Importing Libraries

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

from sklearn.preprocessing import OrdinalEncoder
OE = OrdinalEncoder()

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,accuracy_score

from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier

import warnings
warnings.filterwarnings("ignore")
```

Reading Data

In [2]:
```
df = pd.read_excel("customer_churn_large_dataset.xlsx")
df.head()
```

Out[2]:

	CustomerID	Name	Age	Gender	Location	Subscription_Length_Months	Monthly_Bill	Total_Usage_GB	Churn
0	1	Customer_1	63	Male	Los Angeles	17	73.36	236	0
1	2	Customer_2	62	Female	New York	1	48.76	172	0
2	3	Customer_3	24	Female	Los Angeles	5	85.47	460	0
3	4	Customer_4	36	Female	Miami	3	97.94	297	1
4	5	Customer_5	46	Female	Miami	19	58.14	266	0

In [3]:
```
# understanding data for Nulls, DataTypes, amount of data
df.info()
# No Nulls
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 9 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   CustomerID                 100000 non-null  int64  
 1   Name                       100000 non-null  object 
 2   Age                        100000 non-null  int64  
 3   Gender                     100000 non-null  object 
 4   Location                   100000 non-null  object 
 5   Subscription_Length_Months  100000 non-null  int64  
 6   Monthly_Bill               100000 non-null  float64
 7   Total_Usage_GB             100000 non-null  int64  
 8   Churn                      100000 non-null  int64  
dtypes: float64(1), int64(5), object(3)
memory usage: 6.9+ MB
```

In [4]:
```
# Checking if Data contains duplicated records excluding CustomerID & Name
df.iloc[:,2:].duplicated().sum()
# No duplicates
```

Out[4]: 0

In [5]:
```
# Checking if Data is Balanced
df.Churn.value_counts()
```

Out[5]:
```
0    50221
1    49779
Name: Churn, dtype: int64
```

In [6]:
```
# Statistical analysis
df.describe()
```

Out[6]:

	CustomerID	Age	Subscription_Length_Months	Monthly_Bill	Total_Usage_GB	Churn
count	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000
mean	50000.500000	44.027020	12.490100	65.053197	274.393650	0.497790
std	28867.657797	15.280283	6.926461	20.230696	130.463063	0.499998
min	1.000000	18.000000	1.000000	30.000000	50.000000	0.000000
25%	25000.750000	31.000000	6.000000	47.540000	161.000000	0.000000
50%	50000.500000	44.000000	12.000000	65.010000	274.000000	0.000000
75%	75000.250000	57.000000	19.000000	82.640000	387.000000	1.000000
max	100000.000000	70.000000	24.000000	100.000000	500.000000	1.000000

In [7]:
```
df.sample(5)
```

Out[7]:

	CustomerID	Name	Age	Gender	Location	Subscription_Length_Months	Monthly_Bill	Total_Usage_GB	Churn
94280	94281	Customer_94281	32	Female	Los Angeles	21	40.59	443	0
57085	57086	Customer_57086	32	Female	Chicago	24	83.91	279	1
88421	88422	Customer_88422	60	Male	Los Angeles	20	32.57	484	0
39587	39588	Customer_39588	35	Male	New York	14	80.74	194	1
58943	58944	Customer_58944	21	Male	Chicago	3	92.09	370	0

EDA

Pie Chart

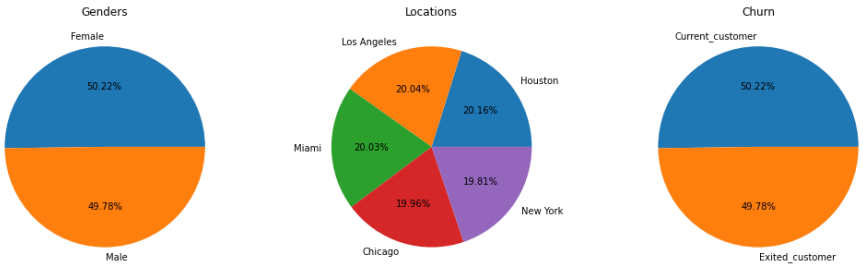
In [9]:
```
# Create a 1x4 grid of subplots
fig, ax = plt.subplots(1, 3, figsize=(18, 5))

# Checking if Gender is Balanced
ax[0].pie(df.Gender.value_counts(), autopct='%1.2f%%', labels=["Female", "Male"])
ax[0].set_title("Genders")

