Project 4 - Unsupervised Machine Learning

Objective

The main objective of my project is to cluster the customers based on the details provided in the dataset.

Imports

In [1]:
```
%config Completer.use_jedi = False
from IPython.display import clear_output
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots
from collections import Counter

from sklearn.cluster import KMeans, DBSCAN
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.metrics import silhouette_score
```

Load Data

Data Description

- Sex
  - 0 = Male
  - 1 = Female
- Marital Status
  - 0 = Unmarried
  - 1 = Married
- Age: Age of Customer
- Education
  - 0 = Primary
  - 1 = middle school
  - 2 = high school
  - 3 = college/graduation
- Income: Income of each customer
- Occupation
  - 0 = Tertiary
  - 1 = Primary
  - 2 = Secondary Occupation
- Settlement size
  - 0 = Urban
  - 1 = Mixed
  - 2 = Rural

In [2]:
```
data = pd.read_csv('../input/customer-clustering/segmentation data.csv')
data.drop('ID', axis=1, inplace=True)
data.head()
```

Out[2]:

	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
0	0	0	67	2	124670	1	2
1	1	1	22	1	150773	1	2
2	0	0	49	1	89210	0	0
3	0	0	45	1	171565	1	1
4	0	0	53	1	149031	1	1

EDA

In [3]:
```
data.isnull().sum()
```

Out[3]:
```
Sex                0
Marital status     0
Age                0
Education          0
Income             0
Occupation         0
Settlement size    0
dtype: int64
```

In [4]:
```python
data.describe()
```

Out[4]:

	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
count	2000.000000	2000.000000	2000.000000	2000.00000	2000.000000	2000.000000	2000.000000
mean	0.457000	0.496500	35.909000	1.03800	120954.419000	0.810500	0.739000
std	0.498272	0.500113	11.719402	0.59978	38108.824679	0.638587	0.812533
min	0.000000	0.000000	18.000000	0.00000	35832.000000	0.000000	0.000000
25%	0.000000	0.000000	27.000000	1.00000	97663.250000	0.000000	0.000000
50%	0.000000	0.000000	33.000000	1.00000	115548.500000	1.000000	1.000000
75%	1.000000	1.000000	42.000000	1.00000	138072.250000	1.000000	1.000000
max	1.000000	1.000000	76.000000	3.00000	309364.000000	2.000000	2.000000

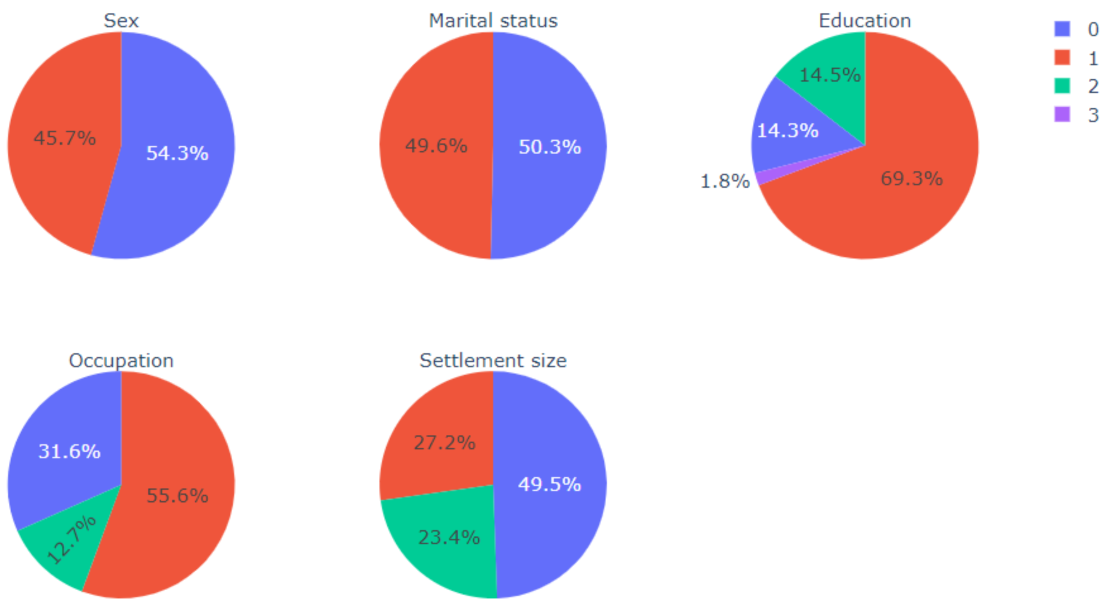
In [5]:
```python
discrete_features = []
continuous_features = []
for feature in data.columns:
    print(feature, len(data[feature].unique()))
    if len(data[feature].unique()) > 10:
        continuous_features.append(feature)
    else:
        discrete_features.append(feature)

print()
print('Discrete Features:', discrete_features)
print('Continuous Features:', continuous_features)
```

```
Sex 2
Marital status 2
Age 58
Education 4
Income 1982
Occupation 3
Settlement size 3

Discrete Features: ['Sex', 'Marital status', 'Education', 'Occupation', 'Settlement size']
Continuous Features: ['Age', 'Income']
```

