INSAID Hiring Exercise

Important: Kindly go through the instructions mentioned below.

- **The Sheet is structured in 4 steps:**

    1. **Understanding data and manipulation**
    2. **Data visualization**
    3. **Implementing Machine Learning models(Note: It should be more than 1 algorithm)**
    4. **Model Evaluation and concluding with the best of the model.**

Importing the data

In [1]:

```
#importing the basic libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df=pd.read_csv('Churn.csv')
df.head()
```

Out[1]:

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

In [2]:

```
df.isna().sum()
```

Out[2]:

```
customerID          0
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
```

In [3]:

```
#converting TotalCharges to float
df["TotalCharges"]=pd.to_numeric(df["TotalCharges"])
df["TotalCharges"]=df["TotalCharges"].astype(float)
df.dtypes
```

Out[3]:

```
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        float64
Churn                object
dtype: object
```

In [4]:

```
df.head()
```

Out[4]:

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

In [5]:

```
#df = df.reset_index()
#df["TotalCharges"]=df.fillna(df["TotalCharges"].mean())
```

```
for c in df["TotalCharges"]:
    df["TotalCharges"] = df["TotalCharges"].replace(np.nan, df["TotalCharges"].mean())
```

In [6]:

```
df.head()
```

Out[6]:

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

Converting the categorical columns into numerical columns

In [7]:

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()

df["gender"]=le.fit_transform(df["gender"])
df["Partner"]=le.fit_transform(df["Partner"])
df["Dependents"]=le.fit_transform(df["Dependents"])
df["PhoneService"]=le.fit_transform(df["PhoneService"])
df["MultipleLines"]=le.fit_transform(df["MultipleLines"])
df["InternetService"]=le.fit_transform(df["InternetService"])
df["OnlineSecurity"]=le.fit_transform(df["OnlineSecurity"])
df["OnlineBackup"]=le.fit_transform(df["OnlineBackup"])
df["DeviceProtection"]=le.fit_transform(df["DeviceProtection"])
df["TechSupport"]=le.fit_transform(df["TechSupport"])
df["StreamingTV"]=le.fit_transform(df["StreamingTV"])
df["StreamingMovies"]=le.fit_transform(df["StreamingMovies"])
df["PaperlessBilling"]=le.fit_transform(df["PaperlessBilling"])
df["TechSupport"]=le.fit_transform(df["TechSupport"])
df["PaymentMethod"]=le.fit_transform(df["PaymentMethod"])
df["Churn"]=le.fit_transform(df["Churn"])
df["Contract"]=le.fit_transform(df["Contract"])
```

In [8]:

```
df.head()
```

Out[8]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecuri
0	7590-VHVEG	0	0	1	0	1	0	1	0	
1	5575-GNVDE	1	0	0	0	34	1	0	0	
2	3668-QPYBK	1	0	0	0	2	1	0	0	
3	7795-	1	0	0	0	45	0	1	0	

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecuri
	CFOCW									
4	9237-HQITU	0	0	0	0	2	1	0	1	

In [9]:

```
df.dtypes
```

Out[9]:

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

Checking for constant, quasi-constant and primary key columns

In [10]:

```
df.shape
```

Out[10]:

```
(7043, 21)
```

In [11]:

```
df['customerID'].nunique()
```

Out[11]:

```
7043
```

In [12]:

```
#dropping customer id since it is a primary key
df=df.drop('customerID',axis=1)
```

In [13]:

```
df['gender'].value_counts()/7043
```

Out[13]:

```
1    0.504756
0    0.495244
Name: gender, dtype: float64
```

Gender column is equally distributed.

In [14]:

```
df['SeniorCitizen'].value_counts()/7043
```

Out[14]:

```
0    0.837853
1    0.162147
Name: SeniorCitizen, dtype: float64
```

In [15]:

```
df['Partner'].value_counts()/7043
```

Out[15]:

```
0    0.516967
1    0.483033
Name: Partner, dtype: float64
```

In [16]:

```
df['Dependents'].value_counts()/7043
```

Out[16]:

