

[8]

Python

df.head()

[9]

Python

	Customer ID	Gender	Age	Married	Number of Dependents	City	Zip Code	Latitude	Longitude	Number of Referrals	...	Payment Method	Monthly Charge	Total Charges	Total Refunds	Total Extra Data Charges	Total Long Distance Charges	Total Revenue	Customer Status	Cat
0	0002-ORFBO	Female	37	Yes	0	Frazier Park	93225	34.827662	-118.999073	2	...	Credit Card	65.6	593.30	0.00	0	381.51	974.81	Stayed	
1	0003-MKNFE	Male	46	No	0	Glendale	91206	34.162515	-118.203869	0	...	Credit Card	-4.0	542.40	38.33	10	96.21	610.28	Stayed	
2	0004-TLHLJ	Male	50	No	0	Costa Mesa	92627	33.645672	-117.922613	0	...	Bank Withdrawal	73.9	280.85	0.00	0	134.60	415.45	Churned	Compl
3	0011-IGKFF	Male	78	Yes	0	Martinez	94553	38.014457	-122.115432	1	...	Bank Withdrawal	98.0	1237.85	0.00	0	361.66	1599.51	Churned	Dissatisf
4	0013-EXCHZ	Female	75	Yes	0	Camarillo	93010	34.227846	-119.079903	3	...	Credit Card	83.9	267.40	0.00	0	22.14	289.54	Churned	Dissatisf

5 rows × 38 columns

df.head(5)

[10]

Python

	Customer ID	Gender	Age	Married	Number of Dependents	City	Zip Code	Latitude	Longitude	Number of Referrals		Payment Method	Monthly Charge	Total Charges	Total Refunds	Total Extra Data Charges	Total Long Distance Charges	Total Revenue	Customer Status	Category
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5 rows × 38 columns

df.columns

[11]

Python

Index(['Customer ID', 'Gender', 'Age', 'Married', 'Number of Dependents',

Creating a copy of the Dataset

```
df1.head(7)
```

[13]

Python

	Customer ID	Gender	Age	Married	Number of Dependents	City	Zip Code	Latitude	Longitude	Number of Referrals		Payment Method	Monthly Charge	Total Charges	Total Refunds	Total Extra Data Charges	Total Long Distance Charges	Total Revenue	Customer Status	Cat
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2	0004-TLHLJ	Male	50	No	0	Costa Mesa	92627	33.645672	-117.922613	0	...	Bank Withdrawal	73.9	280.85	0.00	0	134.60	415.45	Churned	Comp
3	0011-IGKFF	Male	78	Yes	0	Martinez	94553	38.014457	-122.115432	1	...	Bank Withdrawal	98.0	1237.85	0.00	0	361.66	1599.51	Churned	Dissatisf
4	0013-EXCHZ	Female	75	Yes	0	Camarillo	93010	34.227846	-119.079903	3	...	Credit Card	83.9	267.40	0.00	0	22.14	289.54	Churned	Dissatisf
5	0013-MHZWF	Female	23	No	3	Midpines	95345	37.581496	-119.972762	0	...	Credit Card	69.4	571.45	0.00	0	150.93	722.38	Stayed	
6	0013-SMEOE	Female	67	Yes	0	Lompoc	93437	34.757477	-120.550507	1	...	Bank Withdrawal	109.7	7904.25	0.00	0	707.16	8611.41	Stayed	

7 rows x 38 columns

[22]

...

```
df1=df1.dropna()
df.head()
```

	Customer ID	Gender	Age	Married	Number of Dependents	City	Zip Code	Latitude	Longitude	Number of Referrals	...	Payment Method	Monthly Charge	Total Charges	Total Refunds	Total Extra Data Charges	Total Long Distance Charges	Total Revenue	Customer Status	Cat
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5 rows x 38 columns

