Empathize data wrangling and EDA Vis

August 5, 2023

1 Empathize Stage

1.1 Data Wrangling and EDA Visualization

1.1.1 Aavail Project

Necessary libraries:

[ ]:
```
import pandas as pd
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
from pyampute.exploration.md_patterns import mdPatterns
from pyampute.exploration.mcar_statistical_tests import MCARTest
from sklearn.impute import IterativeImputer

sns.set_theme()
```

[ ]:
```
df = pd.read_csv('aavail-data-visualization.csv')
df.head()
```

```
   customer_id   country_name   age     customer_name  is_subscriber  \
0            1  united_states  21.0        Kasen Todd           True
1            2      singapore  31.0      Ensley Garza          False
2            3  united_states  22.0      Lillian Carey          False
3            4  united_states  21.0  Beau Christensen           True
4            5      singapore  22.0     Ernesto Gibson           True

  subscriber_type  num_streams
0  aavail_premium         23.0
1             NaN         12.0
2  aavail_premium         22.0
3    aavail_basic         19.0
4  aavail_premium         23.0
```

Presenting the shape and variables details of the data frame.

[ ]:
```python
print(f'The shape of the DataFrame: {df.shape}')
print('----------')
print(df.info())
```

```
The shape of the DataFrame: (1000, 7)
----------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   customer_id      1000 non-null   int64
 1   country_name     1000 non-null   object
 2   age              1000 non-null   float64
 3   customer_name    1000 non-null   object
 4   is_subscriber    1000 non-null   bool
 5   subscriber_type  928 non-null    object
 6   num_streams      954 non-null    float64
dtypes: bool(1), float64(2), int64(1), object(3)
memory usage: 48.0+ KB
None
```

We found that there are two variables **subscriber_type, num_streams** with *missing data*.

Check the percentage of missing data in each variables.

[ ]:
```python
missColumns = ['subscriber_type', 'num_streams']
df[missColumns].isna().mean()
```

```
subscriber_type    0.072
num_streams        0.046
dtype: float64
```

We have less than *10%* of missing value in each variable.

Check the patterns of Missing Data.

[ ]:
```python
df[missColumns].isna().value_counts()/1000
```

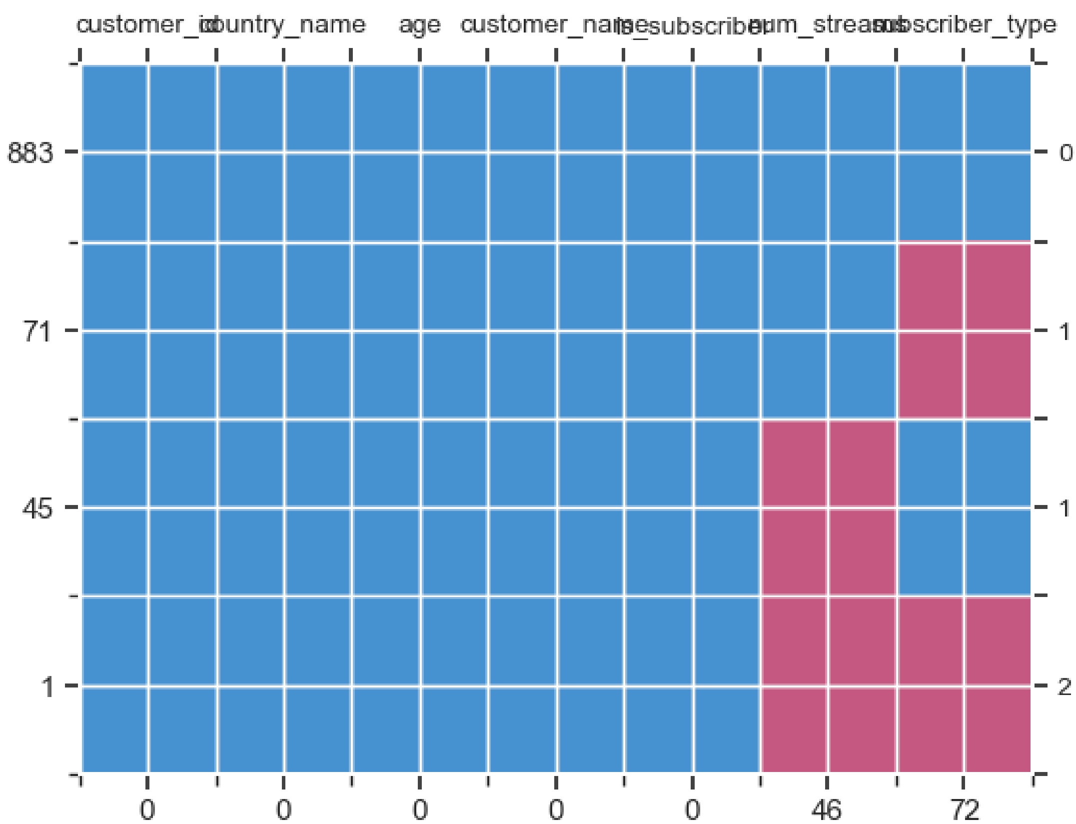
```
subscriber_type  num_streams
False            False          0.883
True             False          0.071
False            True           0.045
True             True           0.001
dtype: float64
```

We found that there is a pattern so we will plot the patterns of Missing Data as a Map, Trying to figure it out.

[ ]:
```python
mdp = mdPatterns()
patterns = mdp.get_patterns(df)
```

```python
print(patterns)
```

```
c:\Users\ASUS\anaconda3\lib\site-
packages\pyampute\exploration\md_patterns.py:120: FutureWarning: The
frame.append method is deprecated and will be removed from pandas in a future
version. Use pandas.concat instead.
  group_values = group_values.append(colsums, ignore_index=True)
```




```
                         row_count  customer_id  country_name  age  \
rows_no_missing                883            1             1    1
1                               71            1             1    1
2                               45            1             1    1
3                                1            1             1    1
n_missing_values_per_col                      0             0    0

                          customer_name  is_subscriber  num_streams  \
rows_no_missing                       1              1            1
1                                     1              1            1
2                                     1              1            0
3                                     1              1            0
n_missing_values_per_col              0              0           46
```

```
                          subscriber_type  n_missing_values
rows_no_missing                         1                 0
1                                       0                 1
2                                       1                 1
3                                       0                 2
n_missing_values_per_col               72               118
```

We found that the missing data have pattern that makes us think that the missing data are not *MCAR*

Some Wrangling and Investigations.

