In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import plotly.figure_factory as ff
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Customer Segmentation

This project aims at the segmentation of customers into different groups using unsupervised learning algorithms. These algorithms include the following;

- Kmeans
- DBSCAN
- Agglomerative Clustering/Hierarchical clustering

For this approach, the Agglomerative clustering would be used instead of the others.

In [2]:
```python
data = pd.read_csv("../data/segmentation_data.csv")
```

Kindly refer to the segementation data legend for the interpretation of the numeric values.

In [3]:
```python
data.sample(n=5,random_state=42)
```

Out[3]:

	ID	Sex	Marital status	Age	Education	Income	Occupation	Settlement size
1860	100001861	1	1	43	1	48632	0	0
353	100000354	0	0	28	0	141847	1	1
1333	100001334	1	1	48	2	116235	0	0
905	100000906	0	0	20	0	116582	2	2
1289	100001290	0	0	49	1	118571	2	2

The ID column nont needed and will dropped, this will in turn save memory

In [4]:
```python
data.columns
```

Out[4]:
```
Index(['ID', 'Sex', 'Marital status', 'Age', 'Education', 'Income',
       'Occupation', 'Settlement size'],
      dtype='object')
```

In [5]:
```python
data.drop('ID',axis=1,inplace=True)
data.columns
```

Out[5]:
```
Index(['Sex', 'Marital status', 'Age', 'Education', 'Income', 'Occupation',
       'Settlement size'],
      dtype='object')
```

In [6]:
```python
data.shape
```

Out[6]:
```
(2000, 7)
```

As shown show in the data description, there are 2,000 data points with 7 columns(ID column dropped).

Preprocessing & EDA

Rename columns

In [7]:
```
data_prep = data
```

In [8]:
```
data_prep.columns = data_prep.columns.str.lower().str.replace(" ","_")
data_prep.columns
```

Out[8]:
```
Index(['sex', 'marital_status', 'age', 'education', 'income', 'occupation',
       'settlement_size'],
      dtype='object')
```

Check for NaN values & duplicated values

In [9]:
```
data_prep.isna().sum()
```

Out[9]:
```
sex                0
marital_status     0
age                0
education          0
income             0
occupation         0
settlement_size    0
dtype: int64
```

In [10]:
```
data_prep.duplicated().sum()
```

Out[10]:
```
0
```

Check memory usage and descriptive statistics

Data-Type	Precision

float16 | 3 float32 | 6 float64 | 15 float128 | 18

Data type	min	max
int8	-128	127
int16	-32768	32767
int32	-2147483648	2147483647
int64	-9223372036854775808	9223372036854775807

In [11]:
```
data_prep.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   sex              2000 non-null   int64
 1   marital_status   2000 non-null   int64
 2   age              2000 non-null   int64
 3   education        2000 non-null   int64
 4   income           2000 non-null   int64
 5   occupation       2000 non-null   int64
 6   settlement_size  2000 non-null   int64
dtypes: int64(7)
memory usage: 109.5 KB
```

occupation, education, settle_size, marital status and sex should all be categorical data points

In [12]:
```
cat = ['sex', 'marital_status', 'education', 'occupation',
       'settlement_size']

for col in cat:
    data_prep[col] = data_prep[col].astype('category')
```

In [13]:
```
data_prep.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   sex              2000 non-null   category
 1   marital_status   2000 non-null   category
 2   age              2000 non-null   int64
 3   education        2000 non-null   category
 4   income           2000 non-null   int64
 5   occupation       2000 non-null   category
 6   settlement_size  2000 non-null   category
dtypes: category(5), int64(2)
memory usage: 41.8 KB
```

Memory size has dropped from 109.5 KB to 41.8 KB

In [14]:
```
data_prep['age'] = data_prep['age'].astype(np.int8)
data_prep['income'] = data_prep['income'].astype(np.int32)
```

In [15]:
```
data_prep.info(memory_usage='deep')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   sex              2000 non-null   category
 1   marital_status   2000 non-null   category
 2   age              2000 non-null   int8
 3   education        2000 non-null   category
 4   income           2000 non-null   int32
 5   occupation       2000 non-null   category
 6   settlement_size  2000 non-null   category
dtypes: category(5), int32(1), int8(1)
memory usage: 20.4 KB
```

Memory size has dropped from 41.8 KB to 20.4 KB

In [16]:
```
data_prep.describe(include=np.number)
```

Out[16]:

	age	income
count	2000.000000	2000.000000
mean	35.909000	120954.419000
std	11.719402	38108.824679
min	18.000000	35832.000000
25%	27.000000	97663.250000
50%	33.000000	115548.500000
75%	42.000000	138072.250000
max	76.000000	309364.000000

Observations

- Mean age is 36, having a mean salar of 120954
- There is minimum deviation inn age, meaning less variance in the dat.
- Median age is 33 years old
- Oldest person is 76 years old.

In [17]:
```
data_prep.describe(include='category')
```

Out[17]:

	sex	marital_status	education	occupation	settlement_size
count	2000	2000	2000	2000	2000
unique	2	2	4	3	3
top	0	0	1	1	0
freq	1086	1007	1386	1113	989

Observations

- There are more males than females in this dataset
- There are more single people that the non-single people
- There are more high scool students than the rest.
- There are more skilled employee/ official people than the rest
- More people come from small cities than mid-sized and big cities

In [18]:
```
eda = data_prep
```

In [19]:
```
print(eda.select_dtypes(include=pd.CategoricalDtype).columns)
print(eda.select_dtypes(include=pd.CategoricalDtype).columns.value_counts().sum())
```

```
Index(['sex', 'marital_status', 'education', 'occupation', 'settlement_size'], dtype='object')
5
```

In [20]:
```
num_list = eda.select_dtypes(exclude=pd.CategoricalDtype).columns.to_list()
num_list
```

Out[20]:
```
['age', 'income']
```

In [21]:
```
def range_cal(arr):
    return arr.max() - arr.min()
```

In [22]:
```
def summary_stats(group:str,column):
    try:
        if eda[column].dtype !=pd.CategoricalDtype:
            group_data = (
                eda.groupby(group)[column].agg(
                    [
                        (f"total_{column}",'sum'),
                        (f'average_{column}','mean'),
                        (f'deviation_{column}','std'),
                        (f"range_{column}",range_cal),
                        (f"skewness_level_{column}","skew")
                    ]
                ).reset_index()
            )
            return group_data
        else:
            group_data = (
                eda.groupby(group)[column].agg(
                    [
                        (f"count_total_{column}",'count')
                    ]
                ).reset_index()
            )
            return group_data
    except KeyError:
        print(f"This is the list of keys: {eda.columns}")
```

Skewness |Range|Comment| |---|---| |skewness is between -0.5 & 0.5|nearly symmetrical.| |skewness is between -1 & -0.5 (negative skewed) or between 0.5 & 1(positive skewed)|slightly skewed.| |skewness is lower than -1 (negative skewed) or greater than 1 (positive skewed)|extremely skewed.|

- If the skewness is between -0.5 & 0.5, the data are nearly symmetrical.
- If the skewness is between -1 & -0.5 (negative skewed) or between 0.5 & 1(positive skewed), the data are slightly skewed.
- If the skewness is lower than -1 (negative skewed) or greater than 1 (positive skewed), the data are extremely skewed.

In [23]:
```
# Custom rc definitions
rc = {
        'axes.spines.right': True,
        'axes.spines.top': True,
        'font.family': ['sans-serif'],
        'font.sans-serif':
        # 'Arial',
        'DejaVu Sans',
        # 'Liberation Sans',
        # 'Bitstream Vera Sans',
        # 'sans-serif',
        "xtick.bottom":True,
```

```python
        'axes.edgecolor': 'violet',
        'xtick.color': 'black',
        'figure.facecolor': "snow",
        'grid.color': 'blue',

}


# font definitions
font_label = {'family': 'serif',
        'color':  'darkred',
        'weight': 'semibold',
        'size': 16,
        }

font_title = {'family': 'serif',
        'color':  'black',
        'weight': 'semibold',
        'size': 16,
        }

font_fig = {'family': 'sans',
        'color':  'chocolate',
        # 'weight': 'bold', # doesn't apply to it. Must be specified independently
        # 'fontsize': 30, # doesn't apply to it. Must be specified independently
        }
```

In [24]:

```python
def plotting_bar(x:str,group:str):
    try:
        fig,ax = plt.subplots(1,2,figsize=(20,10),constrained_layout=True)
        ax = ax.ravel()
        cats = ['sex', 'marital_status', 'education', 'occupation', 'settlement_size']
        for cat in cats:
            if group == cat:
                labels = eda[group].sort_values().unique().to_list()
                name = group
            # else:
            #     labels = ['A',"B","C","D"]
            #     name = group
                grouped_agg = eda.groupby(group)[x].agg(
                    [(f"{x}_mean", 'mean'),(f"{x}_deviation", 'std')]).reset_index()

                # my_palette = sns.color_palette("husl",2)
                sns.set_theme(style='whitegrid',rc=rc,palette='husl')

                sns.barplot(data=grouped_agg, x=group, y=f'{x}_mean', ax=ax[0])
                sns.barplot(data=grouped_agg, x=group, y=f'{x}_deviation', ax=ax[1])

                ax[0].set_title(f'Calculated Mean {x}',fontdict=font_title)
                ax[0].set_xlabel(f"{name}", fontdict=font_label)
                ax[0].set_ylabel(f"Calculated Mean {x}", fontdict=font_label)
                ax[0].set_xticklabels(labels,rotation=45,fontsize=20)

                ax[1].set_title(f'Calculated Deviation {x}',fontdict=font_title)
                ax[1].set_xlabel(f"{name}", fontdict=font_label)
                ax[1].set_ylabel(f"Calculated Deviation {x}", fontdict=font_label)
                ax[1].set_xticklabels(labels,rotation=45,fontsize=20)

                fig.suptitle(f"Mean & Deviation Bar Plots"
                             ,fontdict=font_fig,fontweight='bold'
                             ,fontsize=40)
    except KeyError:
```

```
        print(f"The wrong Key was passed\nPlease look are the information below\n")
        eda.info(memory_usage='deep')
```

Looking into sex

In [25]:
```
# num_list
# ['age', 'income']
```

In [26]:
```
cats = ['sex', 'marital_status', 'education', 'occupation', 'settlement_size']
sex = summary_stats(column=num_list[0],group=cats[0])
sex
```

Out[26]:

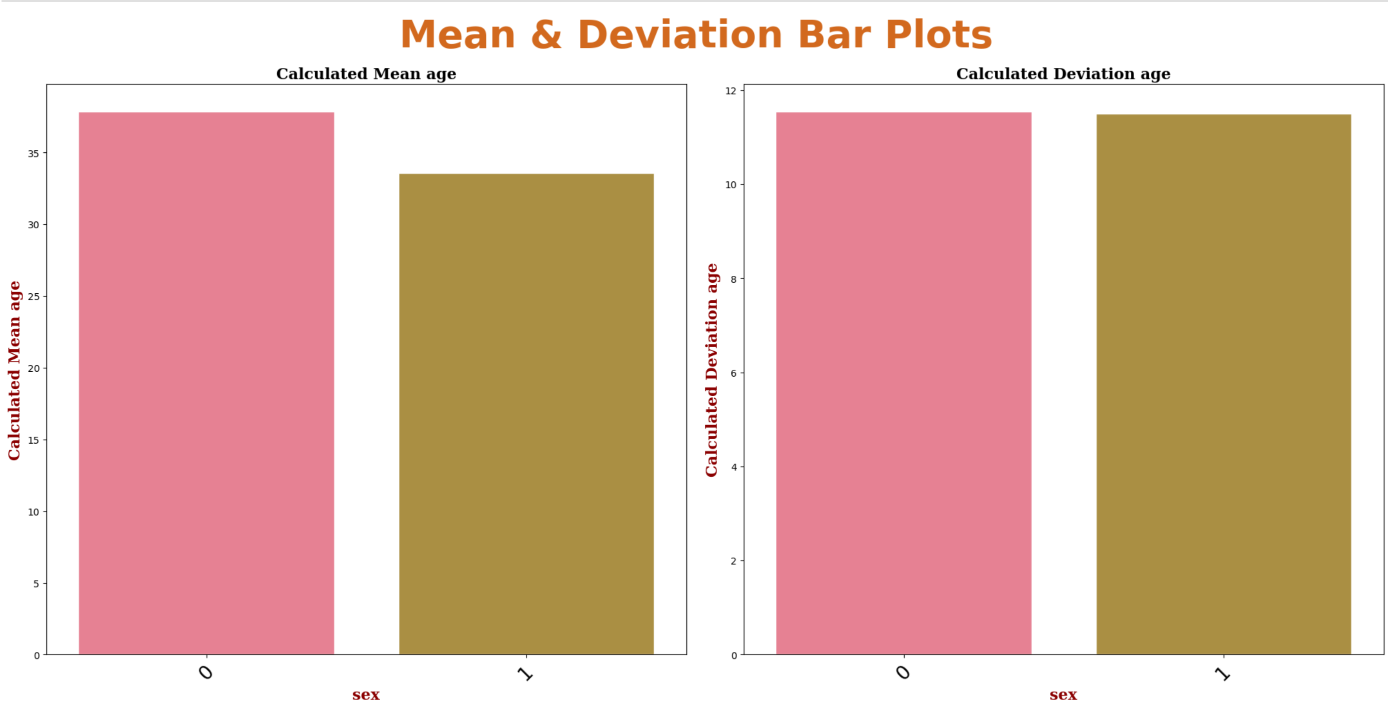
	sex	total_age	average_age	deviation_age	range_age	skewness_level_age
0	0	41132.0	37.874770	11.549013	57	0.856399
1	1	30686.0	33.573304	11.495586	58	1.310032

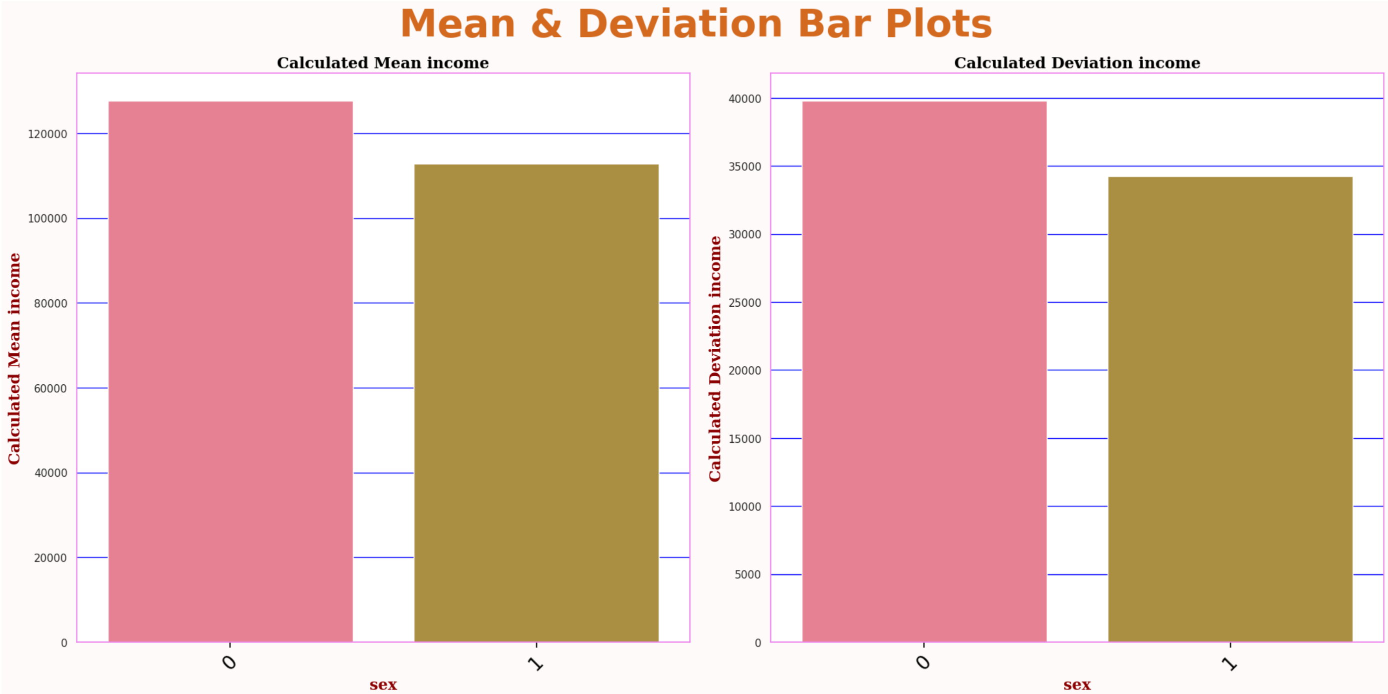
In [27]:
```
cats = ['sex', 'marital_status', 'education', 'occupation', 'settlement_size']
sex = summary_stats(column=num_list[1],group=cats[0])
sex
```

Out[27]:

	sex	total_income	average_income	deviation_income	range_income	skewness_level_income
0	0	138763895	127775.225599	39821.354629	243563	1.062436
1	1	103144943	112850.047046	34266.333929	273532	1.378790

In [28]:
```
for value in num_list:
    plotting_bar(x=value,group='sex')
```





Observations

- Mean age for men is higher than that of females but there deviation is same.
- Men have a higher mean income than that of females but their deviation from mean is quite high; high spread in income for men.
- There is a slight skewness in the income of both genders
- There is a slight skewness in the age of both genders, although men have a lower skewness level than females.