[23]

```
df['Unlimited Data']
```

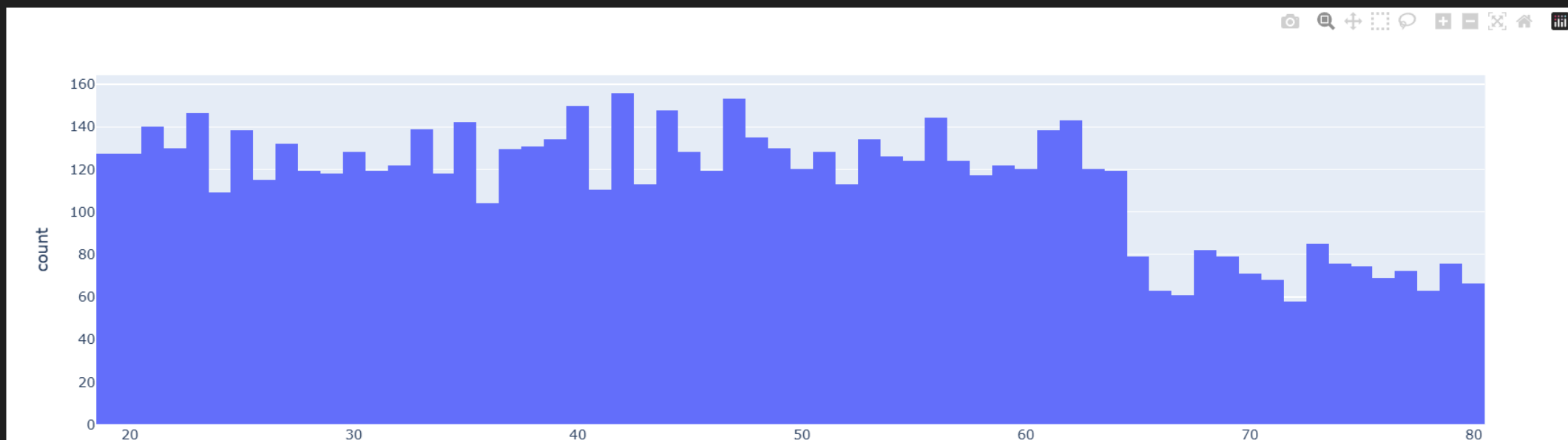
```
[21] import plotly.express as px
```

Python

Visualizing Column 'Age' in the dataset

```
[22] fig = px.histogram(df, x = 'Age')  
fig.show()
```

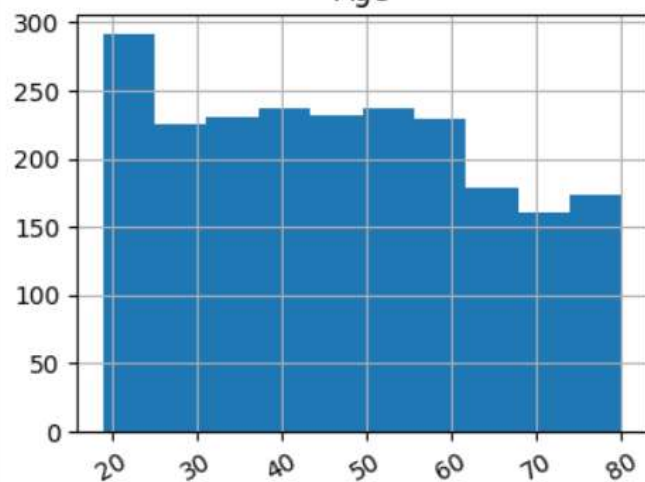
Python



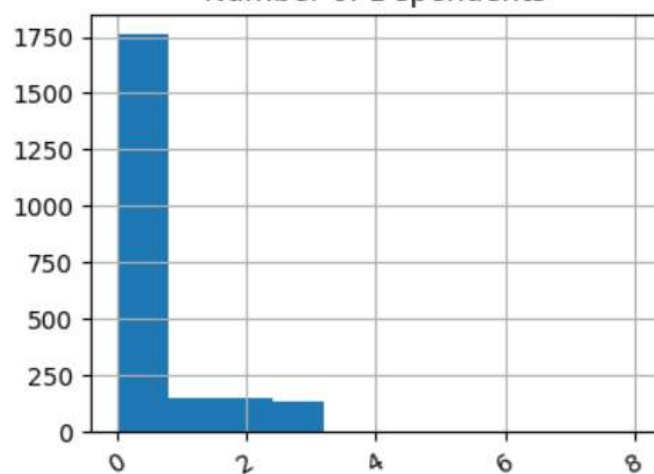
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS JUPYTER

```
Requirement already satisfied: asttokens>=2.1.0 in c:\users\supri\downloads\customer-churn-prediction-main1\customer-churn-prediction-main\venv\lib\site-packages (from stack_data>=0.6.0->ipython) (3.0.1)  
Requirement already satisfied: pure-eval in c:\users\supri\downloads\customer-churn-prediction-main1\customer-churn-prediction-main\venv\lib\site-packages (from stack_data>=0.6.0->ipython) (0.2.3)  
  
C:\Users\supri\Downloads\Customer-Churn-Prediction-main1\Customer-Churn-Prediction-main>  
C:\Users\supri\Downloads\Customer-Churn-Prediction-main1\Customer-Churn-Prediction-main>
```