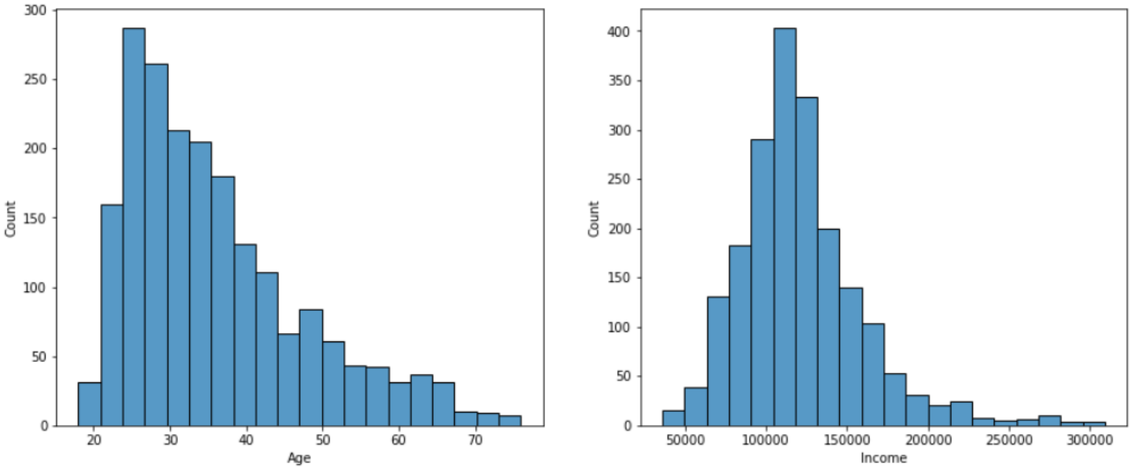
Observations

- There is no missing values.
- ID column contributes nothing to the dataset so dropped it.
- There is a total of 2000 examples or rows in the dataset.
- The data has 5 Discrete and 2 Continuous Features.

In [7]:
```python
fig = make_subplots(rows=2, cols=3, specs=2*[3*[{'type':'domain'}]])
for i in range(1, 3):
    for j in range(1, 4):
        idx = 3 * (i - 1) + j
        if idx <= len(discrete_features):
            curr_feature = discrete_features[idx-1]
            fig.add_trace(go.Pie(labels=list(Counter(data[curr_feature]).keys()),
                                 values=list(Counter(data[curr_feature]).values()),
                                 title=curr_feature, name=''), row=i, col=j)

fig.update_traces(textfont_size=15)
fig.update_layout(height=500, width=900, margin=dict(t=0, b=0, l=0, r=0), font=dict(size=15))
fig.show()
```