Looking into marital_status

In [29]:
```
marital_status = summary_stats(column=num_list[0],group=cats[1])
marital_status
```

Out[29]:

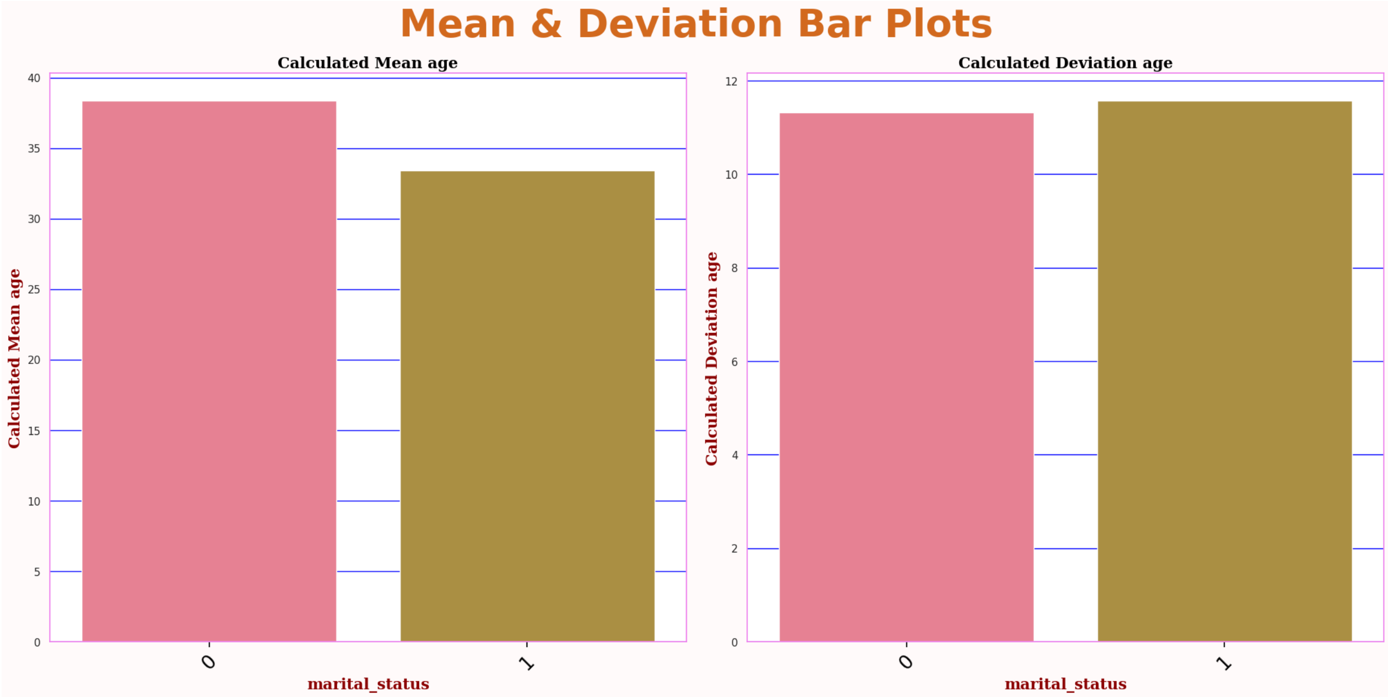
	marital_status	total_age	average_age	deviation_age	range_age	skewness_level_age
0	0	38658.0	38.389275	11.326854	56	0.851805
1	1	33160.0	33.393756	11.579278	58	1.331932

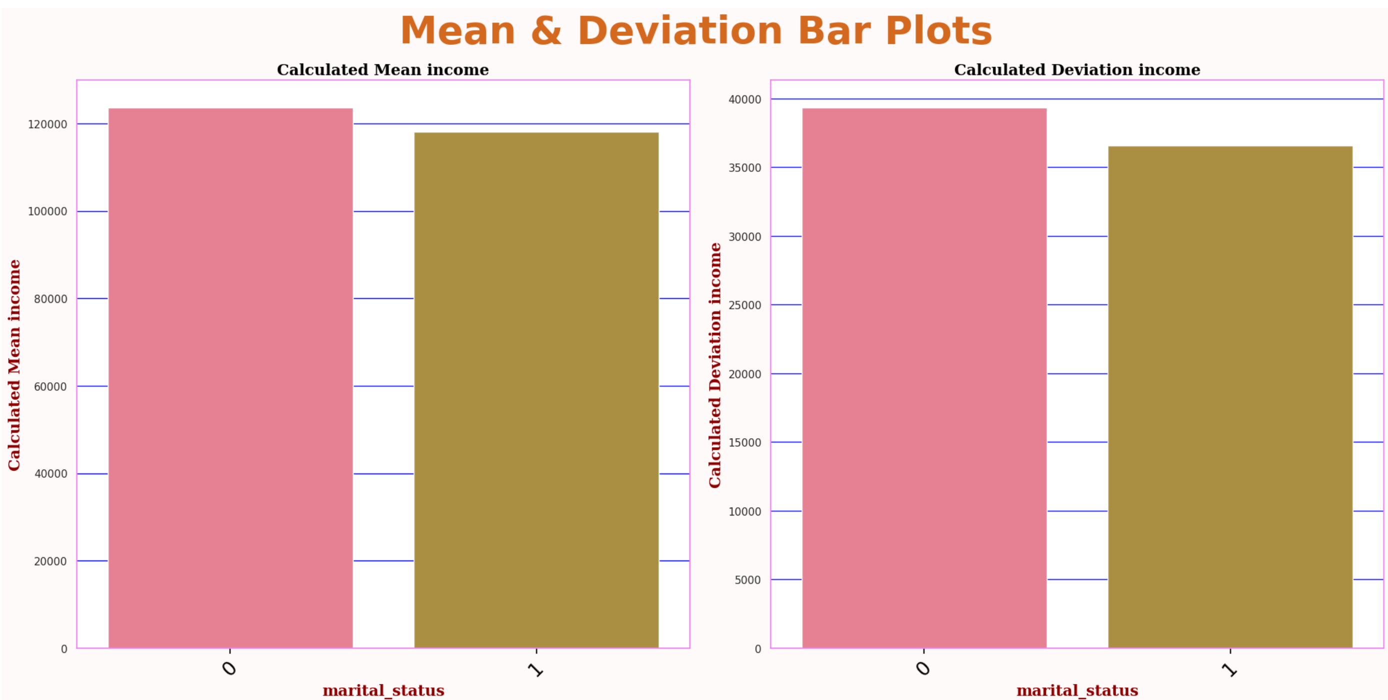
In [30]:
```
marital_status = summary_stats(column=num_list[1],group=cats[1])
marital_status
```

Out[30]:

	marital_status	total_income	average_income	deviation_income	range_income	skewness_level_income
0	0	124602386	123736.232373	39370.686617	250487	1.132365
1	1	117306452	118133.385700	36589.295150	273532	1.258713

In [31]:
```
for value in num_list:
    plotting_bar(x=value,group='marital_status')
```





Observations

- The mean age for single people seems to be greater than than those of the non-single(divorced / separated / married / widowed). Higher life expectancy?
- The age deviation in females is slightly higher than that of males in terms of age; much spread in the data for non-single people.
- Single people have a higher mean income than non-single people.
- Single people have a higher standard deviation that non-people; higher spread in single people.
- Slight skewness in the both marital status in both age and income.

Looking into education

In [32]:
```
education = summary_stats(column=num_list[0],group=cats[2])
education
```

Out[32]:

	education	total_age	average_age	deviation_age	range_age	skewness_level_age
0	0	7866.0	27.407666	3.235134	13	-0.219549
1	1	46211.0	33.341270	8.387785	40	0.518733
2	2	15689.0	53.914089	8.965615	37	0.144253
3	3	2052.0	57.000000	17.381435	51	-0.821601

In [33]:

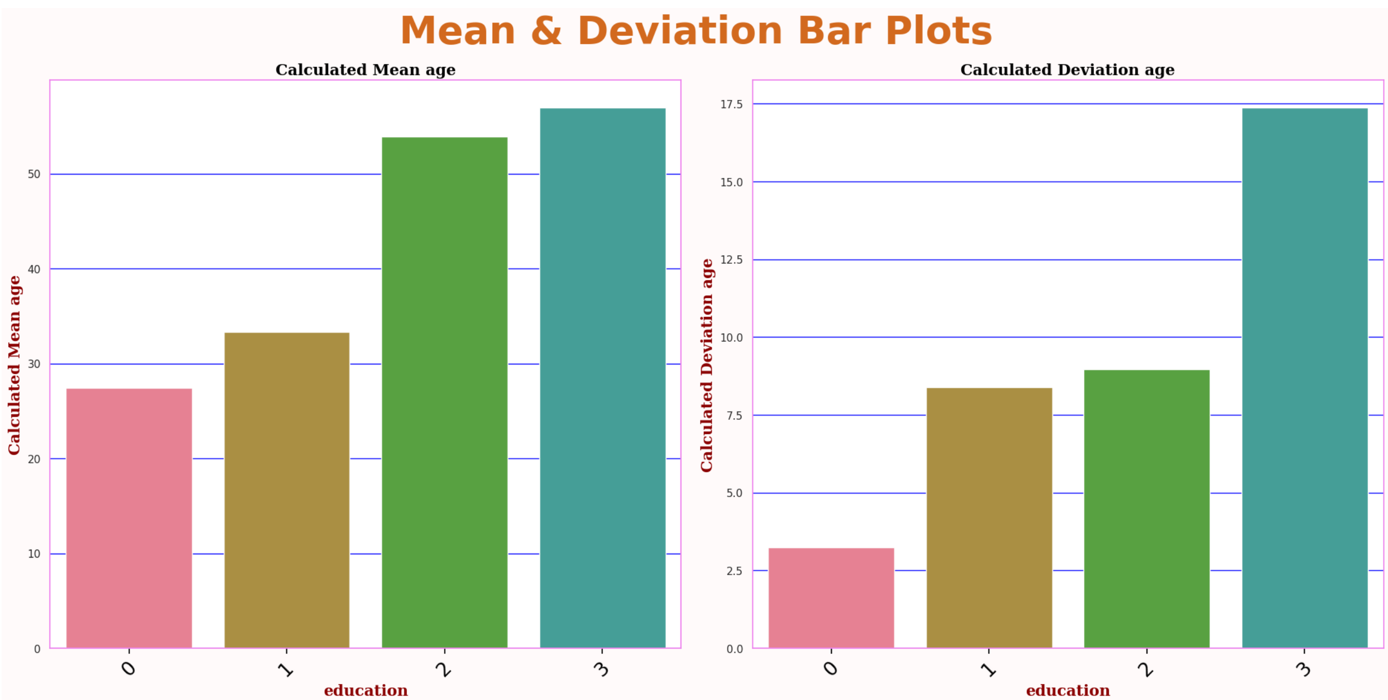
```
education = summary_stats(column=num_list[1],group=cats[2])
education
```

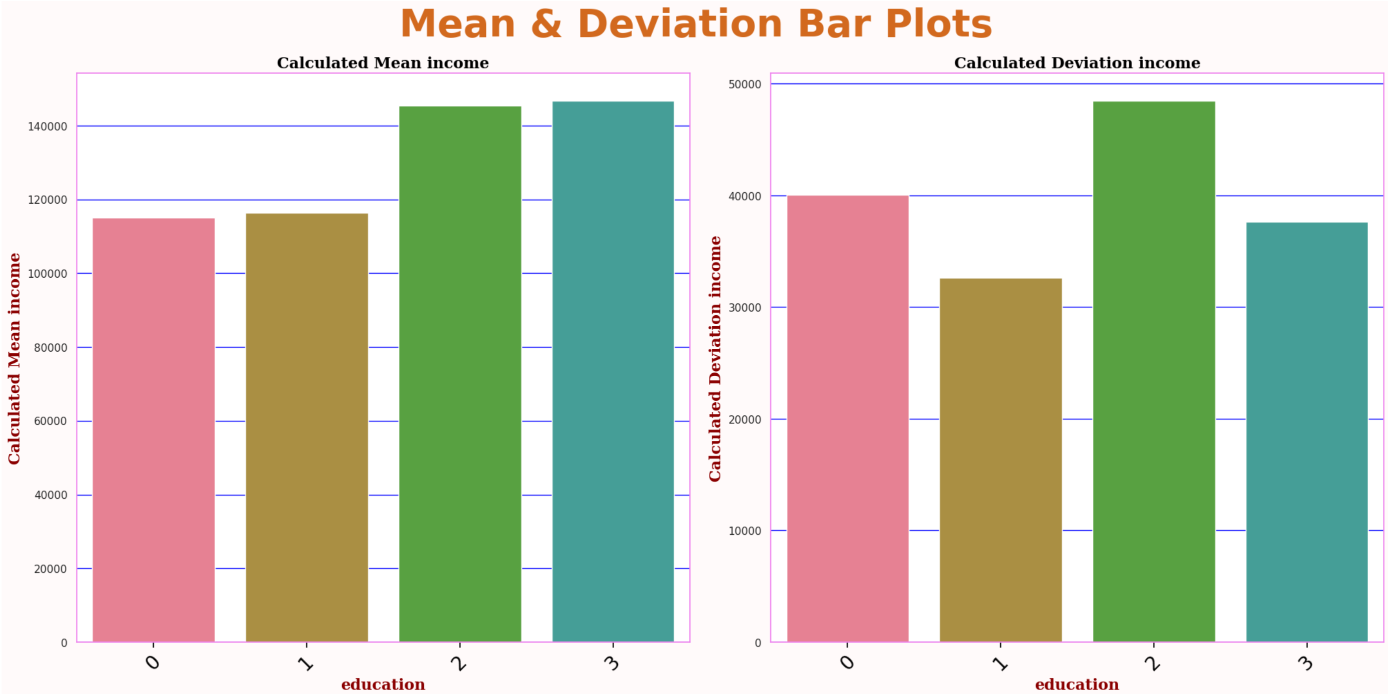
Out[33]:

	education	total_income	average_income	deviation_income	range_income	skewness_level_income
0	0	33024577	115068.212544	40058.777044	211514	0.988842
1	1	161285660	116367.720058	32636.570352	272659	0.950019
2	2	42313141	145405.982818	48501.606672	257482	1.181768
3	3	5285460	146818.333333	37635.665122	144877	-0.303424

In [34]:

```
for value in num_list:
    plotting_bar(x=value,group='education')
```





Observations

- Mean age for education class 0 is the lowest and the highest is education class 3 and same goes for the deviation; less spread for education class 0 and a higher spread for education class 3.
- Mean income for both education class 2 and 3 are almost the same and same goes for education class 0 and 1.
- Standard deviation for educational class 2 is highest amongst all others; higher spread.
- In terms of age, skewness levels are relatively symmetrical except for class 4 which is slighty skewed.
- In terms of income, almost all classes are highly skewed while that of class 4 has the lowest skewness level.