subscriber_type *vs* **country_name**

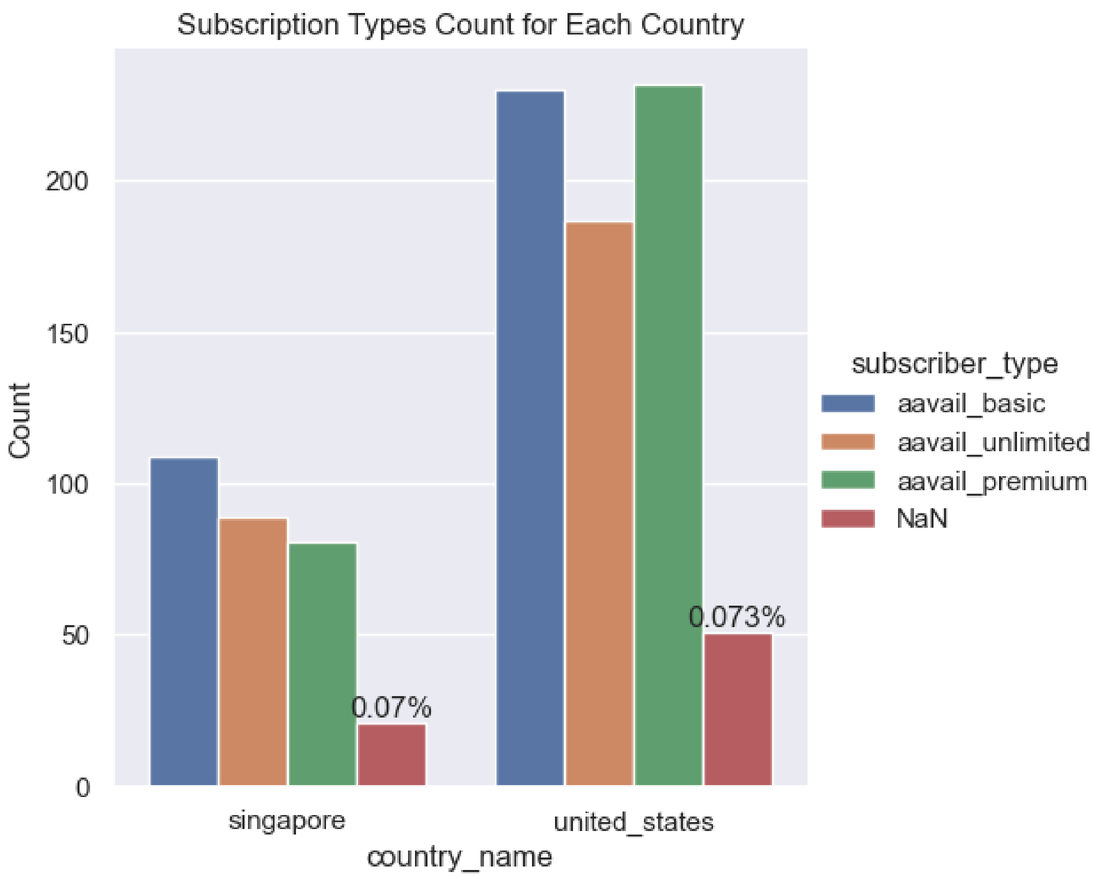
[ ]:
```
df.groupby(['subscriber_type'], dropna=False)['country_name'].value_counts().
 ↪to_frame(name = 'Count').tail(2)
```

```
                                Count
subscriber_type country_name
NaN             united_states      51
                singapore          21
```

This makes us thick that there is a bias due to **Missing Data**, so let's find the percentage for each one.

[ ]:
```
g = df.groupby(['country_name'])['subscriber_type'].value_counts(dropna=False,
 ↪).to_frame(name='Count').reset_index(level = [0,1]).fillna('NaN')

per1 = g.loc[(g['country_name'] == 'singapore') & (g['subscriber_type'] ==
 ↪'NaN'), 'Count'] / g.loc[g['country_name'] == 'singapore', 'Count'].sum()
per2 = g.loc[(g['country_name'] == 'united_states') & (g['subscriber_type'] ==
 ↪'NaN'), 'Count'] / g.loc[g['country_name'] == 'united_states', 'Count'].sum()

chart = sns.catplot(data = g, kind = 'bar', x = 'country_name', y = 'Count',
 ↪hue='subscriber_type')
chart.set(title='Subscription Types Count for Each Country')
ax = chart.facet_axis(0, 0)
c = ax.containers[3]

# labels = [f'{(v.get_height() / 1000):.1f}K' for v in c]
ax.bar_label(c, labels=[str(round(per1.values[0], 3)) + '%', str(round(per2.
 ↪values[0], 3)) + '%'], label_type='edge')
```

```
[Text(0, 0, '0.07%'), Text(0, 0, '0.073%')]
```



Based on the previous there is no bias based on the **Missing Data**, because the percentages of the missing value are almost the same.

In general there is a bias to **united_states**, so this variable is *unbalanced*.

subscriber_type *vs* **is_subscriber**

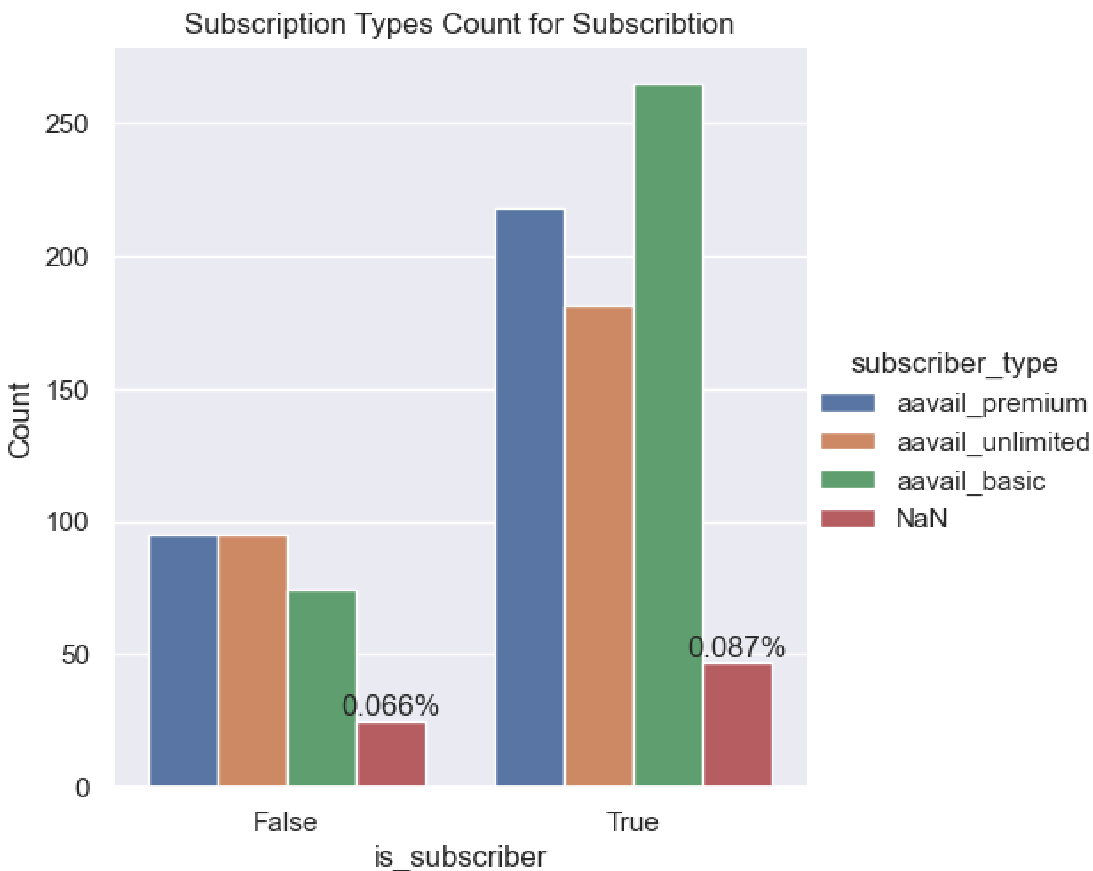
[ ]:
```
df.groupby(['subscriber_type'], dropna=False)['is_subscriber'].value_counts().
    ↪to_frame(name='Count').tail(2)
```

```
                                 Count
subscriber_type is_subscriber
NaN             True                47
                False               25
```

