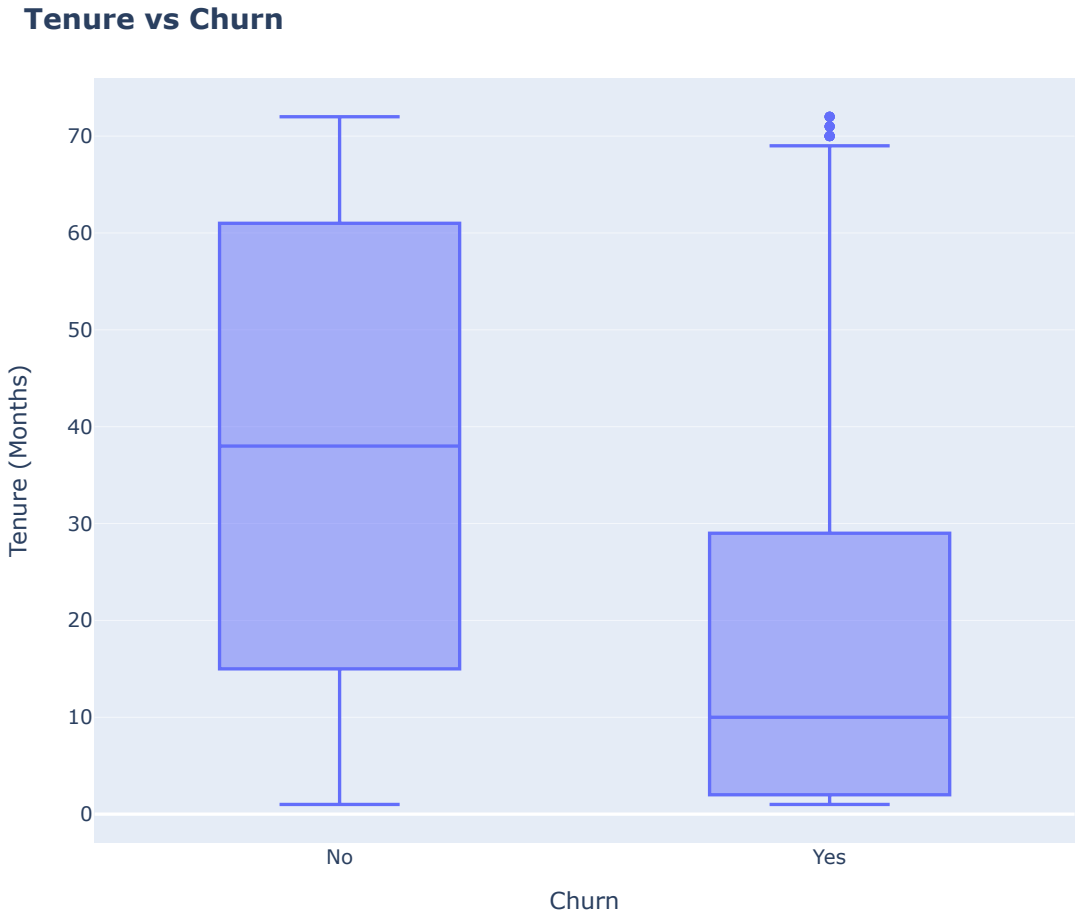


Customers with higher Monthly Charges are also more likely to churn.