Looking into occupation

In [35]:
```
occupation = summary_stats(column=num_list[0],group=cats[3])
occupation
```

Out[35]:

	occupation	total_age	average_age	deviation_age	range_age	skewness_level_age
0	0	22387.0	35.366509	11.342131	55	0.972772
1	1	39032.0	35.069182	11.424119	53	1.019542
2	2	10399.0	40.940945	12.686259	56	1.007765

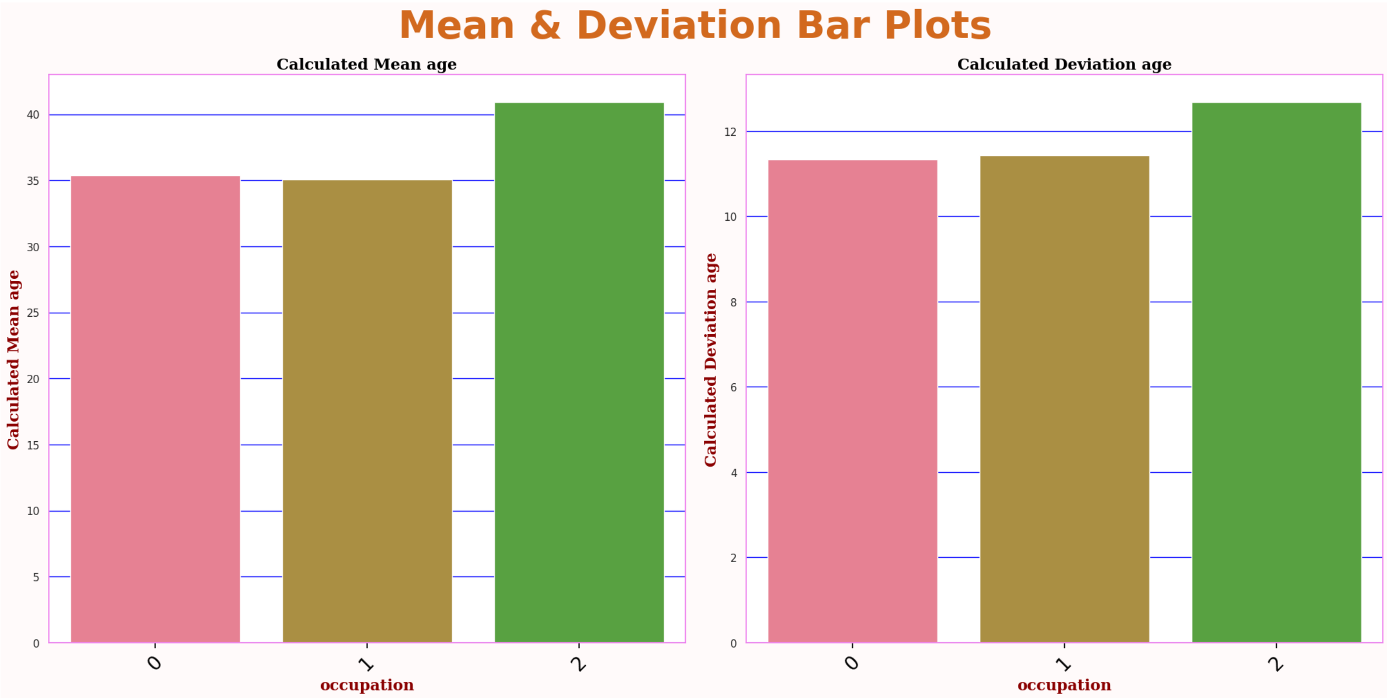
In [36]:
```
occupation = summary_stats(column=num_list[1],group=cats[3])
occupation
```

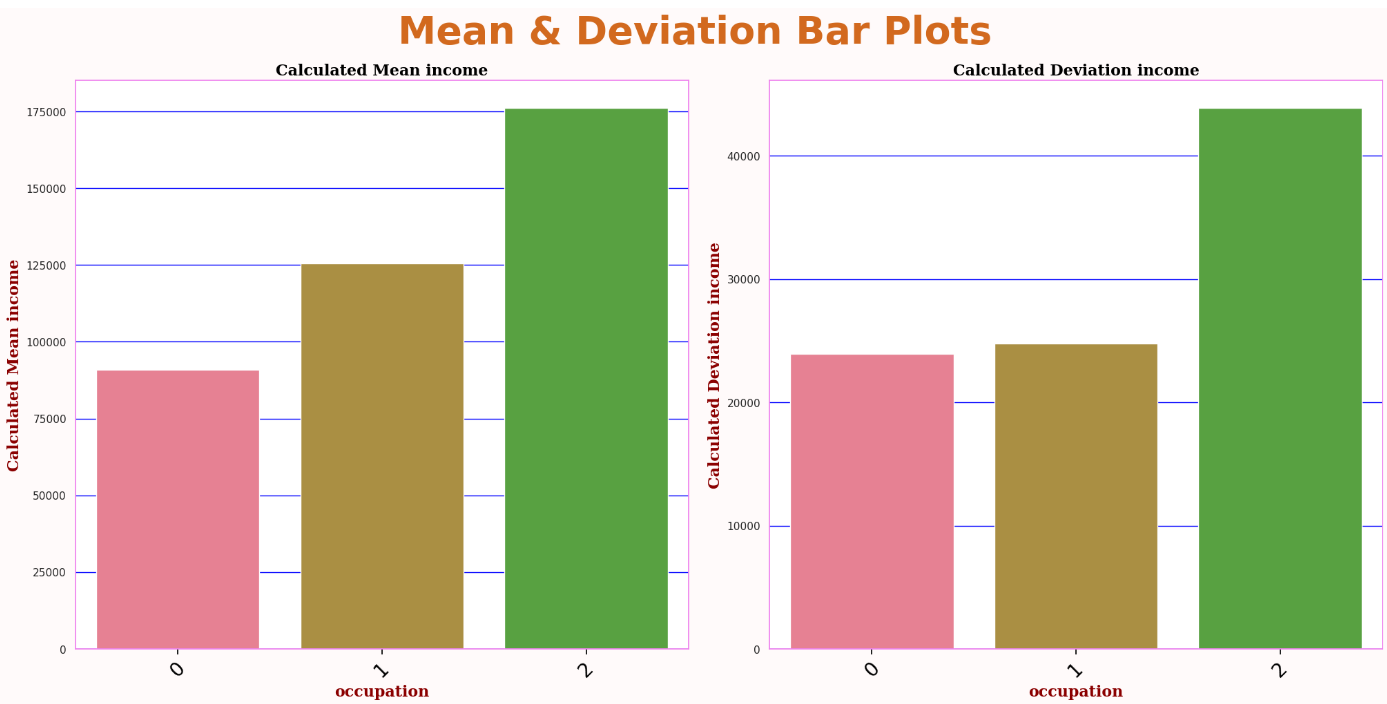
Out[36]:

	occupation	total_income	average_income	deviation_income	range_income	skewness_level_income
0	0	57499968	90837.232227	23943.549449	145171	0.630009
1	1	139653089	125474.473495	24745.006378	185942	1.488324
2	2	44755781	176203.862205	43903.518363	218864	0.882357

In [37]:

```
for value in num_list:
    plotting_bar(x=value,group='occupation')
```





In [38]:

```
print("age")
for value in eda.occupation.sort_values().unique().to_list():
    cond = eda.occupation == value
    print(eda[cond].age.skew())

print()
print("income")
for value in eda.occupation.sort_values().unique().to_list():
    cond = eda.occupation == value
    print(eda[cond].income.skew())
```

```
age
0.9727716442605198
1.019541804530988
1.0077654940285867

income
0.6300092771563237
1.488324165562003
0.882356998311132
```

Observations

- Class 2 is highest in mean and std for age
- class 2 is also highest in mean and std for income; not surprised because class 2 are;
    - management
    - self-employed
    - highly qualified employee
    - officer
- In both age and income, there is some level of high skewness

Looking into settlement_size

In [39]:
```
settlement_size = summary_stats(column=num_list[0],group=cats[4])
settlement_size
```

Out[39]:

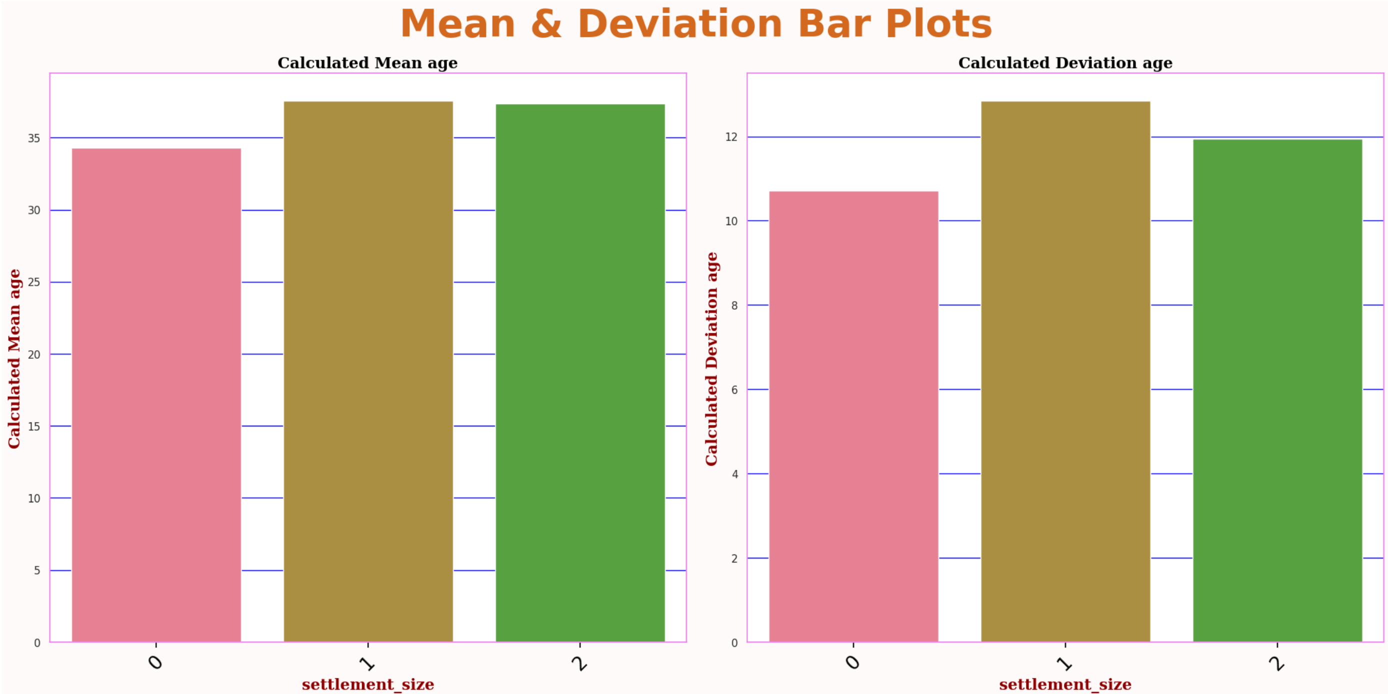
	settlement_size	total_age	average_age	deviation_age	range_age	skewness_level_age
0	0	33920.0	34.297270	10.709856	56	1.113176
1	1	20443.0	37.579044	12.853087	58	0.884697
2	2	17455.0	37.376874	11.939554	52	0.870938

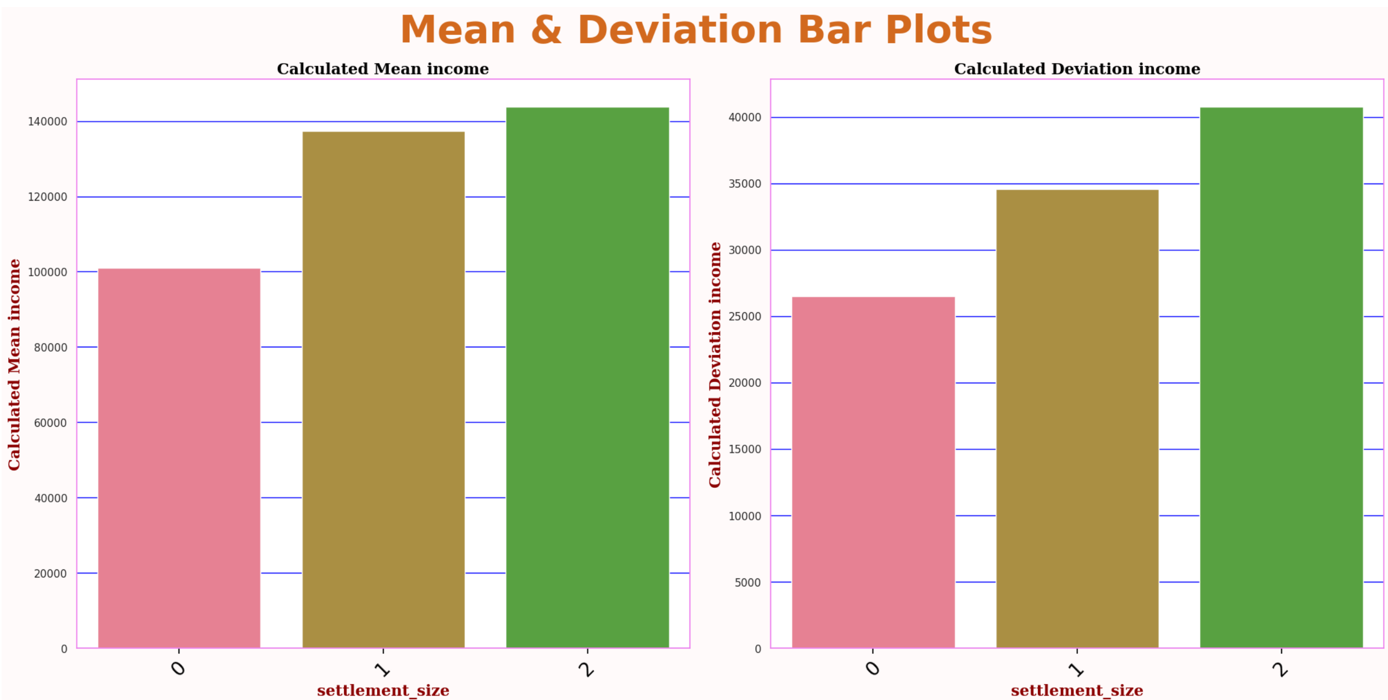
In [40]:
```
settlement_size = summary_stats(column=num_list[1],group=cats[4])
settlement_size
```

Out[40]:

	settlement_size	total_income	average_income	deviation_income	range_income	skewness_level_income
0	0	99950108	101061.787664	26505.919898	183487	0.547405
1	1	74762107	137430.343750	34579.105619	226093	1.473514
2	2	67196623	143889.985011	40781.263863	239877	1.426990