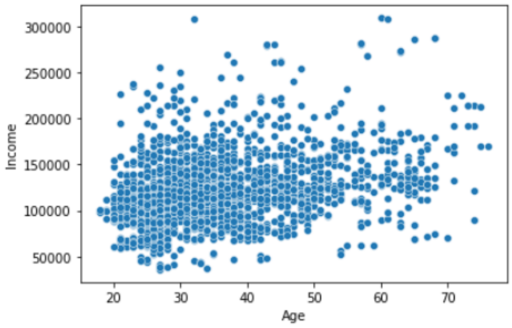


In [7]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 6))

for i, feature in enumerate(continuous_features):
    sns.histplot(ax=ax[i], x=feature, data=data, bins=20)

plt.show()
```

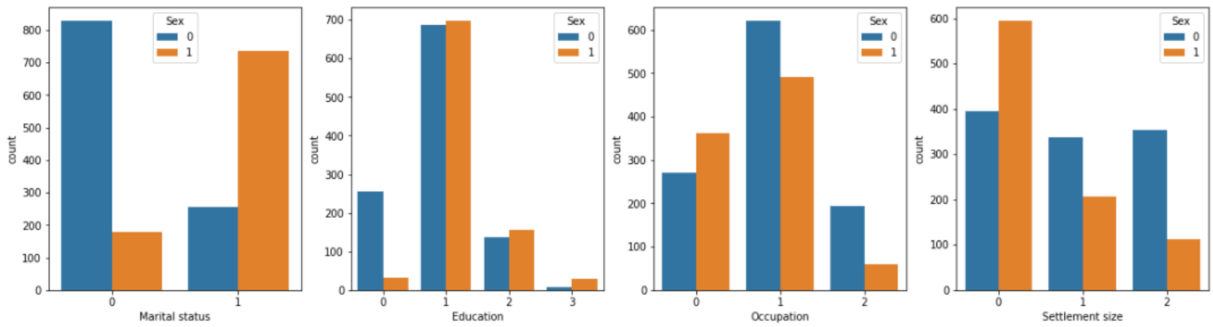


In [8]:
```
sns.scatterplot(x='Age', y='Income', data=data)
```

Out[8]: <AxesSubplot:xlabel='Age', ylabel='Income'>



In [9]:
```
new_discrete_features = discrete_features.copy()
new_discrete_features.remove('Sex')

fig, ax = plt.subplots(1, 4, figsize=(20, 5))

for i in range(4):
    sns.countplot(ax=ax[i], x=new_discrete_features[i], data=data, hue='Sex')

plt.show()
```



Key Insights

- No missing values.
- Sex and Marital status is equally distributed.
- No of Graduate individuals(3) are very low.
- Age and Income data are skewed thus a log transformation is to be applied.
- When count of discrete features wrt Sex is presented,
  - Marital status looks highly imbalanced.
  - Male dominates in Primary and Secondary Occupation.
  - Females are deprived of Primary Education while it is balanced with other tiers of education.

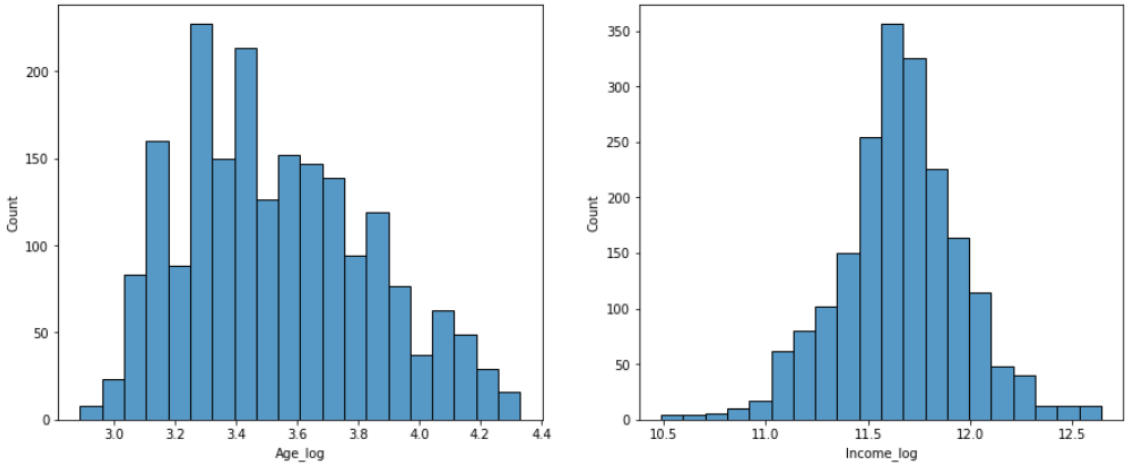
Feature Engineering

In [10]:
```
transformed_data = data[discrete_features].copy()