In [37]:
```
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');
```

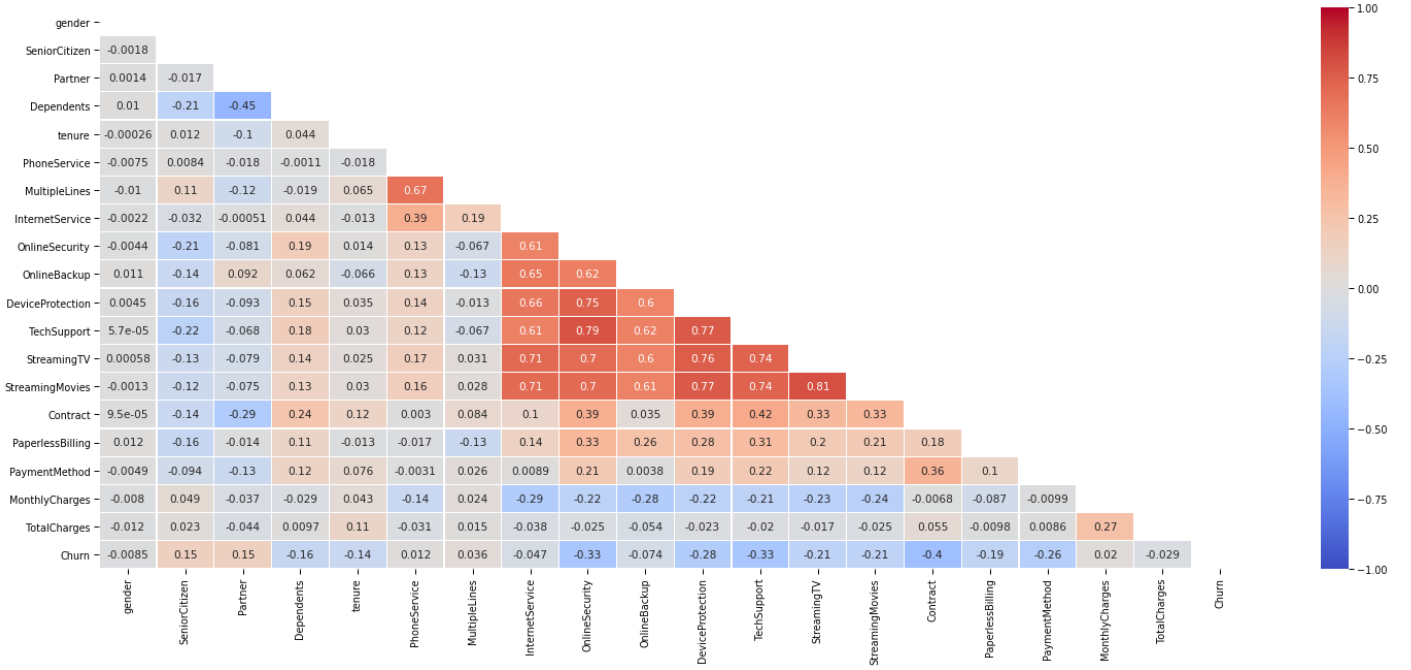


In [38]:
```
fig = px.box(df, x='Churn', y = 'tenure')

# 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 [39]:
```
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.columns, annot=True, linewidths=.2, cmap='coolwarm', vmin=-1, vmax=1)
```



Data Preprocessing

Splitting the data into train and test sets

In [40]:
```
def object_to_int(dataframe_series):
    if dataframe_series.dtype=='object':
        dataframe_series = LabelEncoder().fit_transform(dataframe_series)
    return dataframe_series
```

In [41]:
```
df = df.apply(lambda x: object_to_int(x))
df.head()
```

Out[41]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	Devic
0	0	0	1	0	1	0	1	0	0	2	
1	1	0	0	0	34	1	0	0	2	0	
2	1	0	0	0	2	1	0	0	2	2	
3	1	0	0	0	45	0	1	0	2	0	
4	0	0	0	0	2	1	0	1	0	0	

In [42]:
```
plt.figure(figsize=(14,7))
df.corr()['Churn'].sort_values(ascending = False)
```

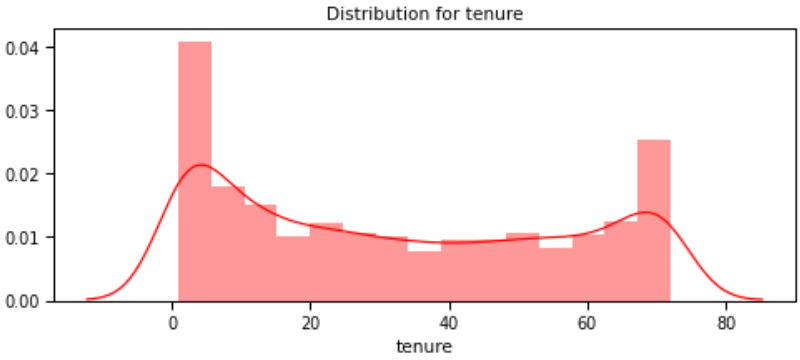
Out[42]:
```
Churn               1.000000
MonthlyCharges      0.192858
PaperlessBilling    0.191454
SeniorCitizen       0.150541
PaymentMethod       0.107852
MultipleLines       0.038043
PhoneService        0.011691
gender             -0.008545
StreamingTV        -0.036303
StreamingMovies    -0.038802
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 1008x504 with 0 Axes>
```

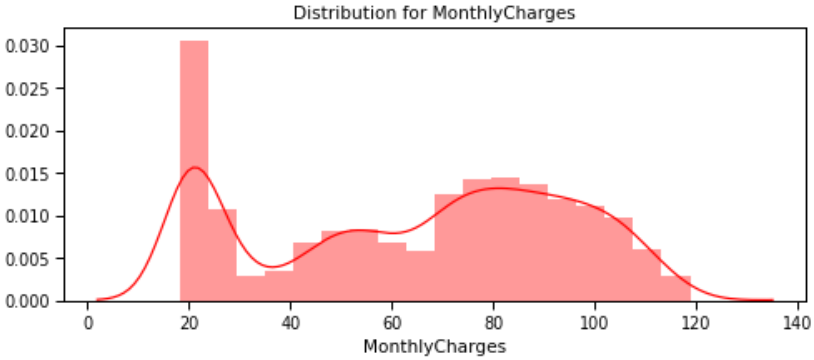
In [43]:
```
X = df.drop(columns = ['Churn'])
y = df['Churn'].values
```

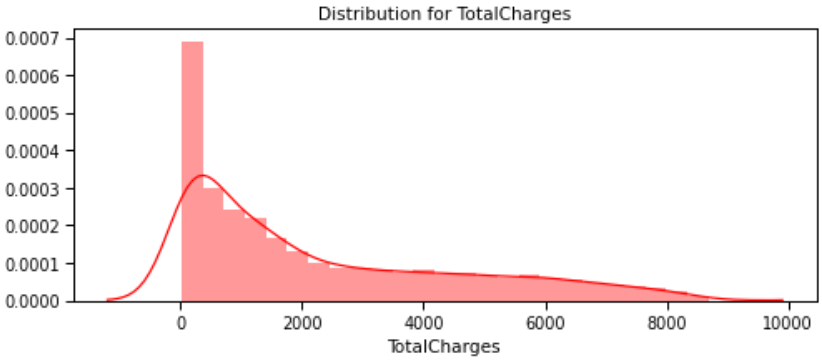
In [44]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.30, random_state = 40, stratify=y)
```