In [41]:
```
for value in num_list:
    plotting_bar(x=value,group='settlement_size')
```





In [42]:

```
# print("age")
# for value in eda.settlement_size.sort_values().unique().to_list():
#     cond = eda.settlement_size == value
#     print(eda[cond].age.skew())

# print()
# print("income")
# for value in eda.settlement_size.sort_values().unique().to_list():
#     cond = eda.settlement_size == value
#     print(eda[cond].income.skew())
```

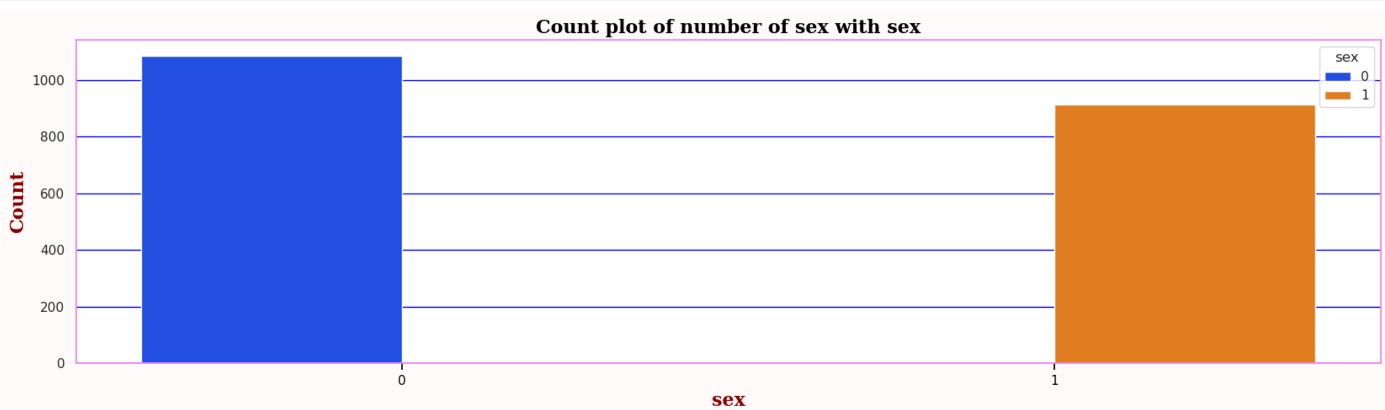
Observations

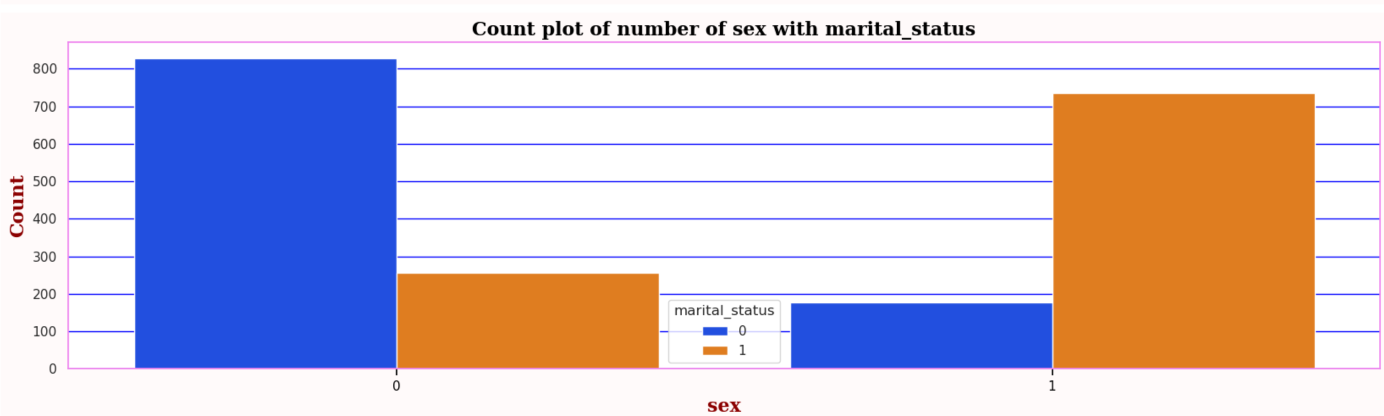
- settlement size 1 has the highest mean and std (high spread) age
- settlement size 2 has the highest mean and std (high spread) income
- age and income have high level of skewness.

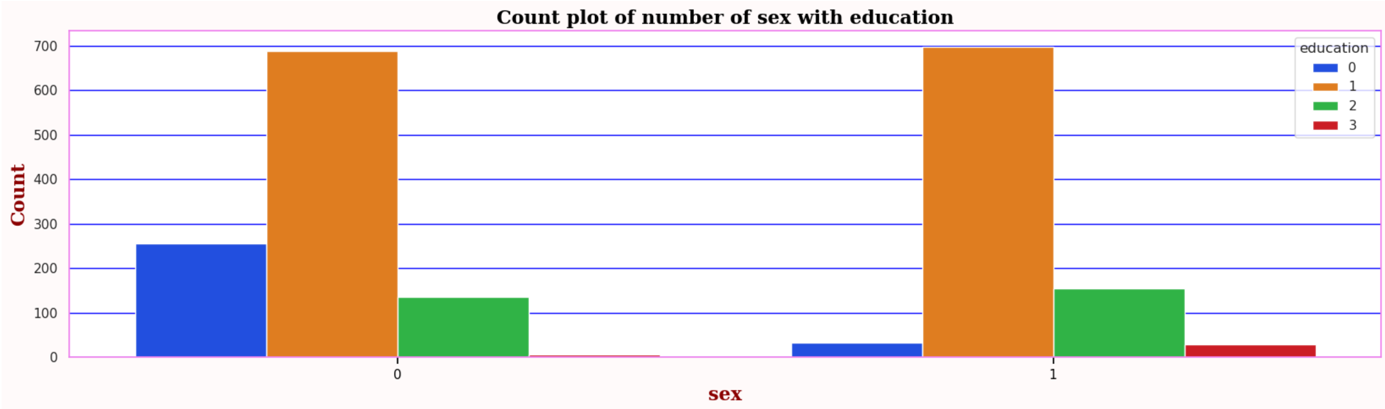
In [43]:
```python
def plotting_count(x:str,hue:str):
    try:
        fig, ax = plt.subplots(figsize=(20,5))
        sns.set_theme(style='whitegrid',rc=rc,palette='bright')

        ordering = eda[x].value_counts()
        # my_palette = sns.color_palette('bright')
        sns.countplot(data=eda, x=x, hue=hue,)
        if x in cat:
            # ax.set_xticklabels(['female','male'],rotation=45,fontsize=20)
            ax.set_title(f'Count plot of number of {x} with {hue}',fontdict=font_title)
            ax.set_xlabel(f"{x}", fontdict=font_label)
            ax.set_ylabel("Count", fontdict=font_label)
        else:
            # ax.set_xticklabels(["A","B","C","D"],rotation=45,fontsize=20)
            ax.set_title(f'Count plot of number of {x} with {hue}',fontdict=font_title)
            ax.set_xlabel(f"{x}", fontdict=font_label)
            ax.set_ylabel("Count", fontdict=font_label)

    except ValueError:
            print(f"The wrong Value was passed\nPlease look are the information below\n")
            eda.info(memory_usage='deep')
    except KeyError:
            print(f"The wrong Key was passed\nPlease look are the information below\n")
            eda.info(memory_usage='deep')
```

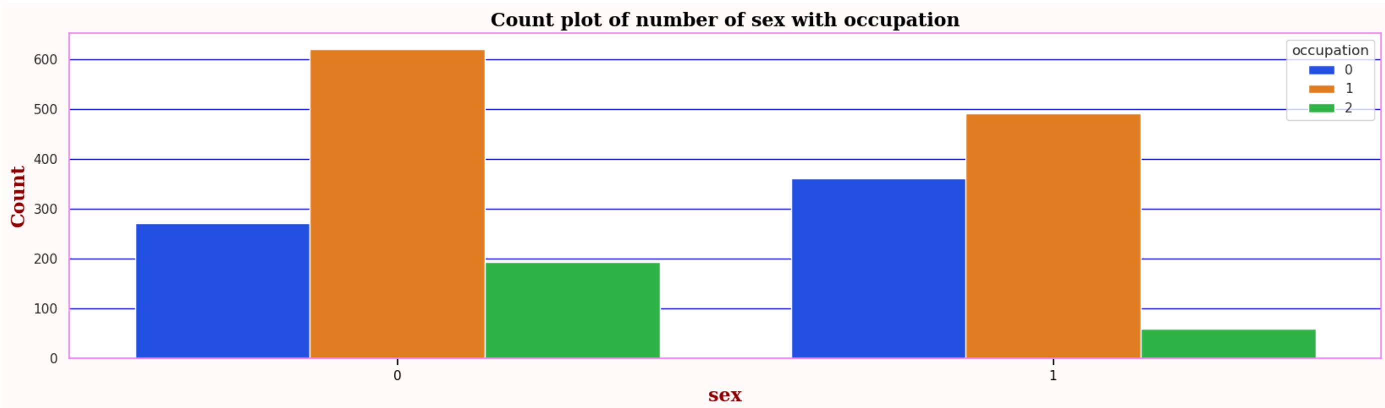
In [44]:
```python
# cat
# ['sex', 'marital_status',
# 'education', 'occupation', 'settlement_size']
```

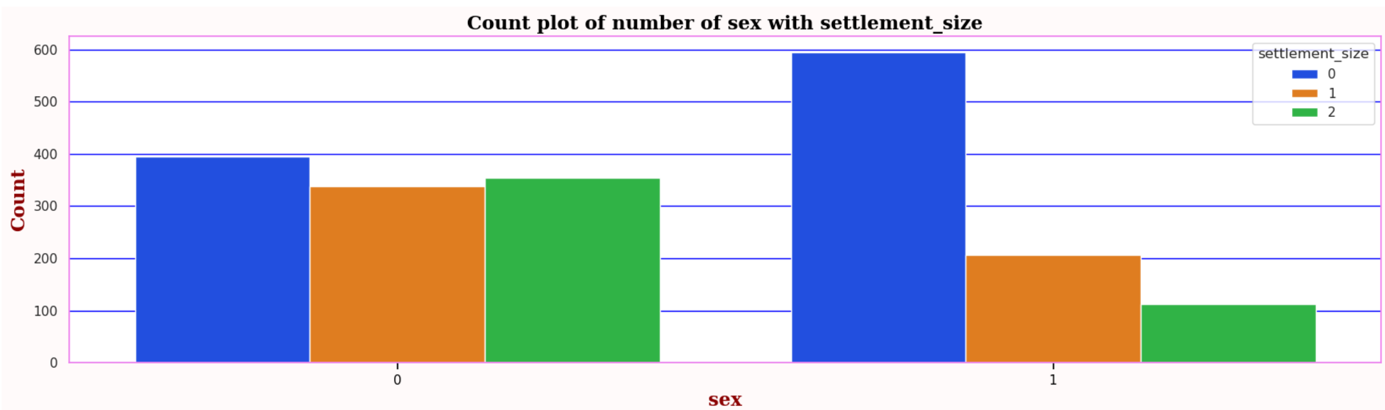
In [45]:
```python
# Will be looking into sex as a group
for x in cat:
    plotting_count('sex',x)
```





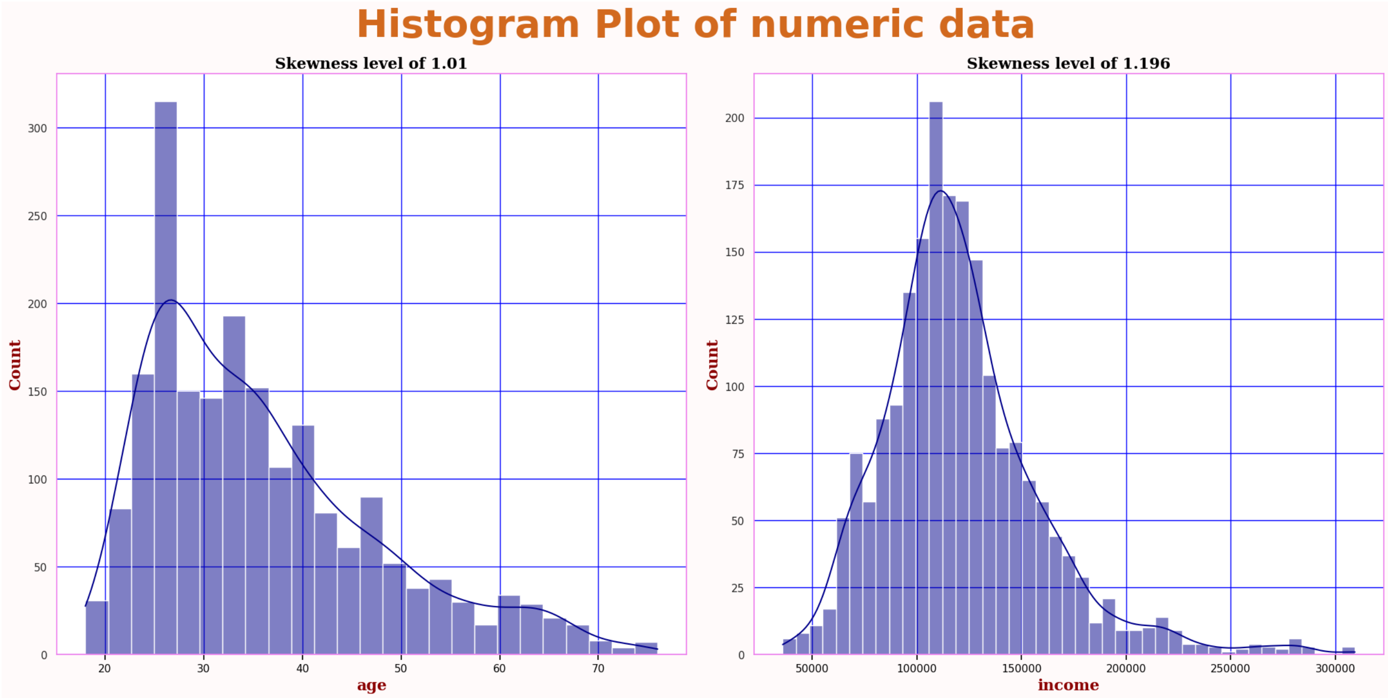






In [46]:

```
fig,ax = plt.subplots(1,2,constrained_layout=True,figsize=(20,10))
ax = ax.ravel()
sns.set_theme(style='whitegrid',rc=rc,palette='bright')

for index,value in enumerate(num_list):
    sns.histplot(data=eda,x=value,ax=ax[index],kde=True,color="darkblue")
    ax[index].set_title(f'Skewness level of {np.around(eda[value].skew(axis=0),3)}',fontdict=fon
    ax[index].set_xlabel(f"{value}", fontdict=font_label)
    ax[index].set_ylabel("Count", fontdict=font_label)
    fig.suptitle(f"Histogram Plot of numeric data",fontdict=font_fig,fontsize=40,fontweight='bol
```