[ ]:
```
g = df.groupby(['is_subscriber'])['subscriber_type'].value_counts(dropna =␣
    ↪False).to_frame(name='Count').reset_index(level=[0, 1]).fillna('NaN')

per1 = g.loc[(g['is_subscriber'] == True) & (g['subscriber_type'] == 'NaN'),␣
    ↪'Count'].values[0] / g.loc[(g['is_subscriber'] == True), 'Count'].sum()
```

```
per2 = g.loc[(g['is_subscriber'] == False) & (g['subscriber_type'] == 'NaN'),␣
↪'Count'].values[0] / g.loc[(g['is_subscriber'] == False), 'Count'].sum()

chart = sns.catplot(data = g, kind = 'bar', x = 'is_subscriber', y = 'Count',␣
↪hue='subscriber_type').set(title='Subscription Types Count for Subscribtion')
ax = chart.facet_axis(0, 0)
c = ax.containers[3]

ax.bar_label(c, labels=[str(round(per1, 3)) + '%', str(round(per2, 3)) + '%'],␣
↪label_type='edge')
```

```
[Text(0, 0, '0.066%'), Text(0, 0, '0.087%')]
```



Based on the previous there is no bias based on the **Missing Data**, because the percentages of the missing value are almost the same.

num_streams *vs* **country_name**

[ ]:
```
df.groupby(['num_streams'], dropna=False)['country_name'].value_counts().
↪to_frame(name = 'Count').tail(2)
```

```
                                 Count
num_streams country_name
NaN         united_states     24
            singapore         22
```

[ ]:
```
per1 = df.loc[(df['country_name'] == 'singapore'), 'num_streams'].isna().sum() /
 ↪ len(df.loc[df['country_name'] == 'singapore'])
per2 = df.loc[(df['country_name'] == 'united_states'), 'num_streams'].isna().
 ↪sum() / len(df.loc[df['country_name'] == 'united_states'])
print(f'singapore missing num of streams: {round(per1, 3)}')
print(f'united_states missing num of streams: {round(per2, 3)}')
```

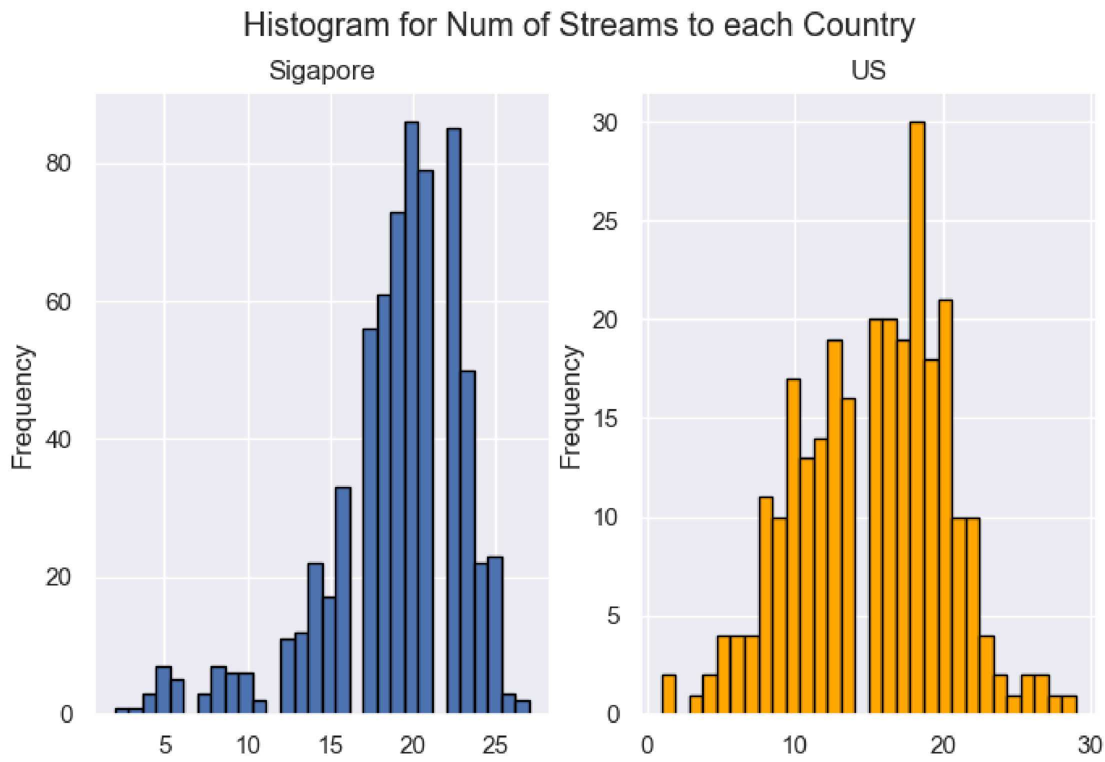
```
singapore missing num of streams: 0.073
united_states missing num of streams: 0.034
```

The missing data percentage in **singapore** is more than the percentage in **united_states**, so this difference causes bias to the **united_states** data.

We can see that in the next Histogram.

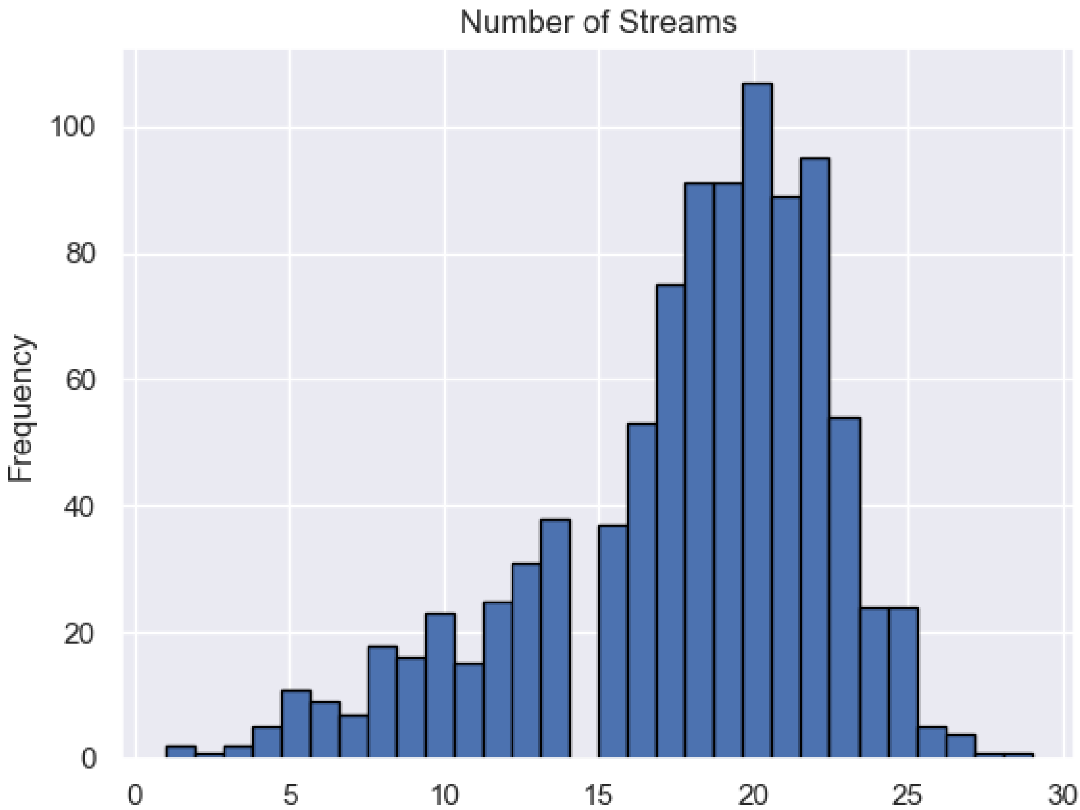
[ ]:
```
figure, axes = plt.subplots(1, 2, figsize=(8,5))
figure.suptitle('Histogram for Num of Streams to each Country')
axes[0].set_title('Sigapore')
axes[1].set_title('US')

df.loc[(df['country_name'] == 'united_states'), 'num_streams'].
 ↪plot(kind='hist', bins = 30, ec='black', ax = axes[0])
df.loc[(df['country_name'] == 'singapore'), 'num_streams'].plot(kind='hist',␣
 ↪bins = 30, ec='black', color = 'orange', ax = axes[1])
```

```
<Axes: title={'center': 'US'}, ylabel='Frequency'>
```




```
[ ]: df['num_streams'].plot(kind='hist', bins = 30, ec='black', title='Number of Streams')
```

```
<Axes: title={'center': 'Number of Streams'}, ylabel='Frequency'>
```