In [45]:
```
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 [46]:
```
num_cols = ["tenure", 'MonthlyCharges', 'TotalCharges']
for feat in num_cols: distplot(feat, df)
```



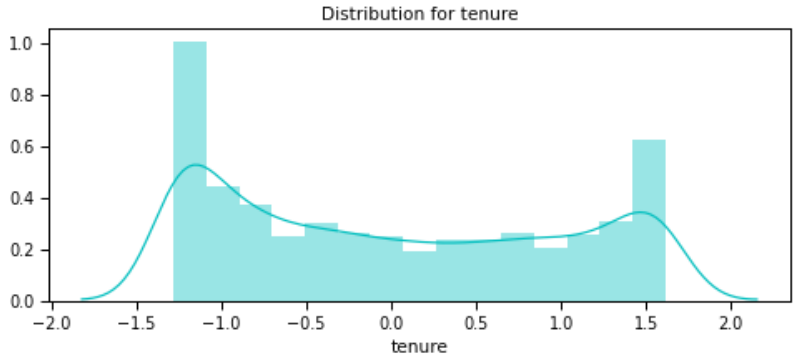


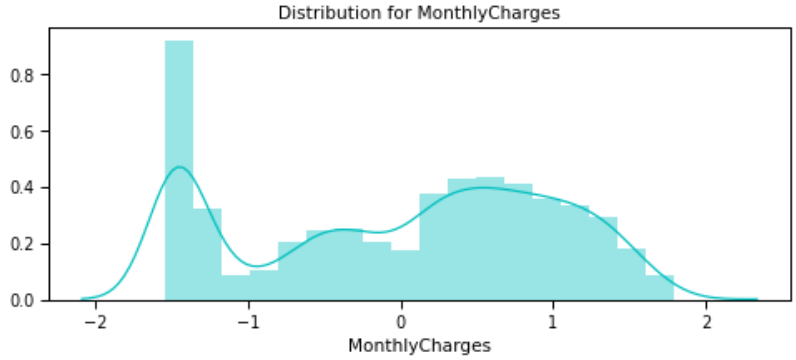


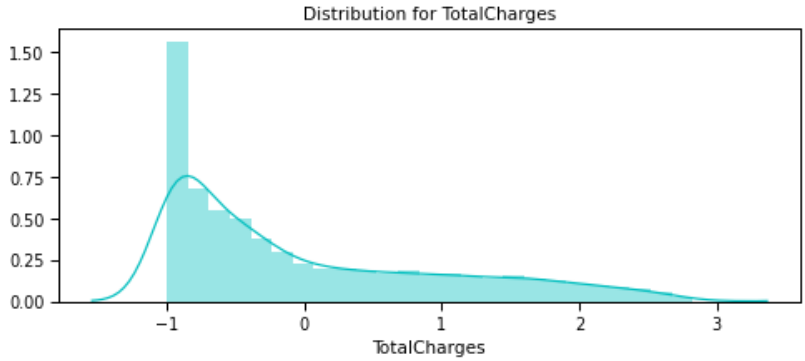
Since the numerical features are distributed over different value ranges, I will use standard scalar to scale them down to the same range.

Standardizing numeric attributes

In [47]:
```
df_std = pd.DataFrame(StandardScaler().fit_transform(df[num_cols].astype('float64')),
                      columns=num_cols)
for feat in numerical_cols: distplot(feat, df_std, color='c')
```







In [48]:
```
# Divide the columns into 3 categories, one ofor standardisation, one for label encoding and one for one hot
encoding