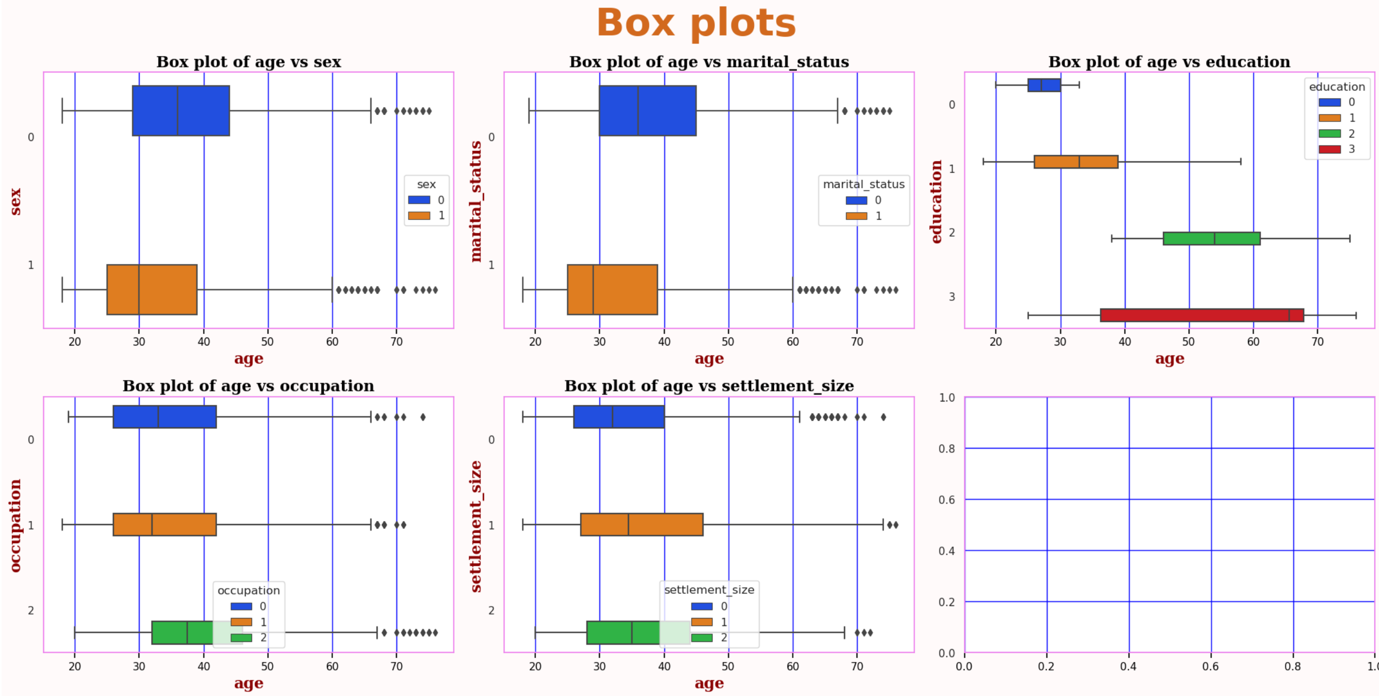
In [47]:
```
len(cat)
```

Out[47]:
```
5
```

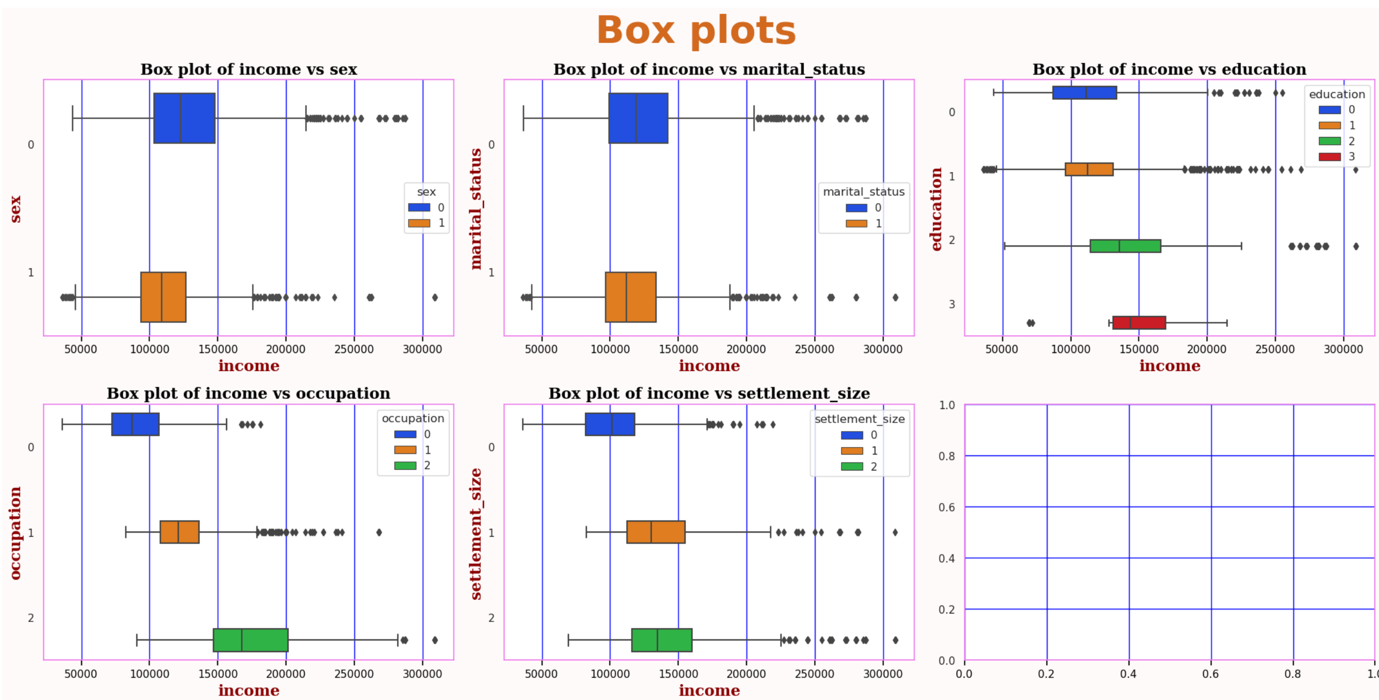
In [48]:
```
# # fig,ax = plt.subplots(2,3,figsize=(20,10),constrained_layout=True)
# # print(ax.shape)
# # print(ax.ravel().shape)
```

In [106…
```
def box_plot(x:str,category:list,data:pd.DataFrame):
    try:
        fig,ax = plt.subplots(2,3,figsize=(20,10),constrained_layout=True)
        sns.set_theme(style='whitegrid',rc=rc,palette='bright')
        ax = ax.ravel()

        for index,value in enumerate(category):
            sns.boxplot(data=data,x=x,y=value,hue=value,ax=ax[index])
            ax[index].set_title(f'Box plot of {x} vs {value}',fontdict=font_title)
            ax[index].set_xlabel(f"{x}", fontdict=font_label)
            ax[index].set_ylabel(f"{value}", fontdict=font_label)
            fig.suptitle("Box plots",fontdict=font_fig,fontsize=40,fontweight='bold')
            plt.legend(loc='center right')
    except ValueError:
            print(f"The wrong Value was passed\nPlease look are the information below\n")
            data.info(memory_usage='deep')
    except KeyError:
            print(f"The wrong Key was passed\nPlease look are the information below\n")
            data.info(memory_usage='deep')
```

In [50]:
```
box_plot('age',cat,eda)
```




```
In [51]: box_plot('income',cat,eda)
```



Clustering

```
In [52]: # Preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# Clustering algo
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram

# Evaluation
from yellowbrick.cluster import KElbowVisualizer
```

In [53]:
```
clustering = eda.copy()
```

In [54]:
```
to_be_transformed = ['age','income']
```

In [55]:
```
columns = eda.columns.to_list()
```

In [56]:
```
indexes = [columns.index(column) for column in to_be_transformed]
print(indexes)
```

```
[2, 4]
```

In [57]:
```
# Using column transformation with scaling
column_transformer = ColumnTransformer(
    transformers=[
        ('standard_scaler',StandardScaler(),indexes)
    ], remainder="passthrough"
)
```

In [58]:
```
scaled = column_transformer.fit_transform(clustering)
```

In [59]:
```
clustering[:2]
```

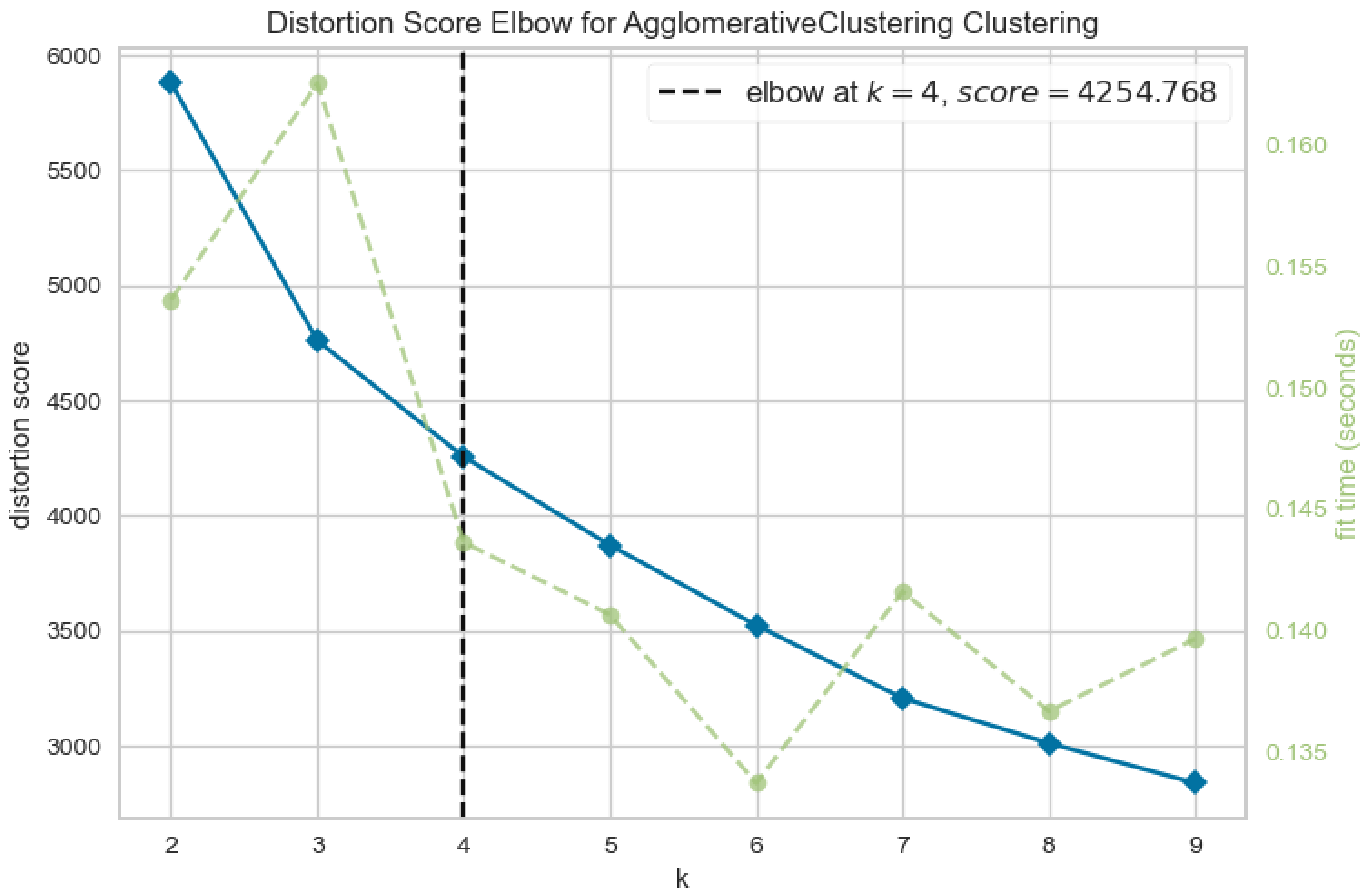
Out[59]:

	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

In [60]:
```
scaled[:2]
# Once the transformation is applied,
# the chosen indices are shifted forward.
# Thereby rearranging the data,
# manual inspection would be needed to convert to
# dataframe if desired
```

Out[60]:
```
array([[ 2.65361447,  0.09752361,  0.        ,  0.        ,  2.        ,
         1.        ,  2.        ],
       [-1.18713209,  0.78265438,  1.        ,  1.        ,  1.        ,
         1.        ,  2.        ]])
```

In [61]:
```
agg = AgglomerativeClustering()
visualiser = KElbowVisualizer(agg,k=(2,10),metric="distortion")
visualiser.fit(scaled)
visualiser.show()
```



Out[61]: <AxesSubplot:title={'center':'Distortion Score Elbow for AgglomerativeClustering Clustering'}, xlabel='k', ylabel='distortion score'>

In [62]:
```
k_data = {
    "k_value": visualiser.k_values_,
    "k_scores":visualiser.k_scores_
}
Elbow_values = pd.DataFrame(k_data)
Elbow_values
```

Out[62]:

	k_value	k_scores
0	2	5876.550594
1	3	4759.215475
2	4	4254.767819
3	5	3871.466935
4	6	3523.527618
5	7	3206.905150
6	8	3011.701593
7	9	2838.581438

In [63]:
```
# Would use a k value of 4
my_pipe = Pipeline(
    [
        ("my_column_transformer",column_transformer),
        ("agg",AgglomerativeClustering(n_clusters=4))
    ]
)
```

In [64]:
```python
result = my_pipe.fit(clustering)
```

In [65]:
```python
my_clusters = result.named_steps['agg']
scaled_data = result.named_steps['my_column_transformer'].transform(clustering)
```

In [66]:
```python
scaled_data[:2]
# 7 columns
```

Out[66]:
```
array([[ 2.65361447,  0.09752361,  0.        ,  0.        ,  2.        ,
         1.        ,  2.        ],
       [-1.18713209,  0.78265438,  1.        ,  1.        ,  1.        ,
         1.        ,  2.        ]])
```