num_streams *vs* **is_subscriber**

[ ]:
```
df.groupby(['num_streams'], dropna=False)['is_subscriber'].value_counts().
↪to_frame(name='Count').tail(2)
```

```
                          Count
num_streams is_subscriber
NaN         True             32
            False            14
```

[ ]:
```
per1 = df.loc[(df['is_subscriber'] == True), 'num_streams'].isna().sum() /␣
↪len(df.loc[df['is_subscriber'] == True])
per2 = df.loc[(df['is_subscriber'] == False), 'num_streams'].isna().sum() /␣
↪len(df.loc[df['is_subscriber'] == False])
print(f'Subscribers missing num of streams: {round(per1, 3)}')
print(f'Not Subscribers missing num of streams: {round(per2, 3)}')
```

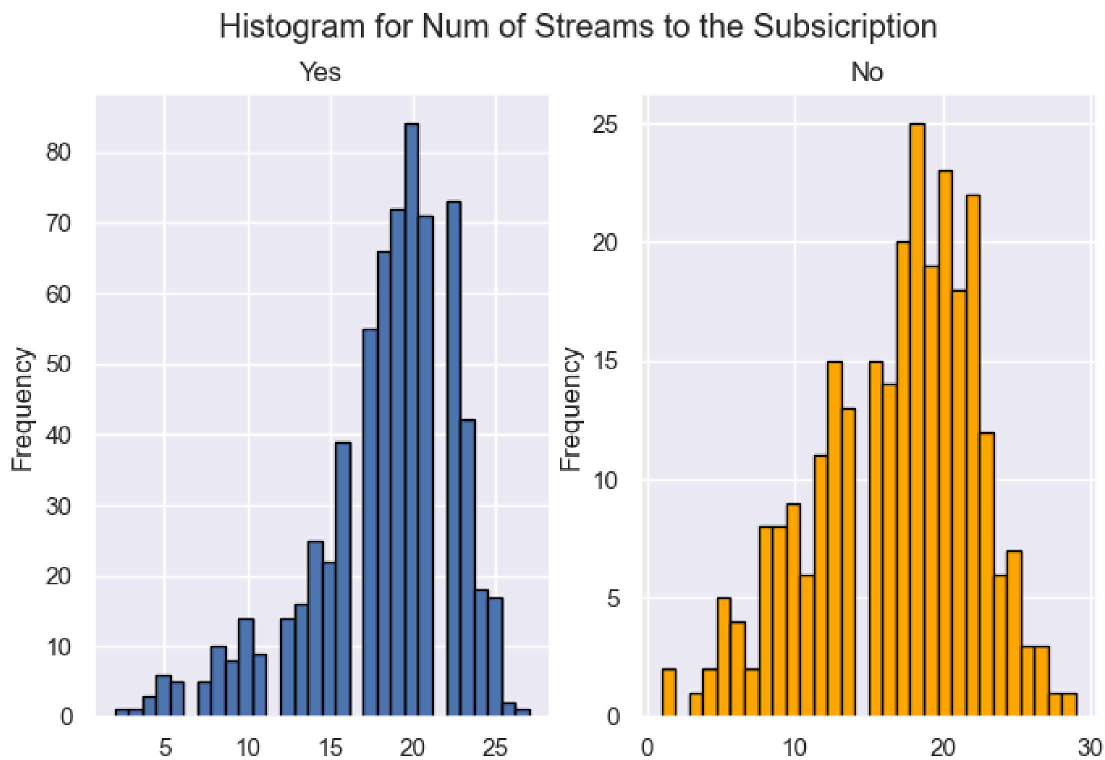
```
Subscribers missing num of streams: 0.045
Not Subscribers missing num of streams: 0.048
```

The Percentage are almost equals so we can say that there is no bias based to the subscribers.

The following is a Histogram for Num of Streams for those who subscribed or not.

[ ]:
```python
figure, axes = plt.subplots(1, 2, figsize=(8,5))
figure.suptitle('Histogram for Num of Streams to the Subsiciption')
axes[0].set_title('Yes')
axes[1].set_title('No')

df.loc[(df['is_subscriber'] == True), 'num_streams'].plot(kind='hist', bins =
    30, ec='black', ax = axes[0])
df.loc[(df['is_subscriber'] == False), 'num_streams'].plot(kind='hist', bins =
    30, ec='black', color = 'orange', ax = axes[1])
```

```
<Axes: title={'center': 'No'}, ylabel='Frequency'>
```



We will moving now to Hypotheses Testing, Starting by do *MCAR test* to the **age** and **num_streams**, with the following state of hypothesis:

- $H_0: **age** and **num_streams** are independent so there is no relation between them that effect the missing data.
- $H_1: They are not.

[ ]:
```python
mt = MCARTest()
value = mt.little_mcar_test( df[['age', 'num_streams']] )
print(f'P-Value: {value}')
```

```
P-Value: 1.8831016136644507e-05
```

Based on the P-value we can reject the Null Hypothesis.

state of Hypothesis for **subscriber_type** and **country_name**:

- $H_0: **subscriber_type** and **country_name** are independent so there is no relation between them that effect the missing data.
- $H_1: They are not.

```
[ ]: cc = pd.crosstab(df['subscriber_type'].fillna('missing'), df['country_name'],)
value = stats.chi2_contingency(cc)
print(f'P-Value: {value[1]}')
```

```
P-Value: 0.26501615774613035
```

Based on the P-value we can not reject the Null Hypothesis.

state of Hypothesis for **subscriber_type** and **age**: * $H_0: **subscriber_type** and **age** are independent so there is no relation between them that effect the missing data. * $H_1: They are not.

```
[ ]: dfTemp = df[['subscriber_type', 'age']]
dfTemp = dfTemp.fillna('missing')

stats.levene(dfTemp.loc[dfTemp['subscriber_type'] == 'aavail_basic']['age'],
            dfTemp.loc[dfTemp['subscriber_type'] == 'aavail_premium']['age'],
            dfTemp.loc[dfTemp['subscriber_type'] == 'aavail_unlimited']['age'],
            dfTemp.loc[dfTemp['subscriber_type'] == 'missing']['age'],
            center = 'mean')
```

```
LeveneResult(statistic=2.070637064929318, pvalue=0.10246646882191954)
```