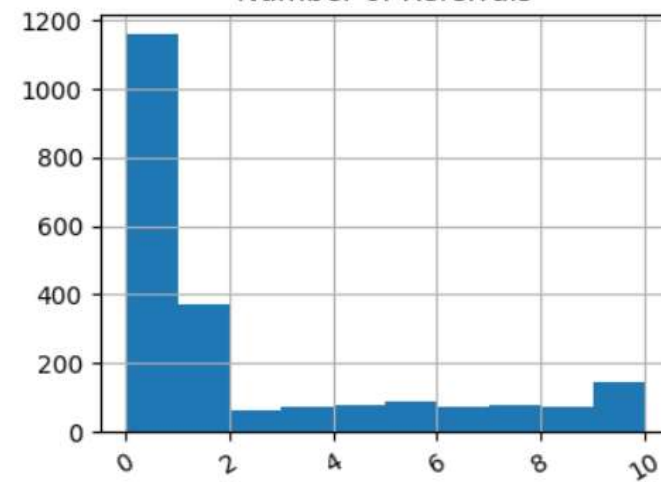
Age



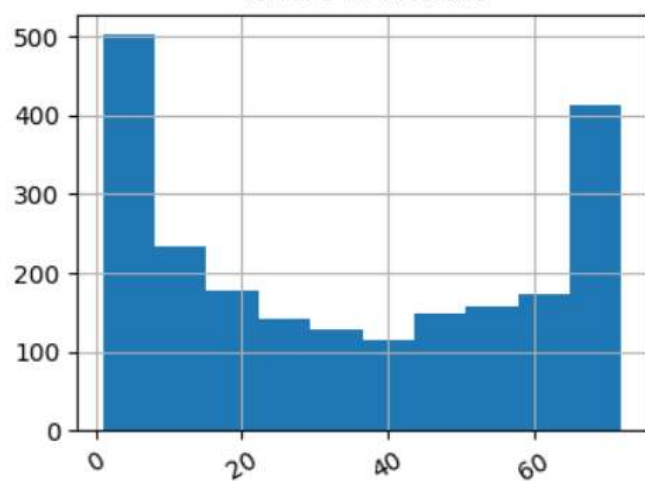
Number of Dependents



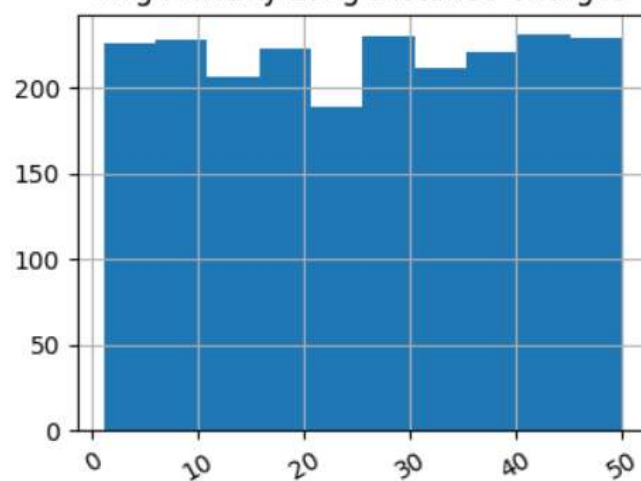
Number of Referrals



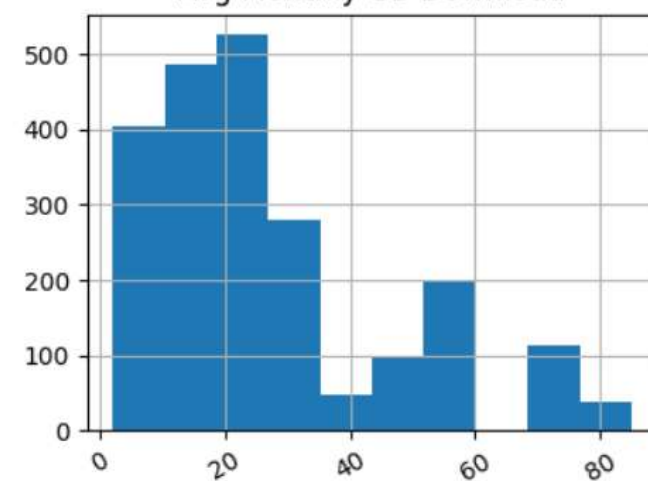
Tenure in Months



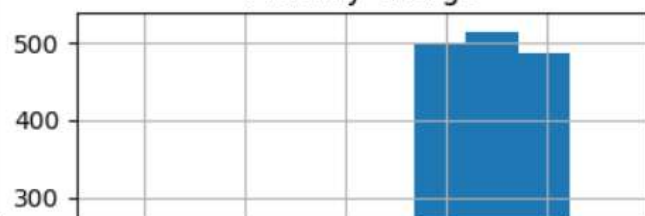
Avg Monthly Long Distance Charges



Avg Monthly GB Download



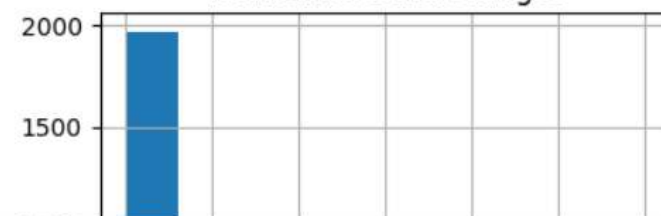
Monthly Charge



Total Charges

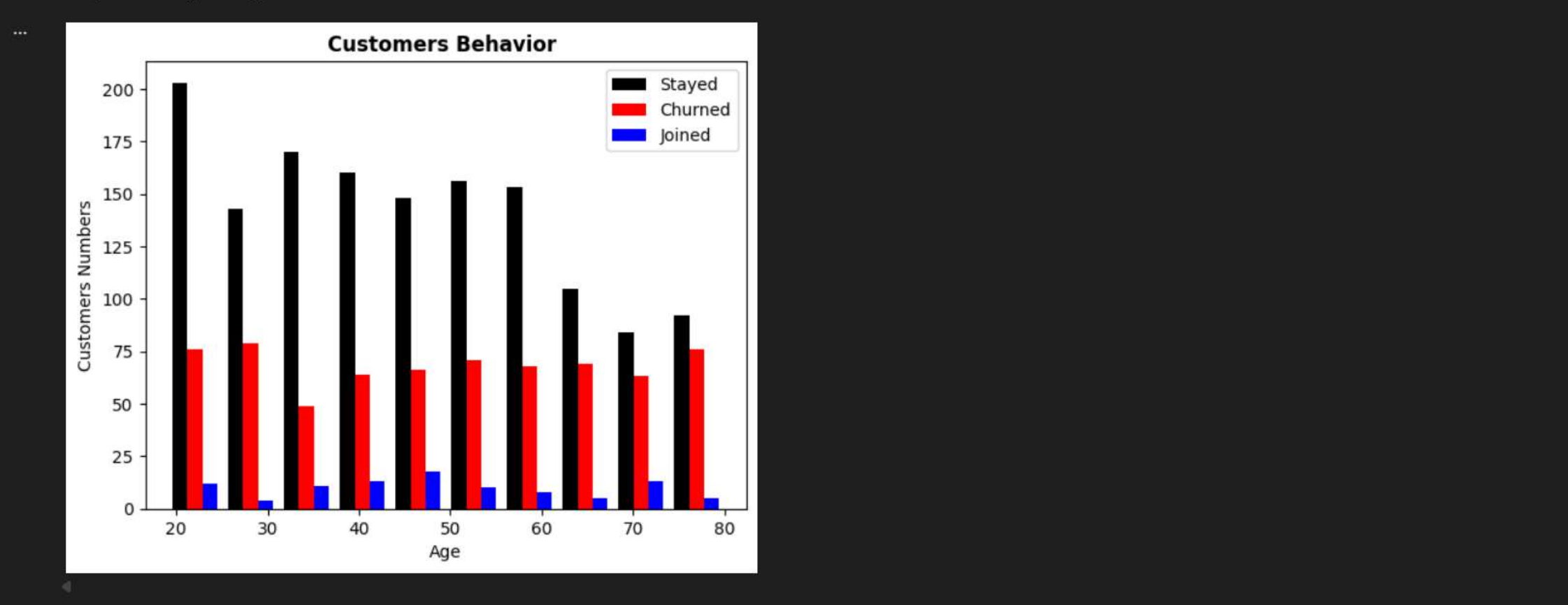


Total Extra Data Charges



```
requirements.txt Customer_Churn_Prediction.ipynb Welcome  
src > Customer_Churn_Prediction.ipynb > Data Visualization > fig = px.histogram(df, x = 'Age')  
Generate + Code + Markdown | Run All Restart Clear All Outputs Go To | Jupyter Variables Outline ...  
plt.title('Customers Behavior ',fontWeight ="bold")  
plt.legend()  
[26] ✓ 0.2s
```

<matplotlib.legend.Legend at 0x23904604830>





Dealing with Imbalance Data

Dropping the Customer_Status

i.e. The column tht we have to predict and set as a dependent variable

```
x = df1.drop('Customer_Status',axis='columns')