# Checking if Location is Balanced
ax[1].pie(df.Location.value_counts(), autopct='%1.2f%%', labels=df.Location.value_counts().index)
ax[1].set_title("Locations")

# Checking if Churn is Balanced
ax[2].pie(df.Churn.value_counts(), autopct='%1.2f%%', labels=["Current_customer", "Exited_customer"])
ax[2].set_title('Churn')

plt.show()
```

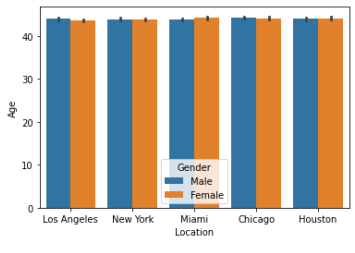


Location-Gender Distribution

In [12]:
```
# Location wise frequency of Male & Female
# [Los Angeles, Chicago --> More Male]
# [Miami --> More Male]
# [New York, Houston --> Equal Mail and Female]

sns.barplot(y='Age', x='Location', hue='Gender', data=df)
```

Out[12]: <AxesSubplot:xlabel='Location', ylabel='Age'>



Subscription Length & Monthly Bill

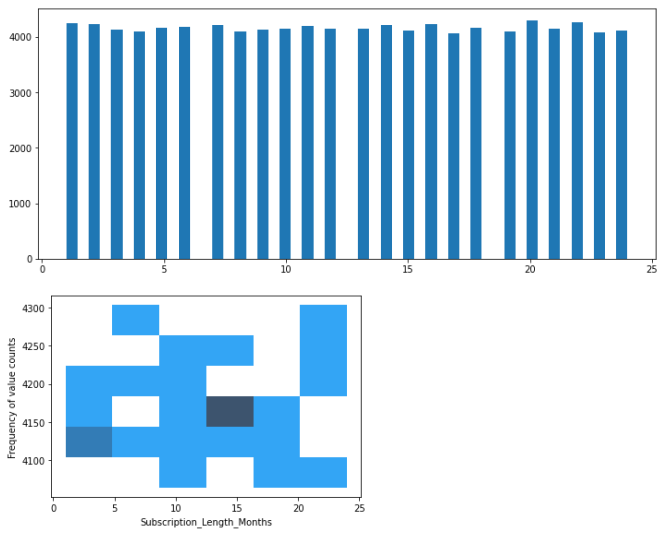
In [10]:
```
fig, ax = plt.subplots(1, figsize=(12, 5))

# Almost similar distribution in Subscription_Length_Months
plt.hist(df.Subscription_Length_Months, bins=50)
plt.show()

# distribution Monthly_Bill
Y_axis = df['Subscription_Length_Months'].value_counts(ascending=True)
X_axis = np.random.randint(1, 25,size=len(Y_axis))

plot  = sns.histplot(x=X_axis, y=Y_axis)
plot.set(xlabel='Subscription_Length_Months', ylabel='Frequency of value counts')

plt.show()
```

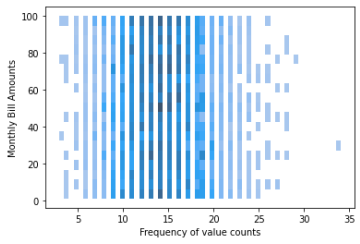


In [11]:
```
# distribution Monthly_Bill
X_axis = df['Monthly_Bill'].value_counts(ascending=True)
Y_axis = np.random.randint(1, 101,size=len(X_axis))

plot  = sns.histplot(x=X_axis, y=Y_axis)

plot.set(ylabel='Monthly Bill Amounts', xlabel='Frequency of value counts')

plt.show()
```



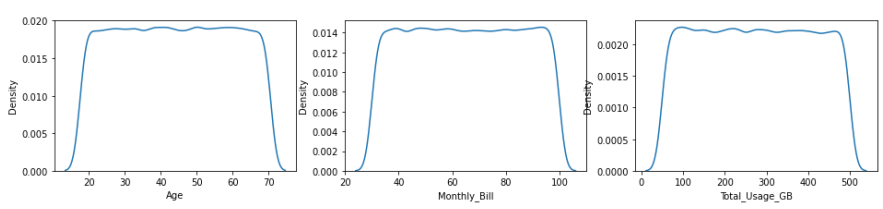
similar user frequencies across groups for different features

In [13]:
```
plt.figure(figsize=(16,3))
# Age group also has similar frequencies of users throughoyt the groups
plt.subplot(1,3,1)
sns.kdeplot(df["Age"])