The groups do not have an equal varience so we can not use *ANOVA*, and instead we will use *Kruskal* which does not have problems with the varience issue.

```
[ ]: dfTemp = df[['subscriber_type', 'age']]
dfTemp = dfTemp.fillna('missing')

stats.kruskal(dfTemp.loc[dfTemp['subscriber_type'] == 'aavail_basic']['age'],
            dfTemp.loc[dfTemp['subscriber_type'] == 'aavail_premium']['age'],
            dfTemp.loc[dfTemp['subscriber_type'] == 'aavail_unlimited']['age'],
            dfTemp.loc[dfTemp['subscriber_type'] == 'missing']['age'],)
```

```
KruskalResult(statistic=3.9345817178236597, pvalue=0.2686153201366135)
```

Based on the P-value we can not reject the Null Hypothesis.

```
[ ]: scp.levene(
    df.dropna().loc[df['is_subscriber'] == True]['num_streams'],
    df.dropna().loc[df['is_subscriber'] == False]['num_streams'], center='mean'
)
```

```
LeveneResult(statistic=20.34474076947048, pvalue=7.341996421949922e-06)
```

```
[ ]: scp.f_oneway(
         df.dropna().loc[df['is_subscriber'] == True]['num_streams'],
         df.dropna().loc[df['is_subscriber'] == False]['num_streams'],
     )
```

```
F_onewayResult(statistic=19.64331883211847, pvalue=1.0509358853845736e-05)
```

```
[ ]: scp.levene(
                 df.dropna().loc[df['subscriber_type'] ==␣
      ↪'aavail_basic']['num_streams'],
                 df.dropna().loc[df['subscriber_type'] ==␣
      ↪'aavail_premium']['num_streams'],
                 df.dropna().loc[df['subscriber_type'] ==␣
      ↪'aavail_unlimited']['num_streams'], center='mean'
     )
```

```
LeveneResult(statistic=13.216481438425454, pvalue=2.2114235890901506e-06)
```

```
[ ]: scp.f_oneway(
                     df.dropna().loc[df['subscriber_type'] ==␣
      ↪'aavail_basic']['num_streams'],
                 df.dropna().loc[df['subscriber_type'] ==␣
      ↪'aavail_premium']['num_streams'],
                 df.dropna().loc[df['subscriber_type'] ==␣
      ↪'aavail_unlimited']['num_streams'],
     )
```

```
F_onewayResult(statistic=1.6117134385494494, pvalue=0.2001338700648013)
```

```
[ ]: scp.levene(
                 df.dropna().loc[df['country_name'] == 'singapore']['num_streams'],
                 df.dropna().loc[df['country_name'] ==␣
      ↪'united_states']['num_streams'], center='mean'
     )
```

```
LeveneResult(statistic=21.083186117667363, pvalue=5.0372487417334555e-06)
```

```
[ ]: scp.f_oneway(
                     df.dropna().loc[df['country_name'] ==␣
      ↪'singapore']['num_streams'],
                 df.dropna().loc[df['country_name'] ==␣
      ↪'united_states']['num_streams'],

     )
```

```
F_onewayResult(statistic=135.35918442184692, pvalue=3.3231749460711966e-29)
```

Based on the previous we can say that the missing data type is not **MCAR** and it is almost **MNAR** for **num_streams** variable, and it's **MAR** for **subscriber_type** variable.

Impute **subcriber_type** missing data:

Based on the previous studies we will impute the missing data by sampling from the existense data, because our Missing Data are **MAR** and it's not related to the other features, at the same time it's mode is not make sense to use it because it's almost the same as the others.

[ ]:
```
mask = df['subscriber_type'].isna()
temp = df.loc[~mask, ['subscriber_type']].sample(72)['subscriber_type'].values
df.loc[mask, ['subscriber_type']] = temp
df.loc[mask, ['subscriber_type']].head()
```

```
     subscriber_type
1   aavail_unlimited
17      aavail_basic
51    aavail_premium
74    aavail_premium
75  aavail_unlimited
```

[ ]:
```
df['subscriber_type'].value_counts()
```

```
aavail_basic        372
aavail_premium      331
aavail_unlimited    297
Name: subscriber_type, dtype: int64
```

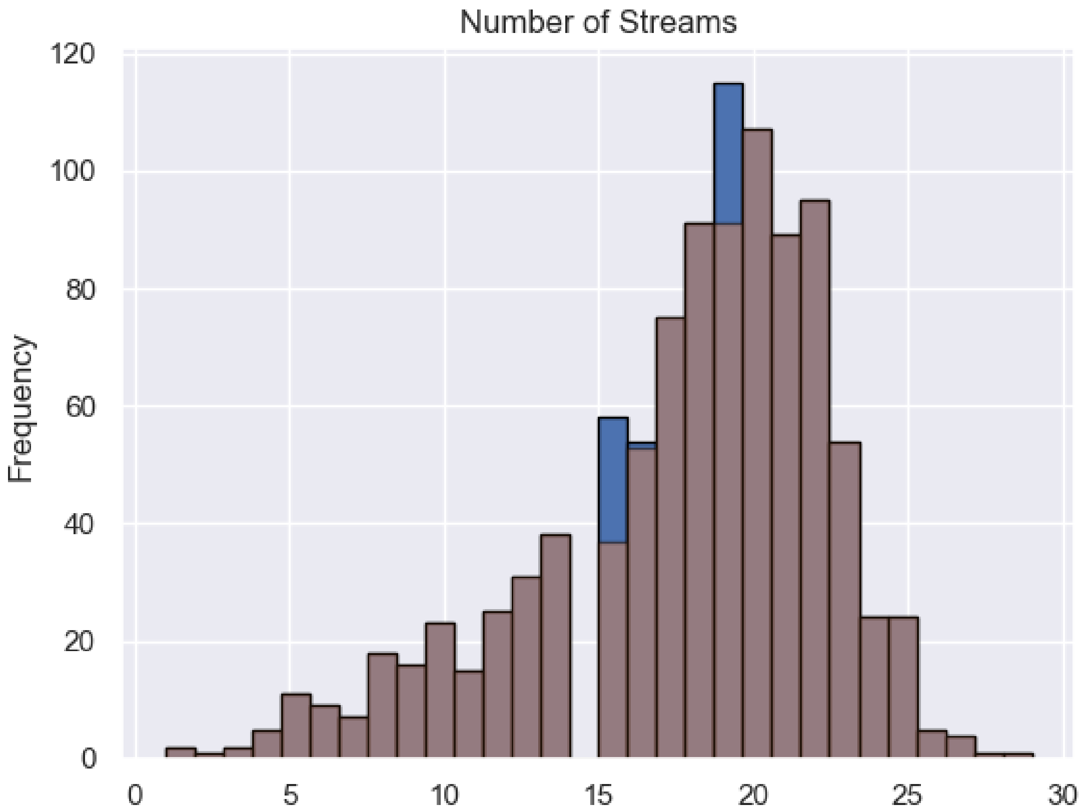
Results: Now we cleared the **subscriber_type** feature from missing data problem.