In [67]:
```python
my_clusters.labels_
```

Out[67]:
```
array([2, 1, 0, ..., 0, 0, 0], dtype=int64)
```

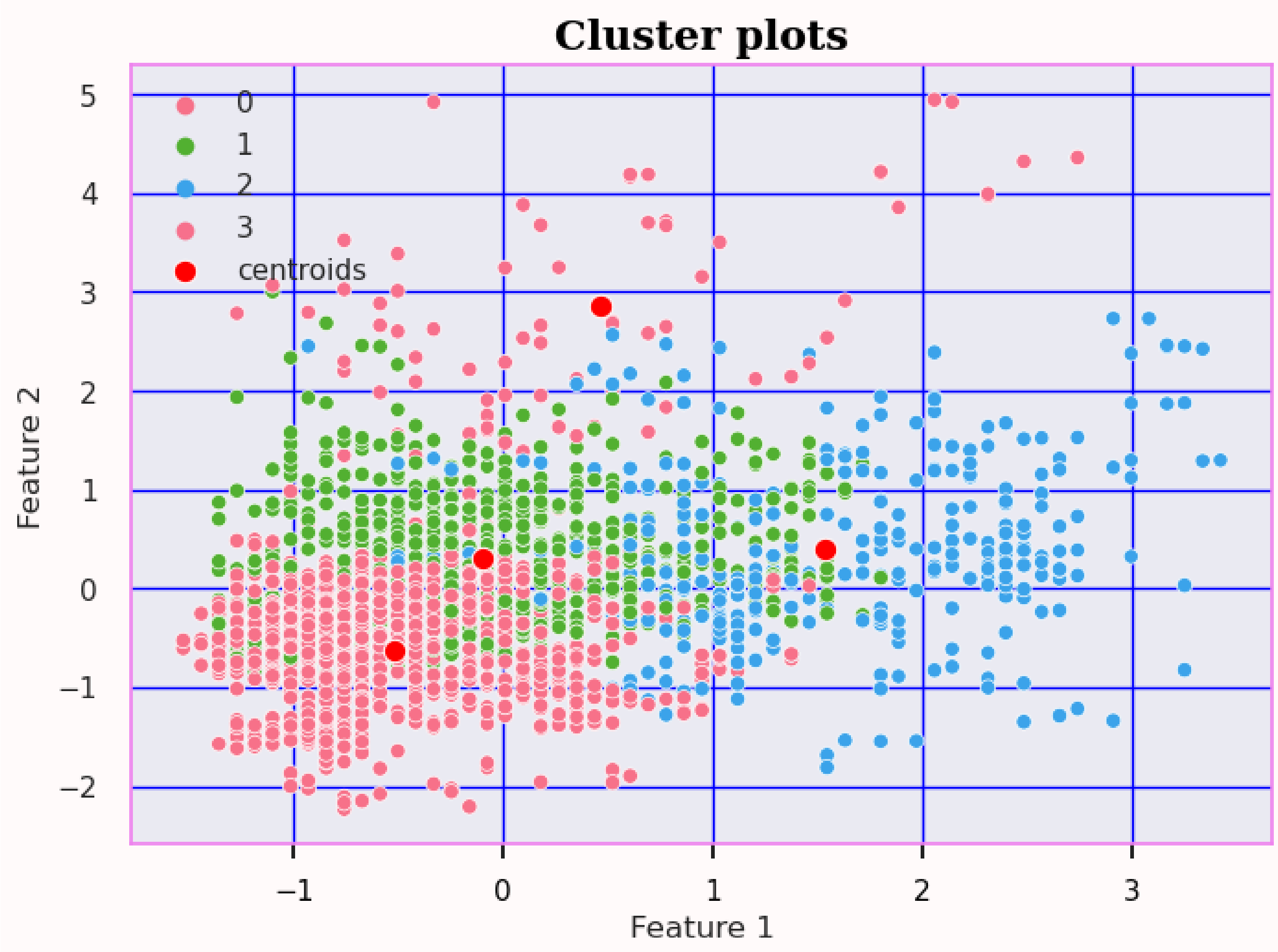
In [68]:
```python
# Computing cluster centers by mean
cluster_centers = []
for cluster_label in np.unique(my_clusters.labels_):
    cluster_points = scaled_data[my_clusters.labels_ == cluster_label ]
    center = np.mean(cluster_points,axis=0)
    cluster_centers.append(center)
```

In [69]:
```python
cluster_centers = np.array(cluster_centers)
cluster_centers
```

Out[69]:
```
array([[-0.52246353, -0.62805848,  0.64971751,  0.62033898,  0.84971751,
         0.45084746,  0.14011299],
       [-0.10193467,  0.29716587,  0.19160839,  0.3020979 ,  0.81258741,
         1.14545455,  1.35244755],
       [ 1.5367348 ,  0.40623614,  0.59815951,  0.66871166,  2.05214724,
         0.8190184 ,  0.79754601],
       [ 0.46335089,  2.85034029,  0.09459459,  0.13513514,  1.        ,
         1.83783784,  1.71621622]])
```

In [70]:
```python
def cluster_plots(x:int,y:int,cluster_data):
    sns.set_theme(rc=rc,style='darkgrid')
    # data points
    sns.scatterplot(x= cluster_data[:,x],
                    y= cluster_data[:,y],
                    palette='husl',
                    hue=my_clusters.labels_)

    # cluster centers
    sns.scatterplot(cluster_centers[:,x],
                    cluster_centers[:,y],
                    markers='X',s=80,label="centroids",
                    color="red")

    # Styling
    plt.xlabel("Feature 1")
    plt.ylabel("Feature 2")
    plt.title("Cluster plots",fontdict=font_title)
    plt.legend(loc='upper left')
```

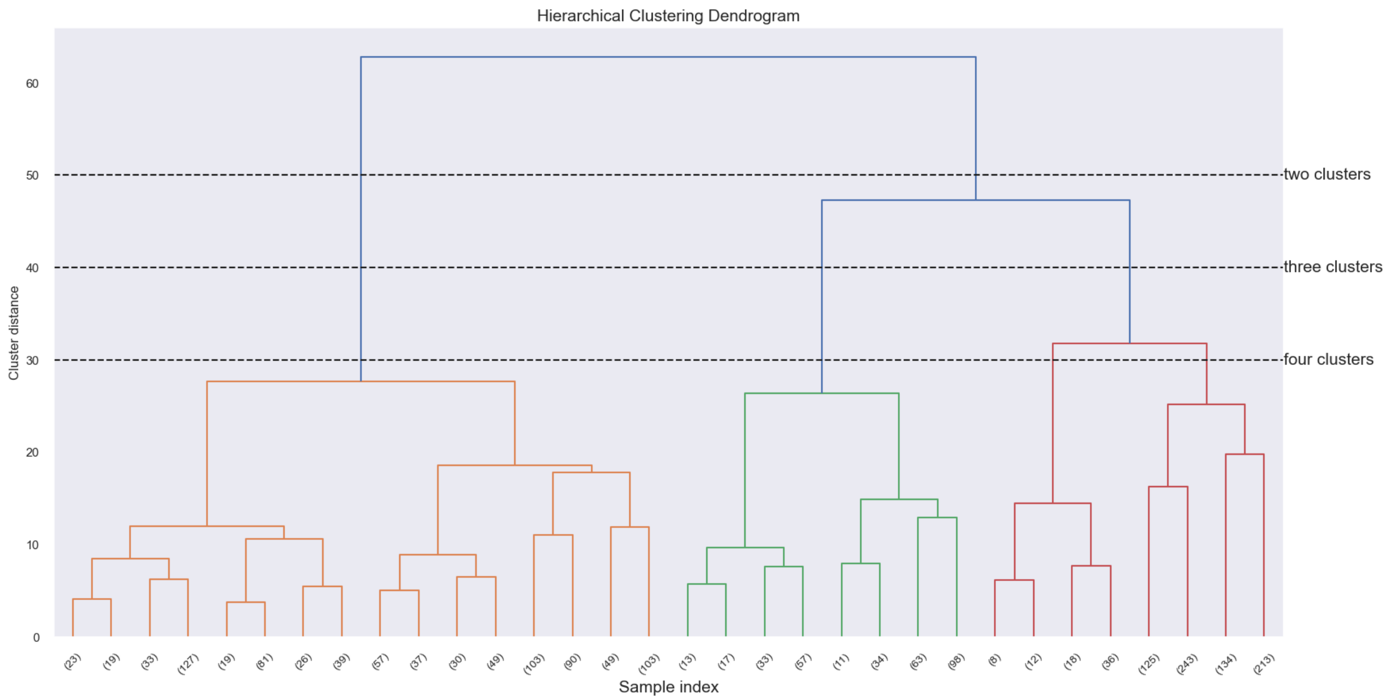
In [71]:
```python
cluster_plots(0,1,scaled_data)
```



In [72]:

```
def plot_dendrogram(model, **kwargs):
    counts = np.zeros(model.children_.shape[0])
    n_samples =len(model.labels_)
    for i,merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack(
        [model.children_,model.distances_,counts]
    ).astype(float)

    # plot corresponding dendrogram
    dendrogram(linkage_matrix,**kwargs)


sns.set_theme(style='dark')
fig,ax = plt.subplots(figsize=(20,10))
# Setting the algorithm
ac = AgglomerativeClustering(distance_threshold =0,n_clusters=None)
agg = ac.fit(scaled_data)
plt.title("Hierarchical Clustering Dendrogram",fontdict={'size':15})
# plot the top 4 levels
plot_dendrogram(agg,truncate_mode='level',p=4)
```

```
ax = plt.gca()
bounds = ax.get_xbound()
ax.plot(bounds, [50, 50], '--', c='k')
ax.plot(bounds, [40,40], '--', c='k')
ax.plot(bounds, [30, 30], '--', c='k')
ax.text(bounds[1],50,'two clusters',va ='center',fontdict={'size':15})
ax.text(bounds[1],40,'three clusters', va ='center',fontdict={'size':15})
ax.text(bounds[1],30,'four clusters', va ='center',fontdict={'size':15})
# plt.xlabel("Number of points in node(or index of point if no parenthesis ).")
plt.xlabel("Sample index",fontdict={'size':15})
# plt.xticks(rotation=45, ha="right",fontsize=10)
plt.xticks(fontsize=10)
plt.ylabel("Cluster distance")
plt.show()
```



In [73]:
```
# def threed_cluster_plots(x:int,y:int,z:int, cluster_data):
#     fig = px.scatter_3d(cluster_data,
#                         x= cluster_data[:,x],
#                         y= cluster_data[:,y],
#                         z=cluster_data[:,z],
#                         opacity=1,
#                         size_max=18,
#                         symbol=my_clusters.labels_,
#                         color=my_clusters.labels_)

#     fig.update_layout(scene = dict(
#                         xaxis_title="Feature 1",
#                         yaxis_title="Feature 2",
#                         zaxis_title="Feature 3"
#                         ),
#                         width=700,
#                         margin=dict(r=20, b=10, l=10, t=10)
#                         )

#     # Hide colorbar axis
#     fig.update_layout(coloraxis_showscale=False)

#     fig.show()

# threed_cluster_plots(0,1,3,scaled_data)
```

Analysing the cluster labels

In [74]:
```
clustering['cluster_labels'] = my_clusters.labels_
clustering.head(5)
```

Out[74]:

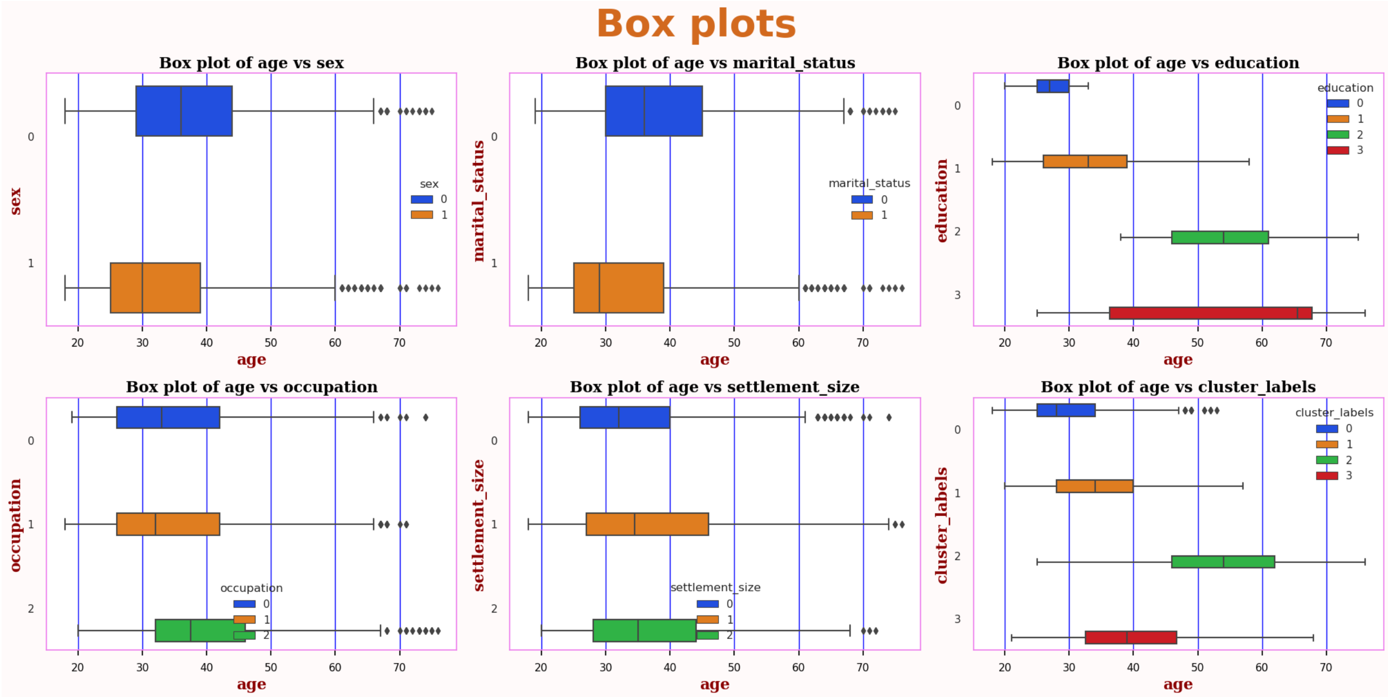
	sex	marital_status	age	education	income	occupation	settlement_size	cluster_labels
0	0	0	67	2	124670	1	2	2
1	1	1	22	1	150773	1	2	1
2	0	0	49	1	89210	0	0	0
3	0	0	45	1	171565	1	1	1
4	0	0	53	1	149031	1	1	1

In [75]:
```
clustering['cluster_labels'] = clustering.cluster_labels.astype("category")
clustering.info(memory_usage='deep')
```

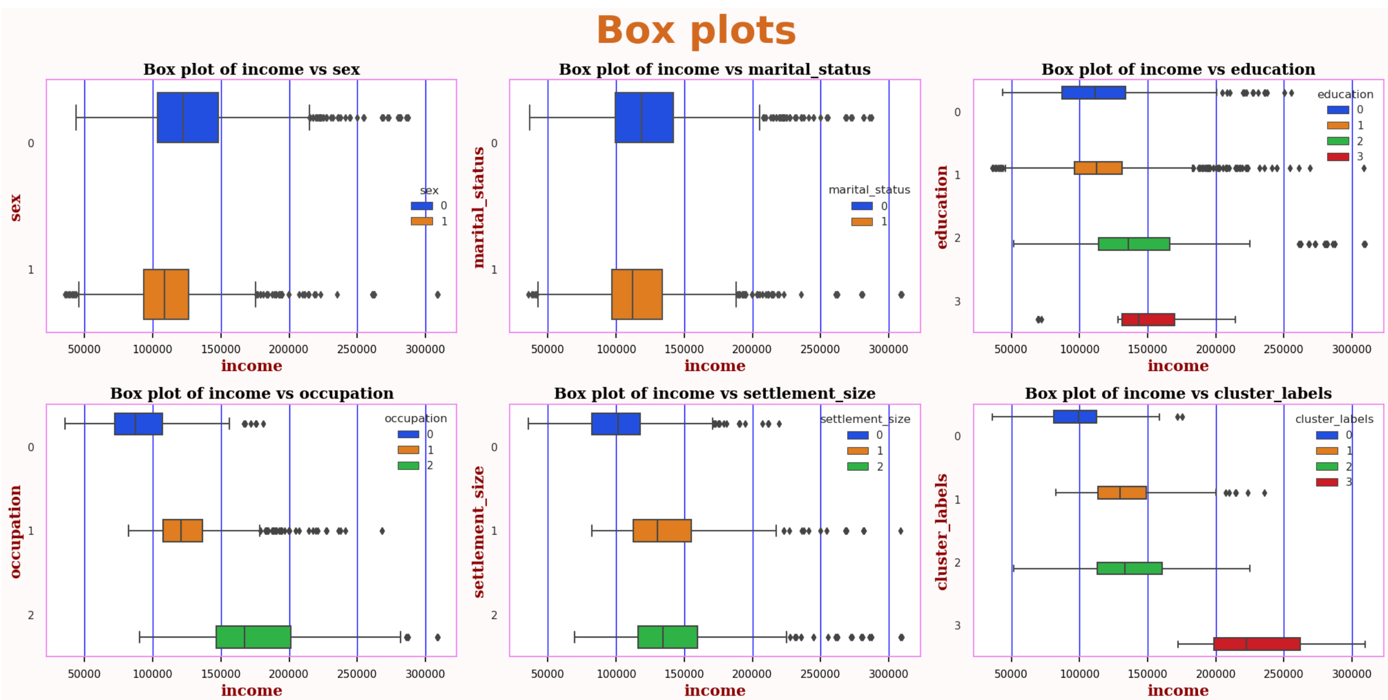
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype   
---  ------           --------------  -----   
 0   sex              2000 non-null   category
 1   marital_status   2000 non-null   category
 2   age              2000 non-null   int8    
 3   education        2000 non-null   category
 4   income           2000 non-null   int32   
 5   occupation       2000 non-null   category
 6   settlement_size  2000 non-null   category
 7   cluster_labels   2000 non-null   category
dtypes: category(6), int32(1), int8(1)
memory usage: 22.5 KB
```

In [76]:
```
cat2 = clustering.select_dtypes(include=pd.CategoricalDtype)
```

In [79]:
```
box_plot('age',cat2,clustering)
```



In [78]:
```python
box_plot('income',cat2,clustering)
```



In [80]:
```python
cluster_anal = clustering.copy()
```

In [82]:
```python
cluster_anal.head()
```

Out[82]:

	sex	marital_status	age	education	income	occupation	settlement_size	cluster_labels
0	0	0	67	2	124670	1	2	2
1	1	1	22	1	150773	1	2	1
2	0	0	49	1	89210	0	0	0
3	0	0	45	1	171565	1	1	1
4	0	0	53	1	149031	1	1	1

In [89]:
```python
# ['sex', 'marital_status',
# 'education', 'occupation', 'settlement_size']
mappings  = {
    'sex':{
        0: 'male',
        1:'female'
    },