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

In [49]:
```
scaler= StandardScaler()

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

Machine Learning Model Evaluations and Predictions

KNN

In [50]:
```
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: 0.7758293838862559
```

In [51]:
```
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
```

SVC

In [52]:
```
svc_model = SVC(random_state = 1)
svc_model.fit(X_train,y_train)
predict_y = svc_model.predict(X_test)
accuracy_svc = svc_model.score(X_test,y_test)
print("SVM accuracy is :",accuracy_svc)
```

```
SVM accuracy is : 0.8075829383886256
```

In [53]:
```
print(classification_report(y_test, predict_y))
```

```
              precision    recall  f1-score   support

           0       0.84      0.92      0.88      1549
           1       0.69      0.50      0.58       561

    accuracy                           0.81      2110
   macro avg       0.76      0.71      0.73      2110
weighted avg       0.80      0.81      0.80      2110
```

Random Forest

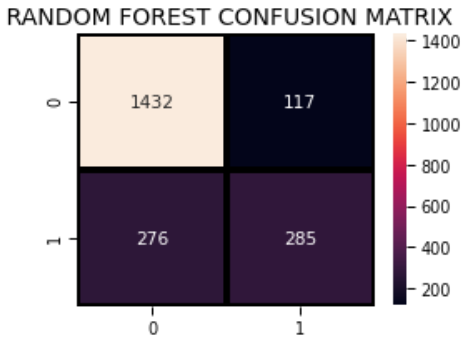
In [54]:
```
model_rf = RandomForestClassifier(n_estimators=500 , oob_score = True, n_jobs = -1,
                                  random_state =50, max_features = "auto",
                                  max_leaf_nodes = 30)
model_rf.fit(X_train, y_train)

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

```
0.8137440758293839
```

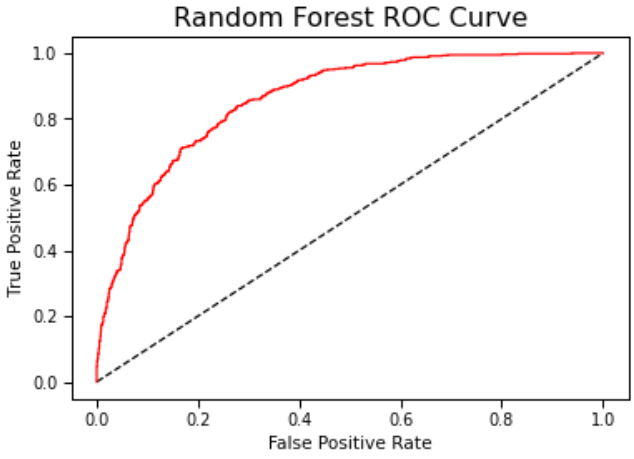
In [55]:
```
print(classification_report(y_test, prediction_test))
```

```
              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 [56]:
```
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 [57]:
```
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

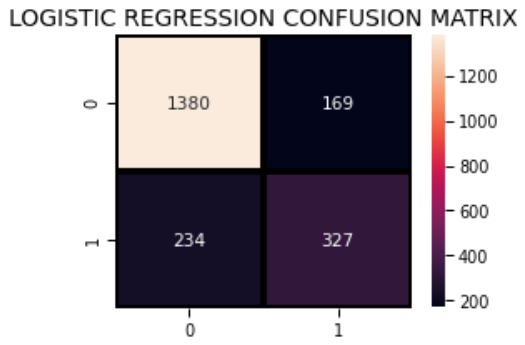
In [58]:
```
lr_model = LogisticRegression()
lr_model.fit(X_train,y_train)
accuracy_lr = lr_model.score(X_test,y_test)
print("Logistic Regression accuracy is :",accuracy_lr)
```