Impute **num_streams** missing data:

We found in the previous studies that the missing data in **num_streams** feature are **MNAR**, and it's relate to the other features, so we need a model to impute it, and we choose *IterativeImputer* with *BayesianRidge* estimator which is the default option.

[ ]:
```
df_impute = pd.concat([df.drop(columns=['country_name']), pd.
 ↪get_dummies(df['country_name'])], axis=1)
imp_num_fet = ['singapore', 'united_states', 'age', 'is_subscriber',␣
 ↪'num_streams']
imputed = IterativeImputer().fit_transform(df_impute[imp_num_fet])
num_streams = imputed[:,4].round()
```

[ ]:
```
df['imputed'] = num_streams
df['imputed'].plot(kind='hist', bins = 30, ec = 'black', title='imputated')
df['num_streams'].plot(kind='hist', bins = 30, ec='black', title='Number of␣
 ↪Streams', alpha=.5)
df['num_streams'] = num_streams
df.drop(columns=['imputed'], inplace = True)
```

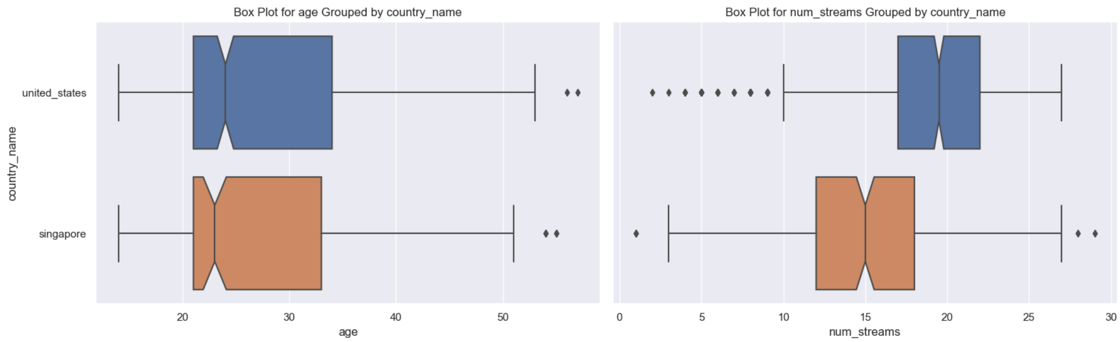


Results: we tried more than one model and the results was the almost the same, now the **num_streams** feature is clear from missing data problem.

1.1.2 EDA

Visualization Box Plots for [**age** | **num_streams**] grouped by **country_name**

[ ]:
```
figure, axis = plt.subplots(1, 2, figsize=(16, 5), sharey = True)
box1 = sns.boxplot(df, x = 'age', y = 'country_name' ,notch=True, orient="h",␣
 ↪ax= axis[0])
box1.set_title("Box Plot for age Grouped by country_name")

box2 = sns.boxplot(df, x = 'num_streams', y = 'country_name', notch = True,␣
 ↪orient = 'h', ax = axis[1])
box2.set_title('Box Plot for num_streams Grouped by country_name')
box2.set_ylabel(None)
plt.tight_layout()
```

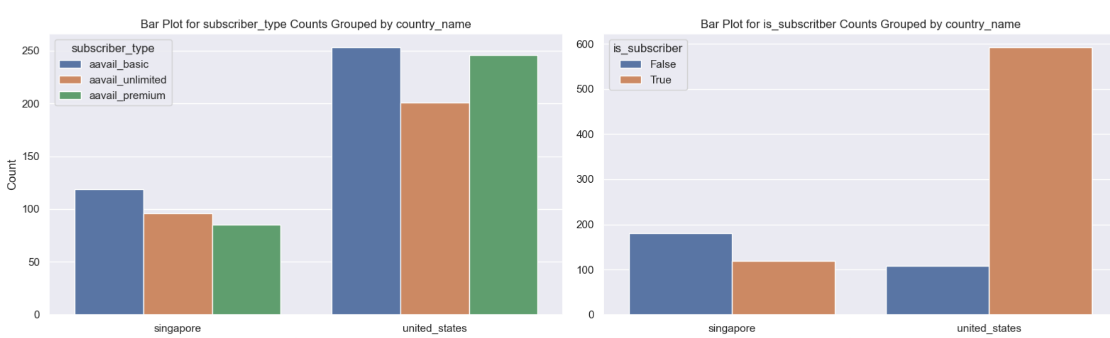


Results:

- For **age**: we found that there is no difference between the distributions for each country, and there is bias to the left.
- For **num_streams**: we found that there is difference between the distributions and the *united_states*'s is higher.

Bar Plots for [**subscriber_type** | **is_subcriber**] counts grouped by **country_name**

[ ]:
```
g = df.groupby(['country_name'])['subscriber_type'].value_counts().
 ↪to_frame(name='Count').reset_index(level=[0,1])
figure, axis = plt.subplots(1, 2, figsize=(16, 5))
bar1 = sns.barplot(g, x = 'country_name', y = 'Count', hue='subscriber_type',␣
 ↪ax = axis[0])
bar1.set_title('Bar Plot for subscriber_type Counts Grouped by country_name')

g = df.groupby(['country_name'])['is_subscriber'].value_counts().
 ↪to_frame(name='Count').reset_index(level=[0,1])

bar2 = sns.barplot(g, x = 'country_name', y = 'Count', hue = 'is_subscriber',␣
 ↪ax = axis[1])
bar2.set_title('Bar Plot for is_subscritber Counts Grouped by country_name')
bar2.set_ylabel(None)

plt.tight_layout()
```



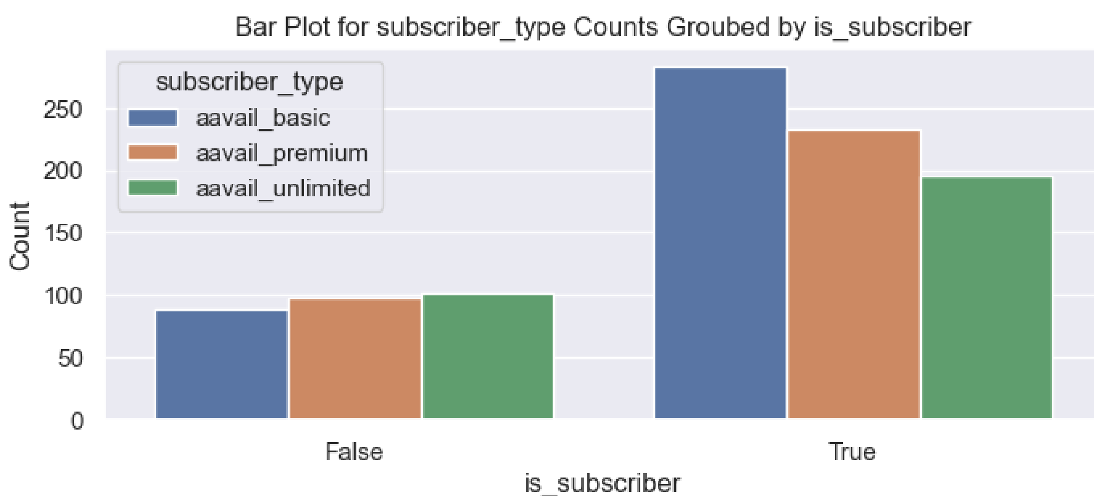
Results:

- For **subscriber_type**: we found that it's almost the same for each country, but *united_states* has more customer than *singapore* by far.
- For **is_subscriber**: we found that in *singapore* the non-subscribers are more than subscribers, but for *united_states* subscribers are the more by far and the number of Non-subscribers are less than the Non-subscribers in *singapore*.