    'marital_status':{
        0:'single',1:"non_single"
    },
    'education':{
        0:'unknown',
        1:"high_school",
        2:"university",
        3:"graduate_school"
    },
    "occupation":{
        0:'unemployed',
        1:"skilled",
        2:'management'
    },
    "settlement_size":{
        0:'small_city',
        1:"mid_size_city",
        2:"big_city"
    }
}
```

In [93]:
```python
mappings['education']
```

Out[93]:
```
{0: 'unknown', 1: 'high_school', 2: 'university', 3: 'graduate_school'}
```

In [94]:
```python
for col in list(mappings.keys()):
    cluster_anal[col] = cluster_anal[col].map(mappings[col])
```

In [95]:
```python
cluster_anal
```

Out[95]:

	sex	marital_status	age	education	income	occupation	settlement_size	cluster_labels
0	male	single	67	university	124670	skilled	big_city	2
1	female	non_single	22	high_school	150773	skilled	big_city	1
2	male	single	49	high_school	89210	unemployed	small_city	0
3	male	single	45	high_school	171565	skilled	mid_size_city	1
4	male	single	53	high_school	149031	skilled	mid_size_city	1
...	...	...	...	...	...	...	...	...
1995	female	single	47	high_school	123525	unemployed	small_city	2
1996	female	non_single	27	high_school	117744	skilled	small_city	0
1997	male	single	31	unknown	86400	unemployed	small_city	0
1998	female	non_single	24	high_school	97968	unemployed	small_city	0
1999	male	single	25	unknown	68416	unemployed	small_city	0

2000 rows × 8 columns

In [96]:
```
cat2
```

Out[96]:

	sex	marital_status	education	occupation	settlement_size	cluster_labels
0	0	0	2	1	2	2
1	1	1	1	1	2	1
2	0	0	1	0	0	0
3	0	0	1	1	1	1
4	0	0	1	1	1	1
...	...	...	...	...	...	...
1995	1	0	1	0	0	2
1996	1	1	1	1	0	0
1997	0	0	0	0	0	0
1998	1	1	1	0	0	0
1999	0	0	0	0	0	0

2000 rows × 6 columns

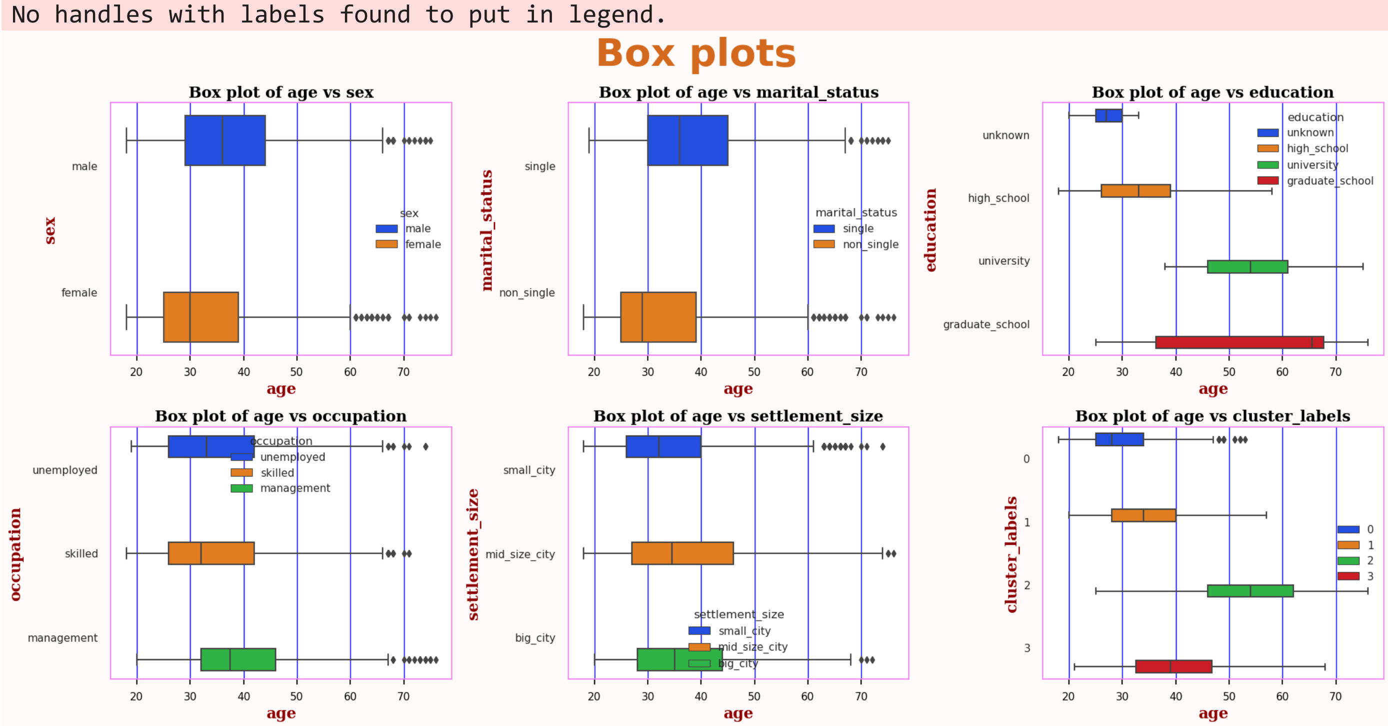
loc	value
'best'	0
'upper right'	1
'upper left'	2
'lower left'	3
'lower right'	4

loc	value
'right'	5
'center left'	6
'center right'	7
'lower center'	8
'upper center'	9
'center'	10

In [108…

```
box_plot('age',cat2,cluster_anal)
```

```
No handles with labels found to put in legend.
No handles with labels found to put in legend.
No handles with labels found to put in legend.
No handles with labels found to put in legend.
No handles with labels found to put in legend.
```



Observations

- Those in cluster 2 seems to be older.
- Those in cluster 0 seems to be younger.
- Now the question is what features contains the above observastions?

In [110…

```
cond_cluster2 = (cluster_anal.cluster_labels == 2)
cluster_anal[cond_cluster2].sample(n=10,random_state=50)
```

Out[110]:

	sex	marital_status	age	education	income	occupation	settlement_size	cluster_labels
163	male	single	70	university	224998	management	big_city	2
944	female	non_single	46	university	121501	skilled	small_city	2
137	male	single	66	university	126003	unemployed	small_city	2
27	female	non_single	42	university	163025	skilled	mid_size_city	2
1110	male	non_single	46	university	168904	management	mid_size_city	2

So it seems those in cluster 2 have a university degree?

In [120…

```
(cluster_anal[cond_cluster2].value_counts().sum())
# There are 326 data points
(cluster_anal[cond_cluster2].education == 'unknown').value_counts()
# There none with "unknown" education
```

Out[120]:

```
False    326
Name: education, dtype: int64
```

In [122…

```
(cluster_anal[cond_cluster2].education == 'high_school').value_counts()
```

Out[122]:

```
False    307
True      19
Name: education, dtype: int64
```

In [124…

```
(cluster_anal[cond_cluster2].education == 'university').value_counts()
```

Out[124]:

```
True     271
False     55
Name: education, dtype: int64
```

In [123…

```
(cluster_anal[cond_cluster2].education == 'graduate_school').value_counts()
```

Out[123]:

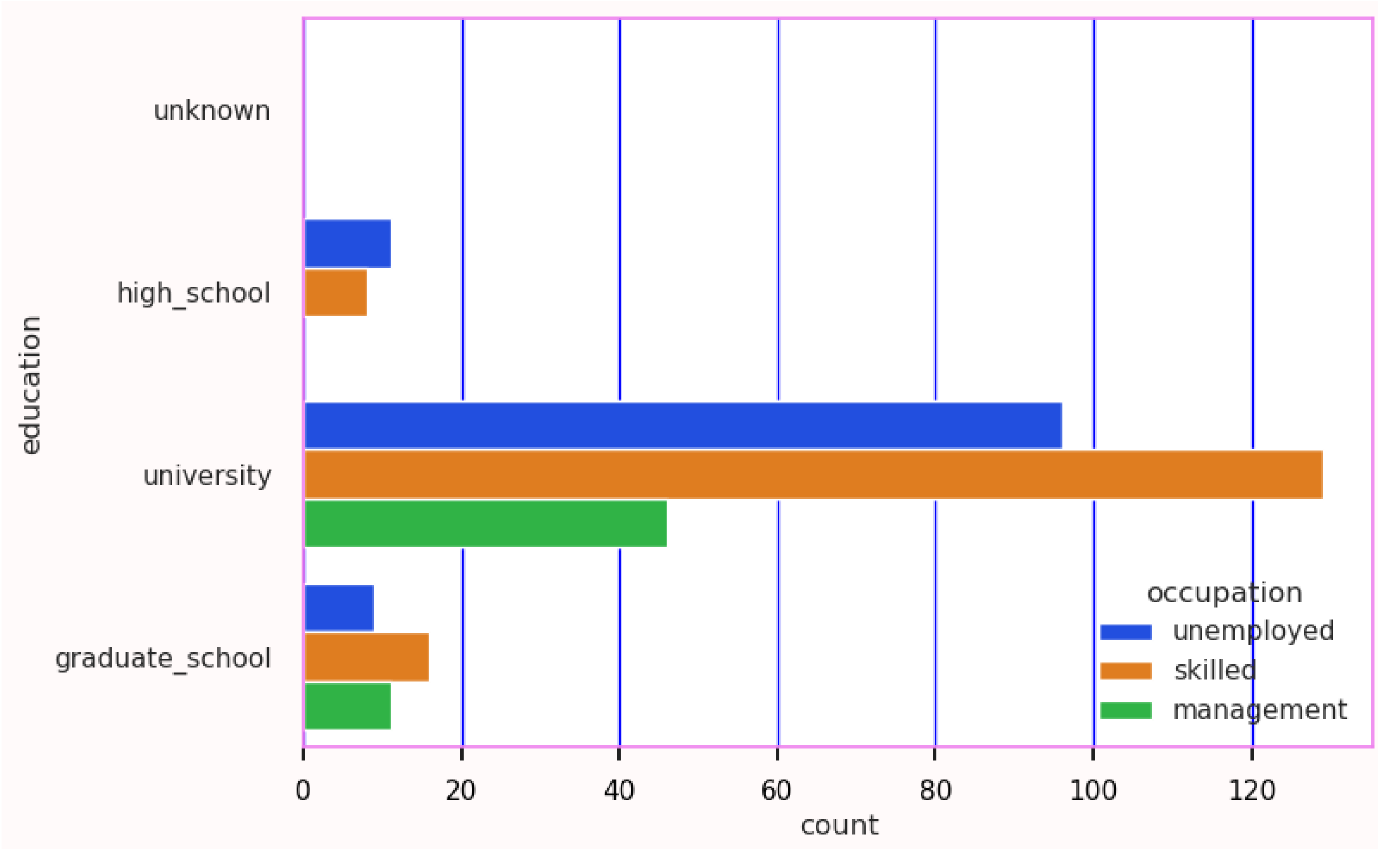
```
False    290
True      36
Name: education, dtype: int64
```

In [129…

```
sns.countplot(
    data=cluster_anal[cond_cluster2],
    y='education',
    hue='occupation'
)
```

Out[129]:

```
<AxesSubplot:xlabel='count', ylabel='education'>
```



So those in cluster 2 mostly have university degree and are skilled workers.

In [128…

```
cond_cluster0 = (cluster_anal.cluster_labels == 0)
cluster_anal[cond_cluster0].sample(n=10,random_state=50)
```

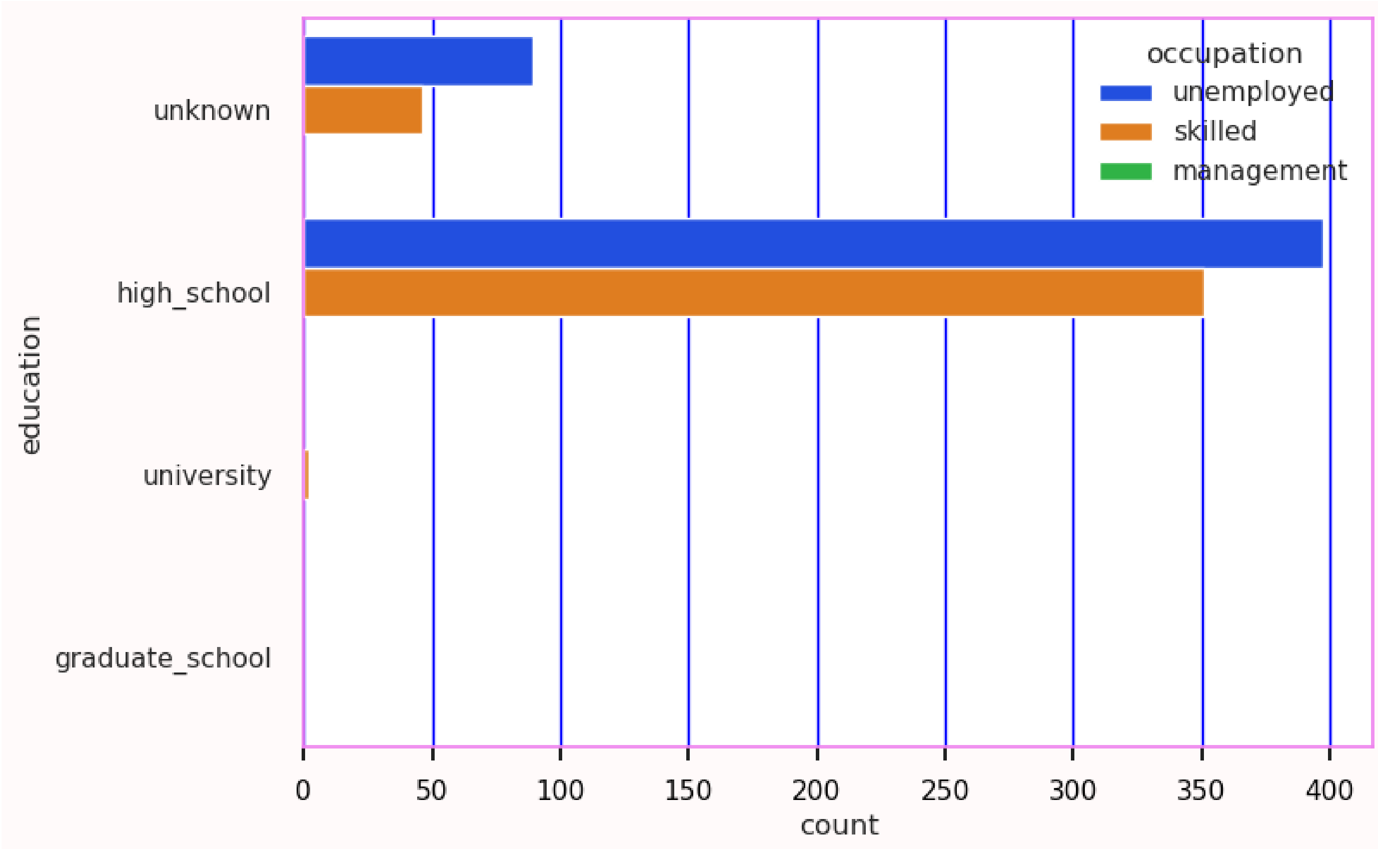
Out[128]:

	sex	marital_status	age	education	income	occupation	settlement_size	cluster_labels
1879	male	single	29	unknown	103439	skilled	small_city	0
1896	female	non_single	26	high_school	109887	skilled	small_city	0
1804	male	non_single	33	high_school	83687	unemployed	small_city	0
1620	female	single	31	unknown	76384	unemployed	small_city	0
364	male	single	25	unknown	43684	unemployed	small_city	0
1622	female	non_single	35	high_school	93155	unemployed	small_city	0
1323	female	non_single	25	high_school	94075	skilled	small_city	0
25	male	single	36	high_school	71909	unemployed	small_city	0
1768	female	single	31	unknown	72361	unemployed	small_city	0
1952	female	single	23	unknown	65062	unemployed	small_city	0

In [130…