# Monthly_Bill group also has similar frequencies of users throughoyt the groups
plt.subplot(1,3,2)
sns.kdeplot(df["Monthly_Bill"])

# Total_Usage_GB group also has similar frequencies of users throughoyt the groups
plt.subplot(1,3,3)
sns.kdeplot(df["Total_Usage_GB"])
```

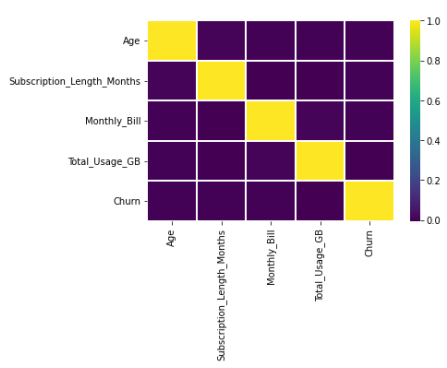
Out[13]: <AxesSubplot:xlabel='Total_Usage_GB', ylabel='Density'>



Heatmap:

In [14]:
```
# Excluding  (CustomerID, Name) as they does not contribute in the prediction
sns.heatmap(df.iloc[:,2:].corr(), cmap="viridis", annot=False, linewidths=2, linecolor='white')
```

Out[14]: <AxesSubplot:>



In [15]:
```
df.iloc[:,2:].corr()
```

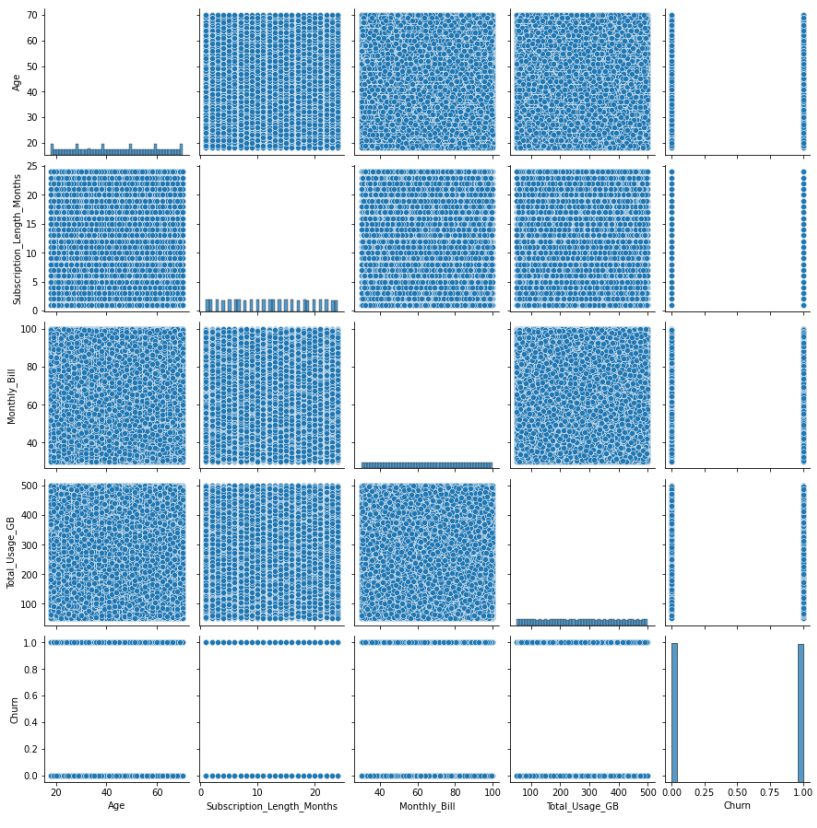
Out[15]:

	Age	Subscription_Length_Months	Monthly_Bill	Total_Usage_GB	Churn
Age	1.000000	0.003382	0.001110	0.001927	0.001559
Subscription_Length_Months	0.003382	1.000000	-0.005294	-0.002203	0.002328
Monthly_Bill	0.001110	-0.005294	1.000000	0.003187	-0.000211
Total_Usage_GB	0.001927	-0.002203	0.003187	1.000000	-0.002842
Churn	0.001559	0.002328	-0.000211	-0.002842	1.000000

Pair Plot

In [16]:
```
1 sns.pairplot(df.iloc[:,2:])
```

Out[16]: <seaborn.axisgrid.PairGrid at 0x1b1c3b721a0>



In [ ]:
```
1
```