Bar Plot for **subscriber_type** counts grouped by **is_subscriber**

[ ]:
```
g = df.groupby(['subscriber_type'])['is_subscriber'].value_counts().
 ↪to_frame(name='Count').reset_index(level = [0, 1])

plt.figure(figsize = (8, 3))
bar1 = sns.barplot(g, x = 'is_subscriber', y = 'Count', hue='subscriber_type')
bar1.set_title('Bar Plot for subscriber_type Counts Groubed by is_subscriber')
```

```
Text(0.5, 1.0, 'Bar Plot for subscriber_type Counts Groubed by is_subscriber')
```



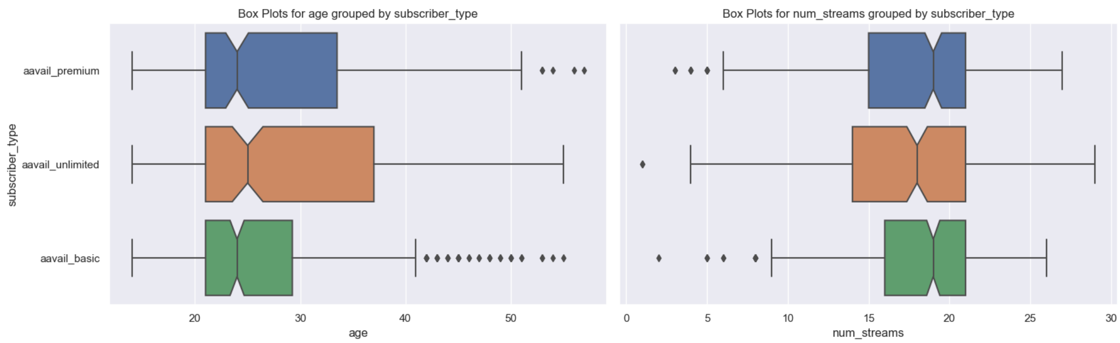
Results:

- Based on the **subscriber_type** the Non-subscribers count are almost the same.

Box Plots for [**age** | **num_streams**] grouped by subscriber_type

[ ]:
```
figure, axis = plt.subplots(1, 2, figsize=(16, 5), sharey = True)
box1 = sns.boxplot(df, x = 'age', y = 'subscriber_type' ,notch=True,␣
 ↪orient="h", ax= axis[0])
box1.set_title("Box Plots for age grouped by subscriber_type")
```

```
box2 = sns.boxplot(df, x = 'num_streams', y = 'subscriber_type', notch = True,␣
 ↪orient = 'h', ax = axis[1])
box2.set_title('Box Plots for num_streams grouped by subscriber_type')
box2.set_ylabel(None)
plt.tight_layout()
```

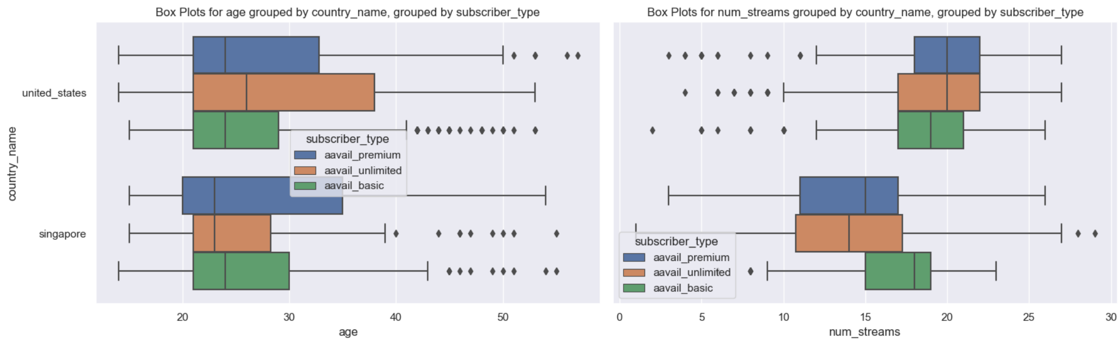


Results:

- For **age**: the distributions has almost the same midians, just the unlimited type has bigger distribution, and it is skewed to the left.
- For **num_streams**: they all similar, with a little bit difference with the median in the unlimited type.

Box Plots for [**age** | **num_streams**] grouped by **country_name**, grouped by ***subscriber_type**

[ ]:
```
figure, axis = plt.subplots(1, 2, figsize = (16, 5), sharey = True)
box1 = sns.boxplot(df, y = 'country_name', x = 'age', hue='subscriber_type',␣
 ↪ax=axis[0])
box1.set_title('Box Plots for age grouped by country_name, grouped by␣
 ↪subscriber_type')

box2 = sns.boxplot(df, y = 'country_name', x = 'num_streams',␣
 ↪hue='subscriber_type', ax=axis[1])
box2.set_title('Box Plots for num_streams grouped by country_name, grouped by␣
 ↪subscriber_type')
box2.set_ylabel(None)

plt.tight_layout()
```



Results:

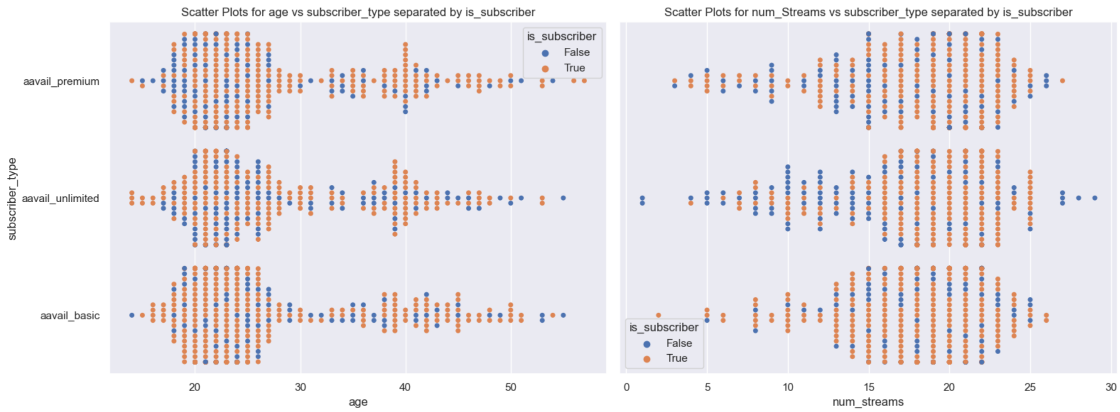
- For **age** and *united_states*: the unlimited type has bigger distribgution, but they all have almost the same midian.
- For **age** and *singapore*: the preimium type has the bigger distribution then the basic and the last one is the unlimited, and they all have similar midians.
- For **num_streams** and *united_states*: they almsot similar, the preimium type has bigger midian.
- For **num_streams** and *singapore*: there is difference between types, the basic type has smaller distribution but higher values and higher midian.