```
0    0.700412
1    0.299588
Name: Dependents, dtype: float64
```

Understanding the data

In [17]:

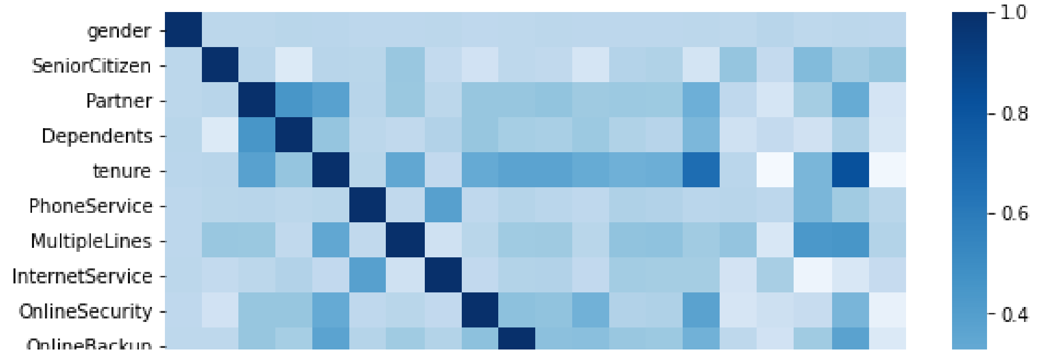
```
df.describe()
```

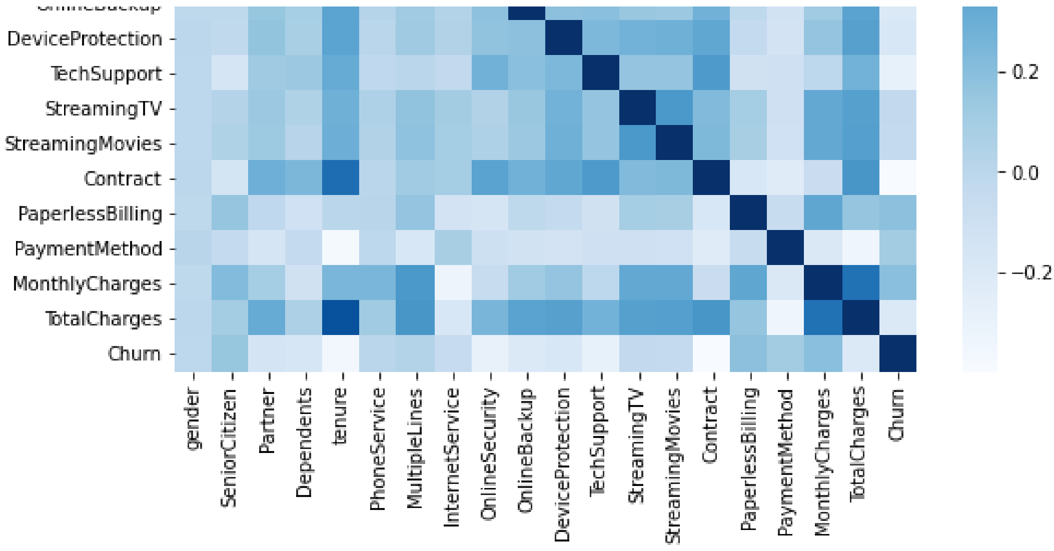
Out[17]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	Online
count	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	7043.000000	704
mean	0.504756	0.162147	0.483033	0.299588	32.371149	0.903166	0.940508	0.872923	
std	0.500013	0.368612	0.499748	0.458110	24.559481	0.295752	0.948554	0.737796	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	9.000000	1.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	29.000000	1.000000	1.000000	1.000000	
75%	1.000000	0.000000	1.000000	1.000000	55.000000	1.000000	2.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	72.000000	1.000000	2.000000	2.000000	

In [18]:

```
#plotting the heatmap
fig,ax=plt.subplots(figsize=(9,7))
sns.heatmap(df.corr(),cmap="Blues")
sns.set()
```



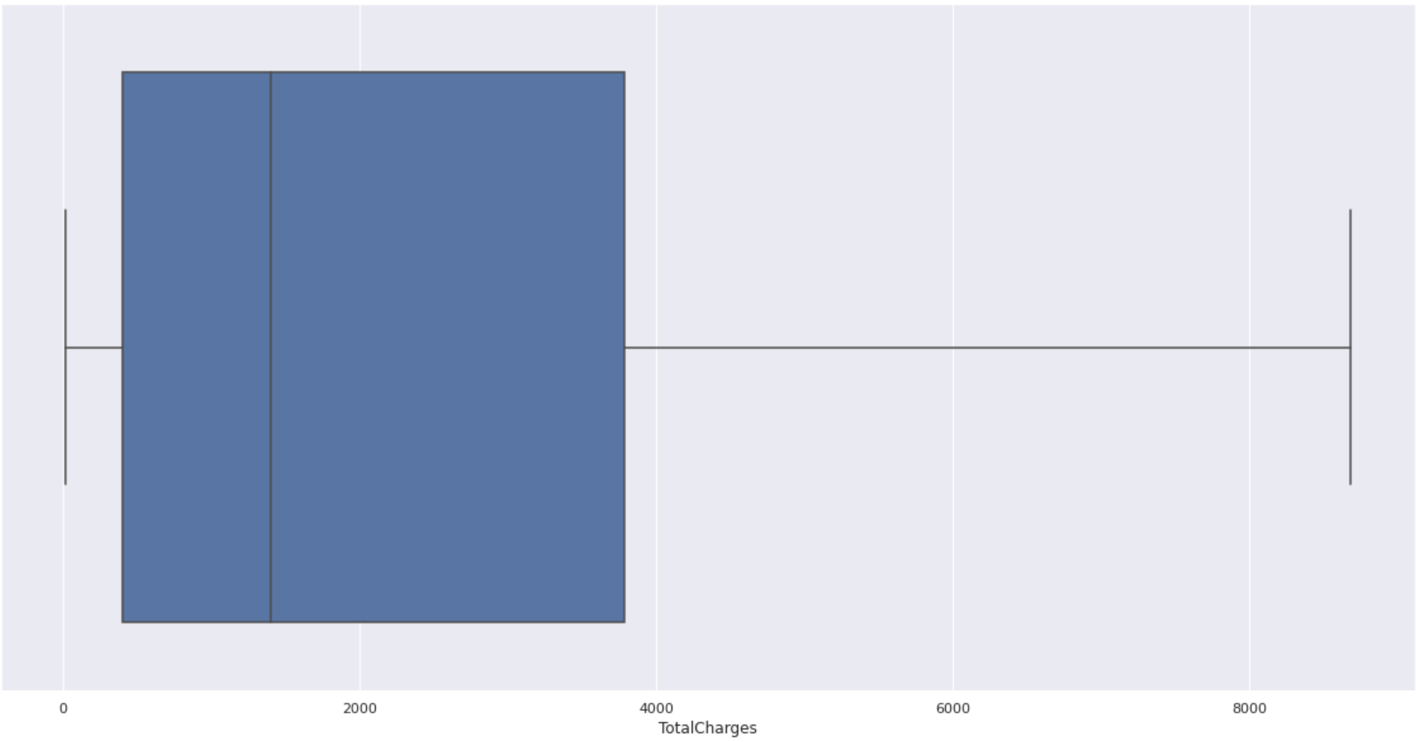


Outlier detection

In [19]:

```
plt.figure(figsize=(20,10))
sns.boxplot(df["TotalCharges"])
plt.show()
#No outliers
```

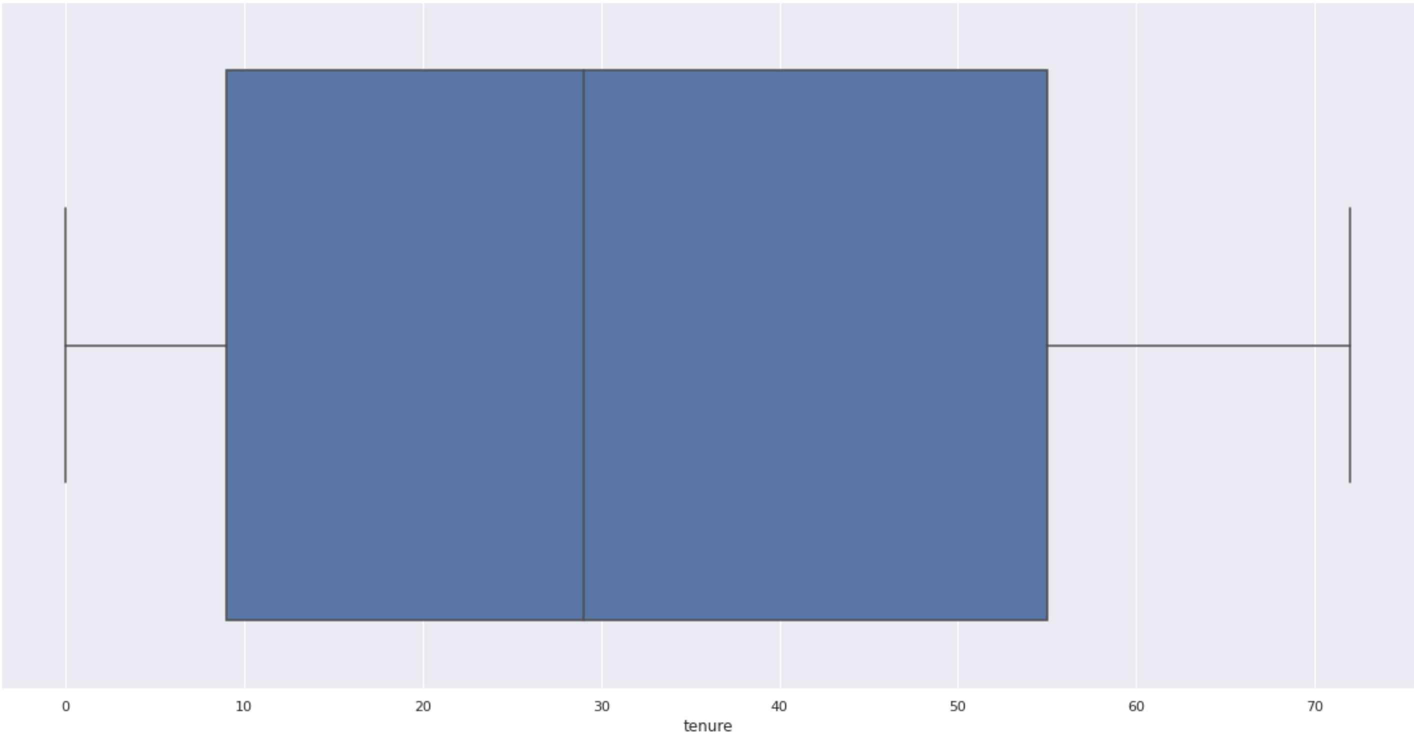
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



In [20]:

```
plt.figure(figsize=(20,10))
sns.boxplot(df["tenure"])
plt.show()
#No outliers
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



Data Visualization and Data Manipulation

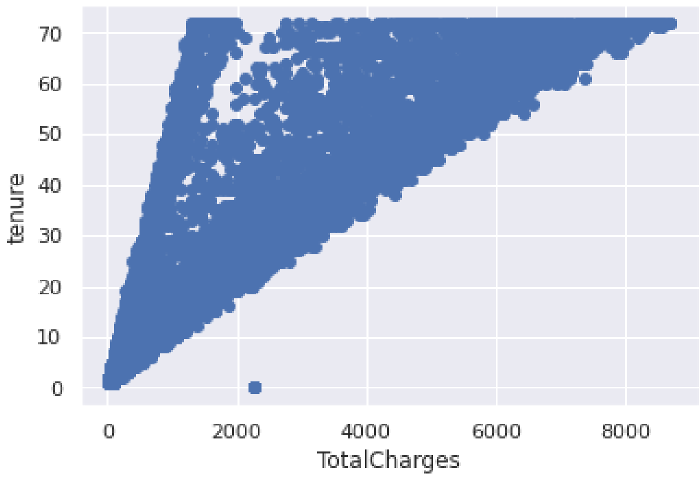
In [21]:

```
# create a figure and axis
fig, ax = plt.subplots()

ax.scatter(df['TotalCharges'], df['tenure'])
# set a title and labels
ax.set_xlabel('TotalCharges')
ax.set_ylabel('tenure')
```

Out[21]:

```
Text(0, 0.5, 'tenure')
```



There is a high correlation between tenure and TotalCharges, as it is indicated by the heatmap as well as the scatterplot. Hence we are going to drop TotalCharges.

In [22]:

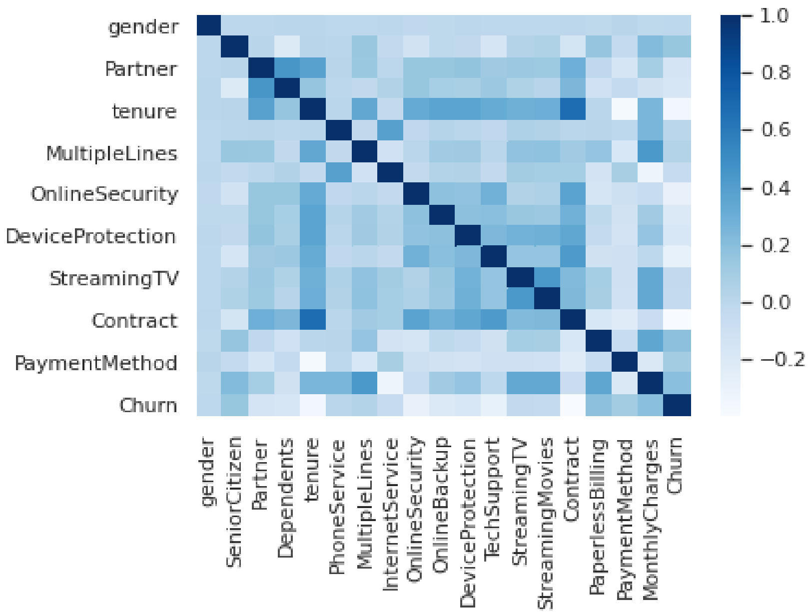
```
df=df.drop("TotalCharges",axis=1)
```

In [23]:

```
sns.heatmap(df.corr(),cmap="Blues")
```

Out[23]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4fc1f2a490>
```

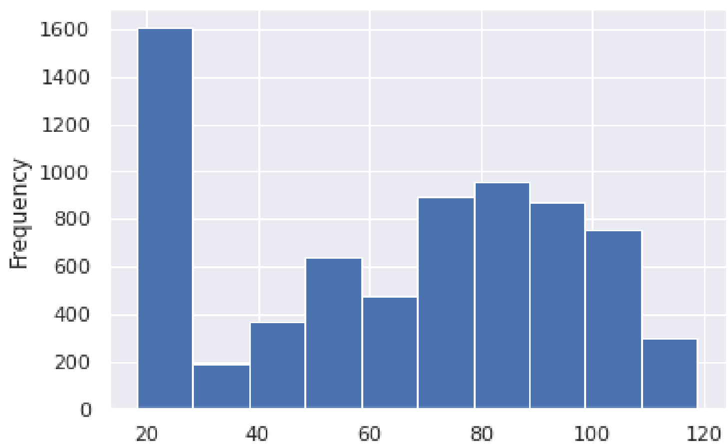


In [24]:

```
df["MonthlyCharges"].plot.hist()
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4fc1e476d0>
```



In [25]:

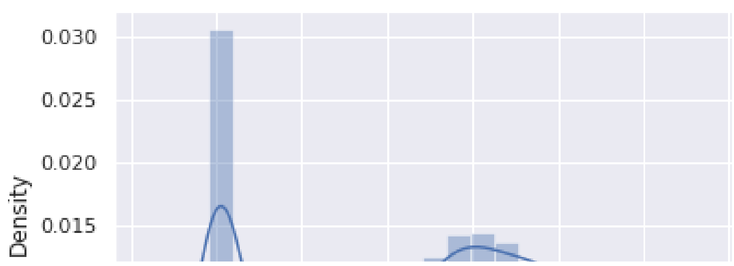
```
print(df["MonthlyCharges"].skew())
sns.distplot(df["MonthlyCharges"])
```

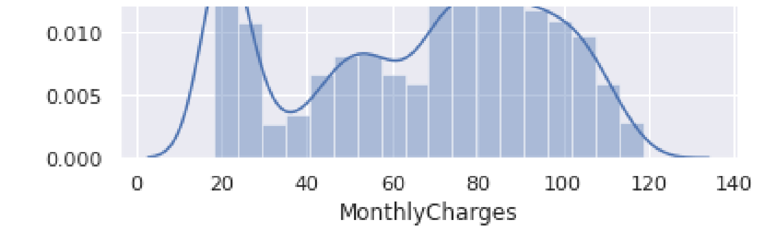
```
-0.22052443394398033
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4fc1dfda50>
```





In [27]:

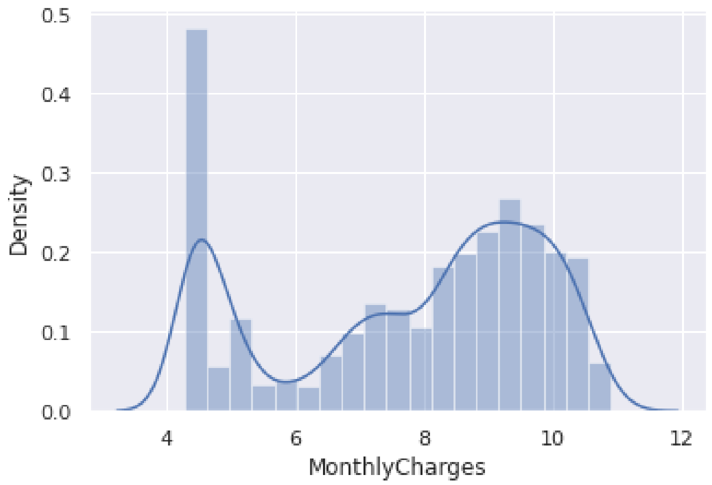
```
y = np.sqrt(df["MonthlyCharges"])
print(y.skew())
sns.distplot(np.sqrt(df["MonthlyCharges"])) #No improvement
```