```
Logistic Regression accuracy is : 0.8090047393364929
```

In [59]:
```
lr_pred= lr_model.predict(X_test)
report = classification_report(y_test,lr_pred)
print(report)
```

```
              precision    recall  f1-score   support

           0       0.86      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      0.81      2110
```

In [60]:
```
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 [61]:
```
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 [62]:
```
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 : 0.7327014218009479
```

In [63]:
```
print(classification_report(y_test, predictdt_y))
```

```
              precision    recall  f1-score   support

           0       0.82      0.81      0.82      1549
           1       0.50      0.53      0.51       561

    accuracy                           0.73      2110
   macro avg       0.66      0.67      0.66      2110
weighted avg       0.74      0.73      0.74      2110
```

AdaBoost Classifier

In [64]:
```
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)
```

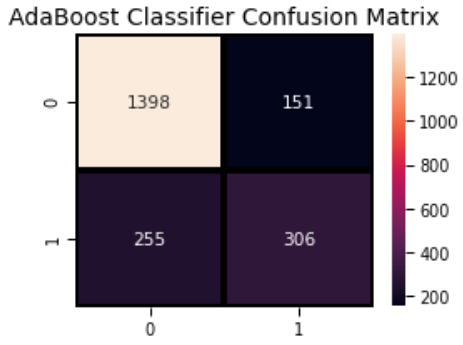
```
AdaBoost Classifier accuracy
```

Out[64]:
```
0.8075829383886256
```

In [65]:
```
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 [66]:
```
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

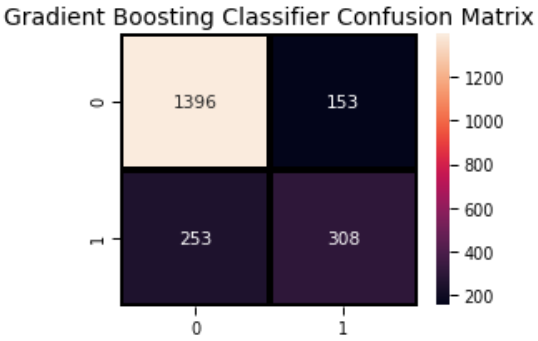
In [67]:
```
gb = GradientBoostingClassifier()
gb.fit(X_train, y_train)
gb_pred = gb.predict(X_test)
print("Gradient Boosting Classifier", accuracy_score(y_test, gb_pred))
```

```
Gradient Boosting Classifier 0.8075829383886256
```

In [68]:
```
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 [69]:
```
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

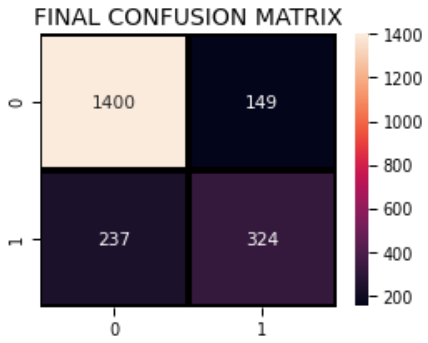
In [70]:
```
from sklearn.ensemble import VotingClassifier
clf1 = GradientBoostingClassifier()
clf2 = LogisticRegression()
clf3 = AdaBoostClassifier()
eclf1 = VotingClassifier(estimators=[('gbc', clf1), ('lr', clf2), ('abc', clf3)], voting='soft')
eclf1.fit(X_train, y_train)
predictions = eclf1.predict(X_test)
print("Final Accuracy Score ")
print(accuracy_score(y_test, predictions))
```

```
Final Accuracy Score
0.8170616113744076
```

In [71]:
```
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 [72]:
```
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.

In [73]:
```
import pickle

# Save the trained VotingClassifier model
vc_model = VotingClassifier(classification_report(y_test, predictions))  # Replace ... with your trained Voti
ngClassifier model

vc_pkl_filename = 'Voting_Classifier.pkl'

with open(vc_pkl_filename, 'wb') as vc_model_pkl:
    pickle.dump(vc_model, vc_model_pkl)

print("VotingClassifier model saved as", vc_pkl_filename)
```

```
VotingClassifier model saved as Voting_Classifier.pkl
```