for feature in continuous_features:
    transformed_data[feature + '_log'] = np.log(data[feature])

transformed_data.head()
```

Out[10]:

	Sex	Marital status	Education	Occupation	Settlement size	Age_log	Income_log
0	0	0	2	1	2	4.204693	11.733426
1	1	1	1	1	2	3.091042	11.923531
2	0	0	1	0	0	3.891820	11.398748
3	0	0	1	1	1	3.806662	12.052717
4	0	0	1	1	1	3.970292	11.911910

In [11]:
```
fig, ax = plt.subplots(1, 2, figsize=(15, 6))

for i, feature in enumerate(continuous_features):
    sns.histplot(ax=ax[i], x=feature + '_log', data=transformed_data, bins=20)

plt.show()
```



In [12]:
```
scalar = MinMaxScaler()
X = scalar.fit_transform(transformed_data)
```

In [13]:
```
X[:5]
```

Out[13]:
```
array([[0.        , 0.        , 0.66666667, 0.5       , 1.        ,
        0.91249369, 0.57839313],
       [1.        , 1.        , 0.33333333, 0.5       , 1.        ,
        0.13931967, 0.66658126],
       [0.        , 0.        , 0.33333333, 0.        , 0.        ,
        0.69527579, 0.42313932],
       [0.        , 0.        , 0.33333333, 0.5       , 0.5       ,
        0.63615327, 0.7265099 ],
       [0.        , 0.        , 0.33333333, 0.5       , 0.5       ,
        0.74975629, 0.66119035]])
```

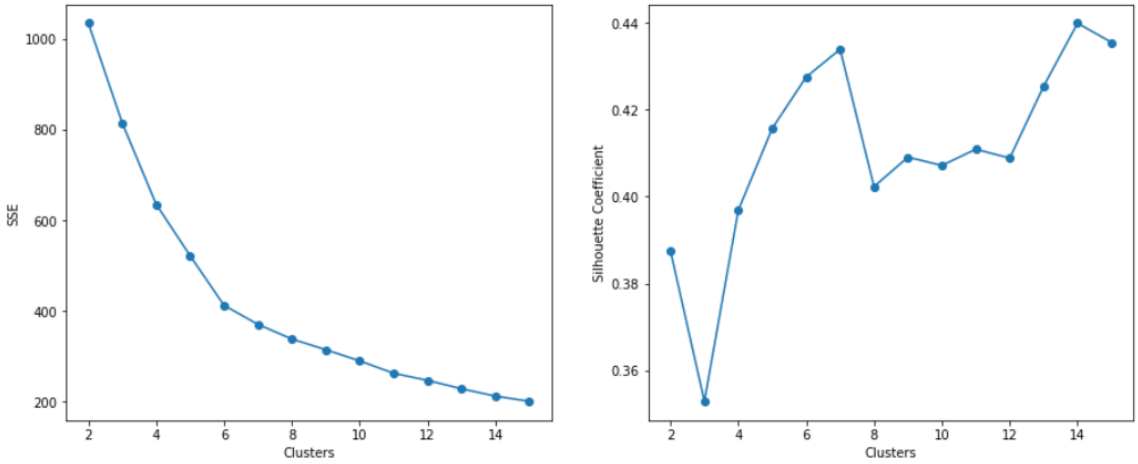
Model Building

KMeans

In [14]:
```
SSE = [] # Sum of Squared Errors
kmean_sil_scores = []
kmean_index = range(2, 16)
for i in kmean_index:
    kmeans = KMeans(n_clusters=i, random_state=42)
    labels = kmeans.fit_predict(X)
    SSE.append(kmeans.inertia_)
    kmean_sil_scores.append(silhouette_score(X, labels))