y = df1['Customer_Status']
```

[83] ✓ 0.0sPython

```
x.head(5)
```

[84] ✓ 0.0sPython

...

	Gender	Age	Married	Number of Dependents	Number of Referrals	Tenure in Months	Phone Service	Avg Monthly Long Distance Charges	Multiple Lines	Internet Service	...	City_Woodland Hills	City_Woody	City_Wrightwood	City_Yermo	City_Yorba Linda	City_Yorkville	City_Yorba Linda
2	1	0.508197	0	0.000	0.0	0.042254	1	0.666462	0	1	...	False	False	False	False	False	False	False
3	1	0.967213	1	0.000	0.1	0.169014	1	0.547386	0	1	...	False	False	False	False	False	False	False
5	0	0.065574	0	0.375	0.0	0.112676	1	0.321691	0	1	...	False	False	False	False	False	False	False
6	0	0.786885	1	0.000	0.1	0.985915	1	0.182598	0	1	...	False	False	False	False	False	False	False
7	1	0.540984	1	0.000	0.8	0.873239	1	0.243873	1	1	...	False	False	False	False	False	False	False

5 rows × 928 columns

```
y.head(5)
```

[85] ✓ 0.0sPython

... 2 0
3 0

```
len(x_train)
```

[87] ✓ 0.0s Python

... 1755

▶ x_train[:10]

[88] ✓ 0.0s Python