```
-0.48455701260718537
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `dis
tplot` is a deprecated function and will be removed in a future version. Please adapt you
r code to use either `displot` (a figure-level function with similar flexibility) or `his
tplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4fcb841f90>
```



In [28]:

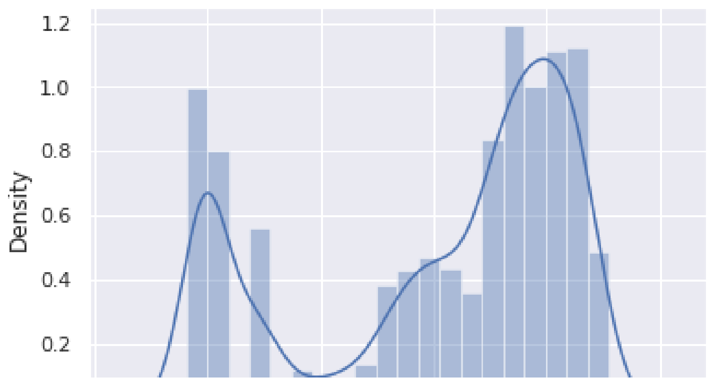
```
x = np.log(df["MonthlyCharges"])
print(x.skew())
sns.distplot(np.log(df["MonthlyCharges"])) #No improvement
```

```
-0.7289749716031325
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `dis
tplot` is a deprecated function and will be removed in a future version. Please adapt you
r code to use either `displot` (a figure-level function with similar flexibility) or `his
tplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4fbfbf3850>
```



In [29]:

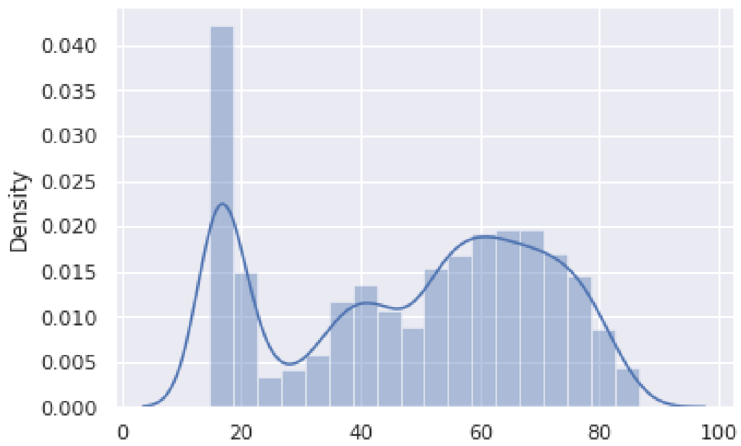
```
from scipy import stats
x2 = stats.boxcox(df["MonthlyCharges"])[0]
x3 = pd.Series(x2)
print(x3.skew())
sns.distplot(x2) #No improvement
```

```
-0.26389712986757285
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `dis
tplot` is a deprecated function and will be removed in a future version. Please adapt you
r code to use either `displot` (a figure-level function with similar flexibility) or `his
tplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[29]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4fbfbb8050>
```



Normalization of data

In [30]:

```
from sklearn.preprocessing import MinMaxScaler

mm=MinMaxScaler()
df_scaled=mm.fit_transform(df)
df_scaled=pd.DataFrame(data=df_scaled,columns=df.columns)
df_scaled.head()
```

Out[30]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineB
0	0.0	0.0	1.0	0.0	0.013889	0.0	0.5	0.0	0.0	
1	1.0	0.0	0.0	0.0	0.472222	1.0	0.0	0.0	1.0	
2	1.0	0.0	0.0	0.0	0.027778	1.0	0.0	0.0	1.0	
3	1.0	0.0	0.0	0.0	0.625000	0.0	0.5	0.0	1.0	
4	0.0	0.0	0.0	0.0	0.027778	1.0	0.0	0.5	0.0	

Splitting our data

In [31]:

```
X=df_scaled.drop("Churn",axis=1)
```

```
y=df_scaled["Churn"]
```

In [32]:

```
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,stratify=df_scaled["Chu
rn"],random_state=21)
```

In [33]:

```
(X_train.shape,y_train.shape)
```

Out[33]:

```
((5634, 18), (5634,))
```

In [34]:

```
(X_test.shape,y_test.shape)
```

Out[34]:

```
((1409, 18), (1409,))
```

Processing our ML Models

Stochastic Gradient Descent Classifier

In [35]:

```
from sklearn.linear_model import SGDClassifier

sgd_c=SGDClassifier()
sgd_c.fit(X_train,y_train)
print("Training complete.")
```

```
Training complete.
```

SVM Classifier

In [36]:

```
from sklearn import svm

support = svm.LinearSVC(random_state=20)
support.fit(X_train,y_train)
print("Training complete.")
```

```
Training complete.
```

Ensemble Learning

Bagging Classifier

In [37]:

```
from sklearn.ensemble import BaggingClassifier
from sklearn import tree
model_bg = BaggingClassifier(tree.DecisionTreeClassifier(random_state=10))
model_bg.fit(X_train, y_train)
print("Training complete.")
```

```
Training complete.
```

XGBoostClassifier

In [38]:

```
import xgboost as xgb
model_xgb=xgb.XGBClassifier(random_state=10,learning_rate=0.01)
model_xgb.fit(X_train, y_train)
print("Training complete.")
```

```
Training complete.
```

Gradient Boosting Classifier

In [39]:

```
from sklearn.ensemble import GradientBoostingClassifier
model_gbc= GradientBoostingClassifier(learning_rate=0.01,random_state=1)
model_gbc.fit(X_train, y_train)
print("Training complete.")
```

```
Training complete.
```

RandomForest Classifier

In [40]:

```
from sklearn.ensemble import RandomForestClassifier
cf=RandomForestClassifier()
cf.fit(X_train,y_train)
print("Training complete.")
```

```
Training complete.
```

Model Evaluation

Stochastic Gradient Descent Classifier

In [41]:

```
sgd_c.score(X_test,y_test)*100
```

Out[41]:

```
79.13413768630234
```

SVM Classifier

In [42]:

```
support.score(X_test,y_test)*100
```

Out[42]:

```
80.34066713981547
```

Bagging Classifier

In [43]:

```
model_bg.score(X_test,y_test)*100
```

Out[43]:

```
76.93399574166075
```

XGBoost Classifier

In [44]:

```
model_xgb.score(X_test,y_test)*100
```

```
model_xgb.score(X_test,y_test)*100
```

Out[44]:

```
78.56635911994321
```

In [45]:

```
model_gbc.score(X_test,y_test)*100
```

Out[45]:

```
77.2888573456352
```

In [46]:

```
cf.score(X_test,y_test)*100
```

Out[46]:

```
77.43080198722498
```

Final Conclusion

We can see that with this data, the *Linear Support Vector Classifier* works best, with a score of 80.34%. Hence, we will use this ML model for deployment. The cells below include a final analysis of the ROC Score of the model:

In [47]:

```
y_pred=support.predict(X_test)
```

In [48]:

```
unique_elements, counts_elements = np.unique(y_pred, return_counts=True)

for i in range(0,2):
  print(f"{unique_elements[i]}:{counts_elements[i]}")
```

```
0.0:1100
1.0:309
```

In [49]:

```
predict_prob=support._predict_proba_lr(X_test)
from sklearn.metrics import roc_curve, roc_auc_score
fpr1, tpr1, thresh1 = roc_curve(y_test, predict_prob[:,1], pos_label=1)
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
```

In [50]:

```
auc_score1 = roc_auc_score(y_test, predict_prob[:,1])
print(auc_score1)
```

```
0.8374693223798082
```

In [51]:

```
plt.style.use('seaborn')

# plot roc curves
plt.plot(fpr1, tpr1, linestyle='--',color='orange', label='SVM Classifier')
plt.plot(p_fpr, p_tpr, linestyle='--', color='blue')
# title
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')
```

```
plt.legend(loc='best')
plt.savefig('ROC',dpi=300)
plt.show()
```