    clear_output(wait=True)
    print('Intertia at i =', i, ':', kmeans.inertia_)
    print("Silhouette Coefficient: %0.3f" % silhouette_score(X, labels))
```

```
Intertia at i = 15 : 200.1216568716734
Silhouette Coefficient: 0.435
```

In [15]:
```python
fig, ax = plt.subplots(1, 2, figsize=(15, 6))

ax[0].plot(kmean_index, SSE, marker='o')
ax[0].set_xlabel('Clusters')
ax[0].set_ylabel('SSE')

ax[1].plot(kmean_index, kmean_sil_scores, marker='o')
ax[1].set_xlabel('Clusters')
ax[1].set_ylabel('Silhouette Coefficient')

plt.show()
```

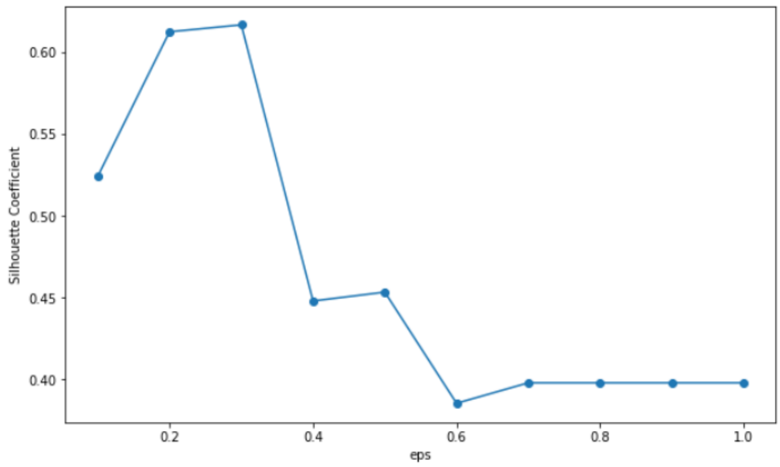


DBSCAN

In [16]:
```python
dbscan_sil_scores = []
dbscan_index = np.arange(0.1, 1.1, 0.1)

for i in dbscan_index:
    dbscan = DBSCAN(eps=i, min_samples=2)
    labels = dbscan.fit_predict(X)
    dbscan_sil_scores.append(silhouette_score(X, labels))
```

In [17]:
```python
plt.figure(figsize=(10, 6))
plt.plot(dbscan_index, dbscan_sil_scores, marker='o')
plt.xlabel('eps')
plt.ylabel('Silhouette Coefficient')
```

Out[17]:
```
Text(0, 0.5, 'Silhouette Coefficient')
```



Best Model ?

With **KMeans at clusters = 6 or 7** provides high Silhouette score. Also looking at the clusters vs inertia graph, the **elbow method** is applied which interprets the clusters at 6 or 7 to look as elbow point.

Considering the **DBSCAN**, different values of eps and min_samples are tried where variable eps are tested with its Silhouette score. At **eps = 0.2 to 0.3**, DBSCAN provide a good score.

Thus, my conclusion is either KMeans and DBSCAN can be used at the provided parameters to obtain efficient results.

Future Scope

- While revisiting the dataset, will try more in-depth analysis of the dataset.
- Will try other clustering algorithms and compare the results.

Notebook File available at: **GitHub**

Thank You for reviewing,
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