	Gender	Age	Married	Number of Dependents	Number of Referrals	Tenure in Months	Phone Service	Avg Monthly Long Distance Charges	Multiple Lines	Internet Service	...	City_Woodland Hills	City_Woody	City_Wrightwood	City_Yermo	City_Yorba Linda	City_Yorkville
5086	1	0.213115	0	0.000	0.0	0.126761	1	0.135417	0	1	...	False	False	False	False	False	False
1686	0	0.000000	0	0.000	0.0	0.140845	1	0.815768	0	1	...	False	False	False	False	False	False
3655	1	0.737705	0	0.000	0.0	0.000000	1	0.154003	1	1	...	False	False	False	False	False	False
697	1	0.983607	1	0.000	0.1	0.408451	1	0.959967	1	1	...	False	False	False	False	False	False
6685	0	0.721311	0	0.000	0.0	0.478873	1	0.247549	1	1	...	False	False	False	False	False	False
5617	0	0.262295	0	0.000	0.0	0.084507	1	0.367034	1	1	...	False	False	False	False	False	False
2938	1	0.098361	0	0.000	0.0	0.873239	1	0.443423	1	1	...	False	False	False	False	False	False
6323	1	0.688525	0	0.000	0.0	0.000000	1	0.257557	0	1	...	False	False	False	False	False	False
3382	1	0.868852	0	0.000	0.0	0.014085	1	0.825368	0	1	...	False	False	False	False	False	False
1184	1	0.377049	1	0.375	0.8	0.774648	1	0.813725	1	1	...	False	False	False	False	False	False