Scatter Plots for [**age** | **num_streams**] vs **subscriber_type** separated by **is_subscriber**

[ ]:
```
figure, axis = plt.subplots(1, 2,figsize = (16, 6), sharey = True)

sca1 = sns.swarmplot( data=df, x = 'age', y = 'subscriber_type', hue =␣
 ↪'is_subscriber', ax = axis[0])
sca1.set_title('Scatter Plots for age vs subscriber_type separated by␣
 ↪is_subscriber')

sca2 = sns.swarmplot(data = df, x = 'num_streams', y = 'subscriber_type', hue =␣
 ↪'is_subscriber', ax = axis[1])
sca2.set_title('Scatter Plots for num_Streams vs subscriber_type separated by␣
 ↪is_subscriber')
sca2.set_ylabel(None)

plt.tight_layout()
```

```
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 6.9% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 16.4% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
```

```
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 16.9% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 11.1% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 27.4% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 28.4% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 18.2% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 38.7% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 13.0% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 8.4% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 23.1% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 24.2% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 13.5% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
c:\Users\ASUS\anaconda3\lib\site-packages\seaborn\categorical.py:3544:
UserWarning: 34.4% of the points cannot be placed; you may want to decrease the
size of the markers or use stripplot.
  warnings.warn(msg, UserWarning)
```



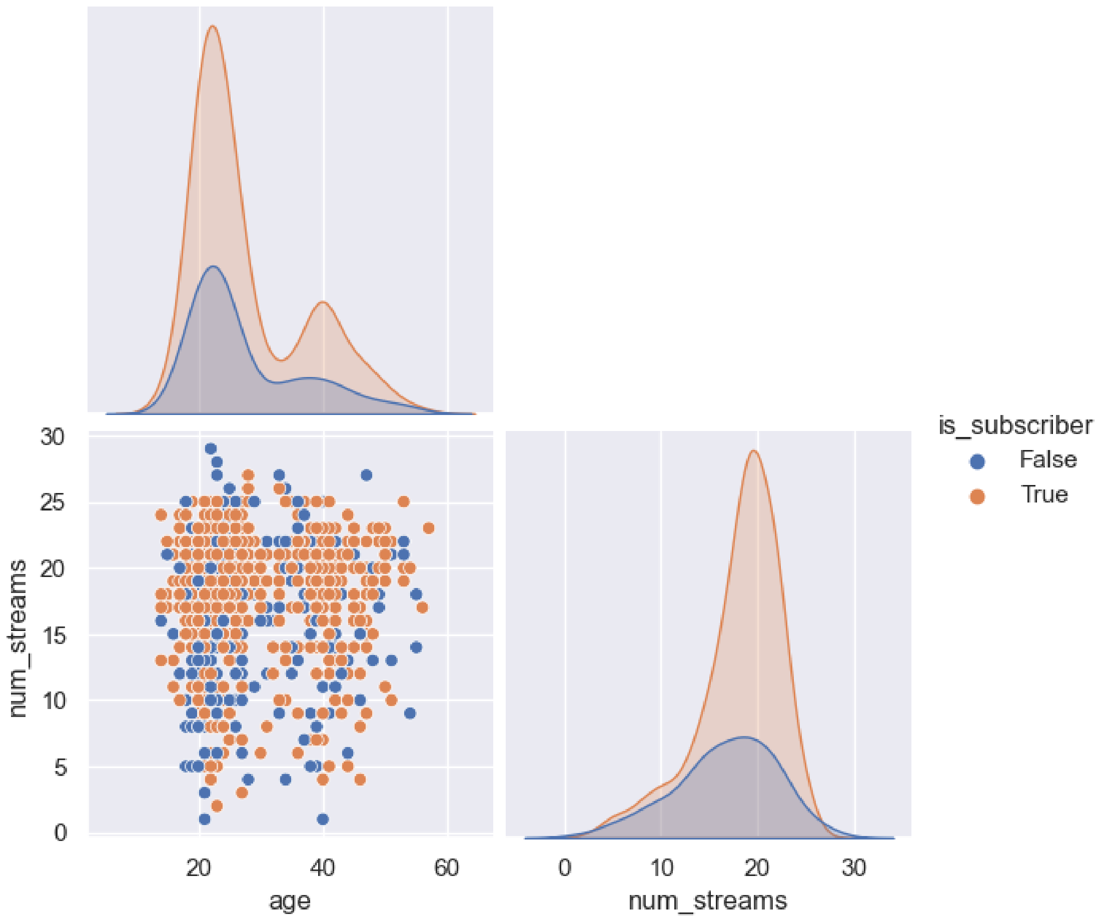
Results:

- For **age**: we found that the Non-subscribers with preimium type are centered around the age of 20, and around 23 with the unlimited type.
- For **num_streams**: we found that people with higher and lower number of streams have the highest number of Non-subscribers.

Scatter and density Plots for **age** vs **num_streams** separated by **is_subscriber**

[ ]:
```
sns.pairplot(df[['age', 'num_streams', 'is_subscriber']], hue='is_subscriber',␣
↪corner=True, height=3)
```

```
<seaborn.axisgrid.PairGrid at 0x21a31e70190>
```



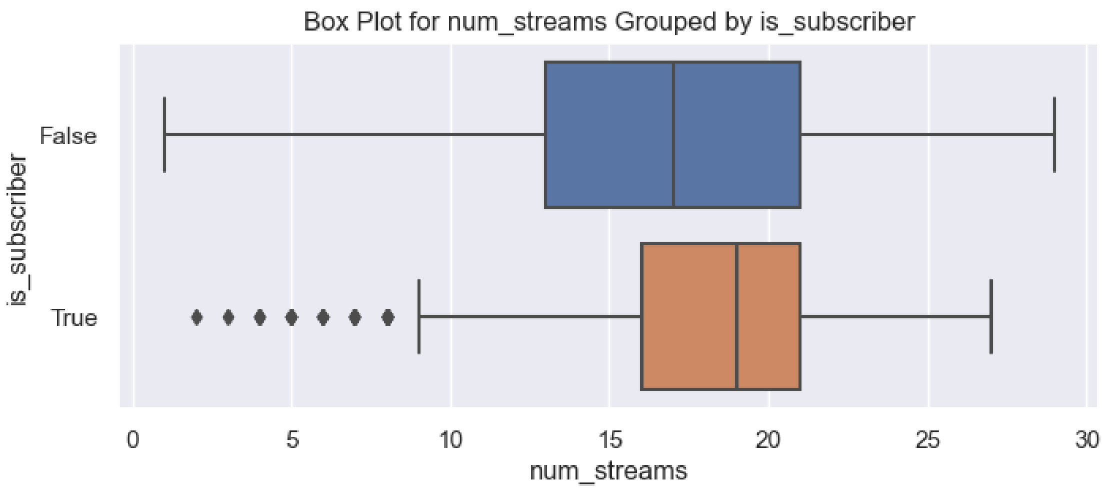
Results:

- There is no clear relation between **age** and **num_streams**.

Box Plot for **num_streams** grouped by **is_subscriber**

[ ]:
```
plt.figure(figsize=(8, 3))
box = sns.boxplot(data=df, x = 'num_streams', y = 'is_subscriber', orient='h')
box.set_title('Box Plot for num_streams Grouped by is_subscriber')
```

```
Text(0.5, 1.0, 'Box Plot for num_streams Grouped by is_subscriber')
```



Results:

- Non_subscribers have bigger distribution than subscribers, but the median is lower.