10 rows × 928 columns

Importing the required files for the model that is to applied

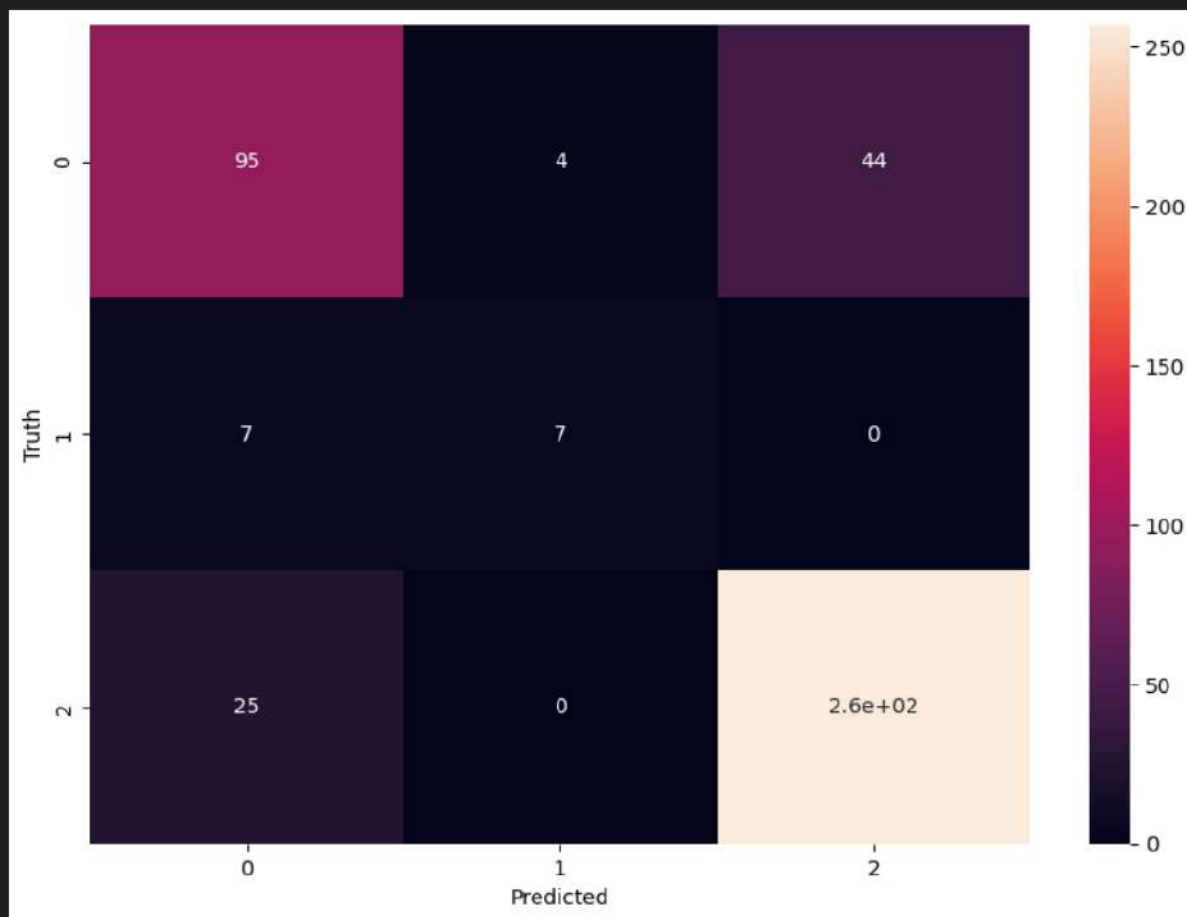
- 1. Random Forest Classifier
- 2. Logistic Regression

	model	best_score	best_params
0	random_forest	0.798291	{'n_estimators': 10}
1	logistic_regression	0.790313	{'C': 1}
2	naive_bayes_gaussian	0.388604	{}
3	decision_tree	0.792023	{'criterion': 'entropy'}
4	XGB_Classifier	0.828490	{'base_score': 0.5}

```
plt.xlabel('Predicted')
plt.ylabel('Truth')
```

[228] ✓ 0.1s Python

Text(95.7222222222221, 0.5, 'Truth')



```
[229] ✓ 0.0s from sklearn.metrics import classification_report
```

Python

```
[230] ✓ 0.0s print(classification_report(y_test, y_predicted))
```

Python

...		precision	recall	f1-score	support
	0	0.75	0.66	0.70	143
	1	0.64	0.50	0.56	14
	2	0.85	0.91	0.88	282
	accuracy				0.82
	macro avg				0.75
	weighted avg				0.81

```
[231] ✓ 0.0s from sklearn.metrics import accuracy_score
accuracy_score(y_test, y_predicted)
```

Python

... 0.8177676537585421

In the end we conclude that the Telecom Customer Churn Prediction was best worked with XGB_Classifier with an accuracy score of 80.86%