```
sns.countplot(
    data=cluster_anal[cond_cluster0],
    y='education',
    hue='occupation'
)
```

Out[130]: <AxesSubplot:xlabel='count', ylabel='education'>



- For cluster 0, there is absolutely none in graduate school and none in management too.
- They mostly have high school diplomas and are having a high rate of unemployment.

In [147…

```
my_frame = cluster_anal[cond_cluster0].education.value_counts()
my_frame= my_frame.to_frame().reset_index()
my_frame.rename(columns={'index':'education','education':'total_count'}, inplace=True)
my_frame
```

Out[147]:

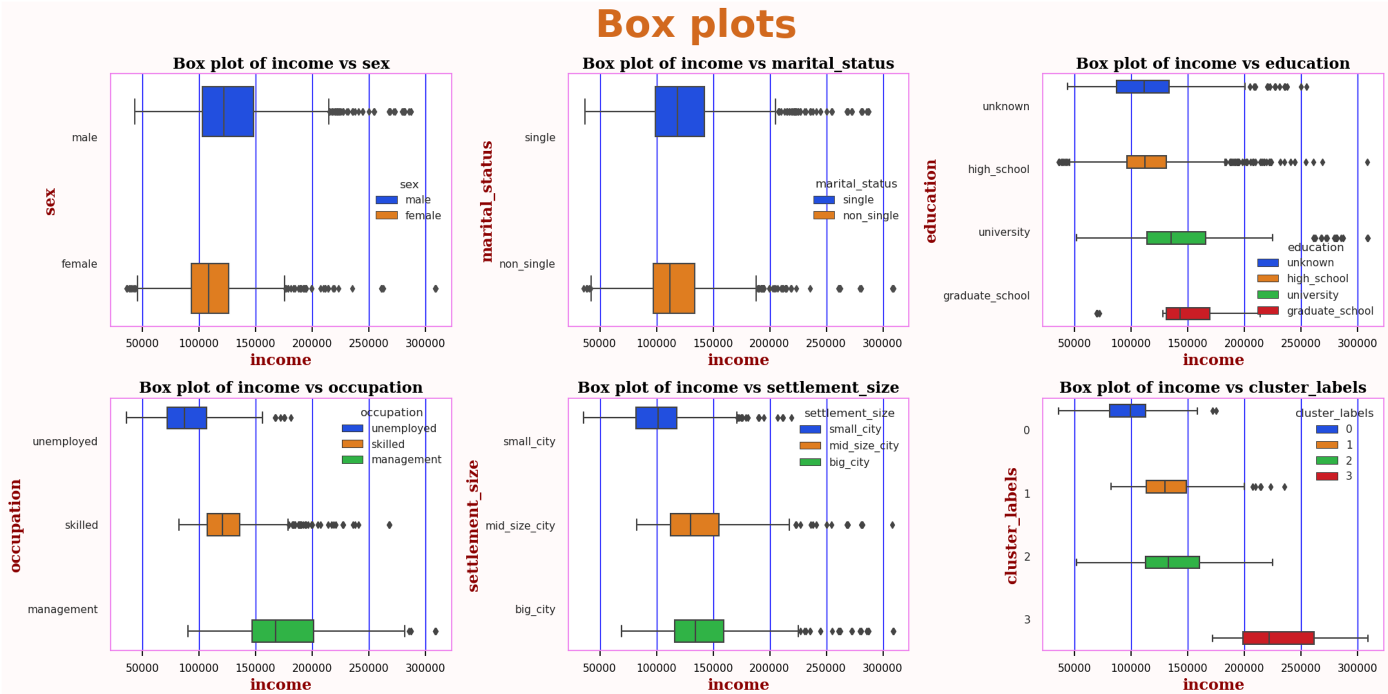
	education	total_count
0	high_school	748
1	unknown	135
2	university	2
3	graduate_school	0

In [148…

```
colors = ['gold', 'mediumturquoise', 'darkorange', 'lightgreen']

fig = go.Figure(data=[go.Pie(labels=my_frame.education,
                             values=my_frame.total_count)])


fig.update_layout(
width=1000,
title={"x": 0.5, "xanchor":"center",
"font_family":"Times New Roman",
"text":"SEGEMENATION OF EDUCATION"})

fig.update_traces(hoverinfo='label+percent', textinfo='value', textfont_size=20,
                  marker={'colors':colors, 'line_color':'#000000','line_width':2})
```

```
fig.show()
```

In [98]:
```
box_plot('income',cat2,cluster_anal)
```



Those in cluster 3 seems to have a higher income than others

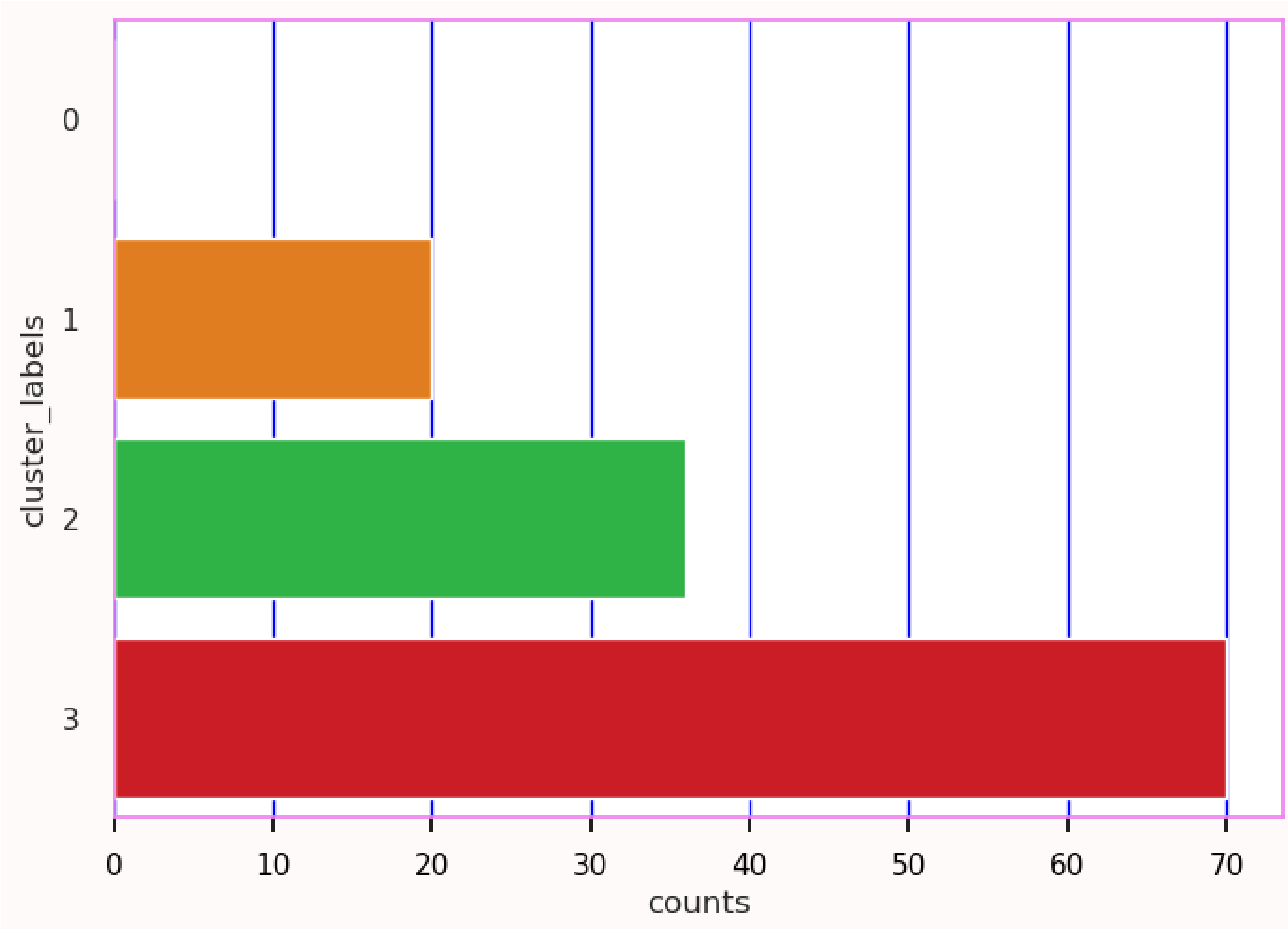
In [155…
```
cond_income = cluster_anal.income >= 180000
above_threshold = cluster_anal[cond_income].cluster_labels.value_counts().to_frame().reset_index
above_threshold
```

Out[155]:

	cluster_labels	counts
0	3	70
1	2	36
2	1	20
3	0	0

In [162…
```
sns.barplot(
    data=above_threshold,
    y= "cluster_labels",
    x= 'counts'
)
```

Out[162]: <AxesSubplot:xlabel='counts', ylabel='cluster_labels'>

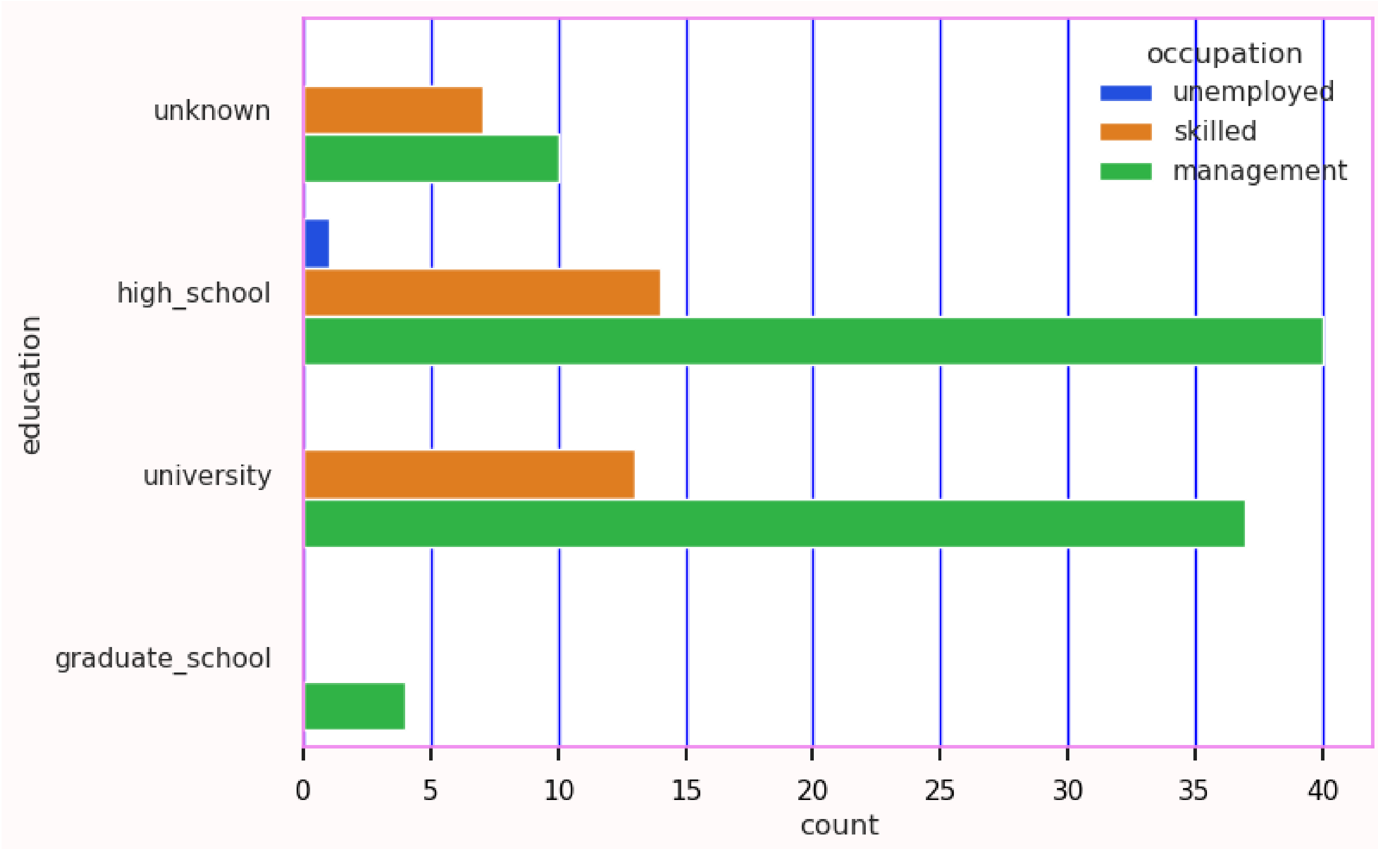


So cluster 3 has the highest count than other clusters with an earning above 180000

In [132…

```
sns.countplot(
    data=cluster_anal[cond_income],
    y='education',
    hue='occupation'
)
```

Out[132]: <AxesSubplot:xlabel='count', ylabel='education'>



- So those above or equal to an income of 180,000 are mostly in management positions.
- Seems like those with high school degrees are high in number.

In [133…

```
cond_age = (cluster_anal.age >=30) & (cluster_anal.age < 50)
cond_occupation = cluster_anal.occupation == 'management'
cond_education = cluster_anal.education == 'high_school'
final_cond  = cond_age & cond_occupation & cond_education
cluster_anal[final_cond]
```

Out[133]:

	sex	marital_status	age	education	income	occupation	settlement_size	cluster_labels
7	male	single	35	high_school	193621	management	mid_size_city	3
34	female	non_single	33	high_school	155569	management	mid_size_city	1
45	female	non_single	35	high_school	138387	management	mid_size_city	1
74	male	single	40	high_school	140888	management	big_city	1
99	male	single	36	high_school	195465	management	big_city	3
...	...	...	...	...	...	...	...	...
1278	male	single	35	high_school	150237	management	big_city	1
1289	male	single	49	high_school	118571	management	big_city	1
1296	male	single	33	high_school	151339	management	mid_size_city	1
1366	female	single	31	high_school	143321	management	mid_size_city	1
1465	female	non_single	36	high_school	135896	management	mid_size_city	1

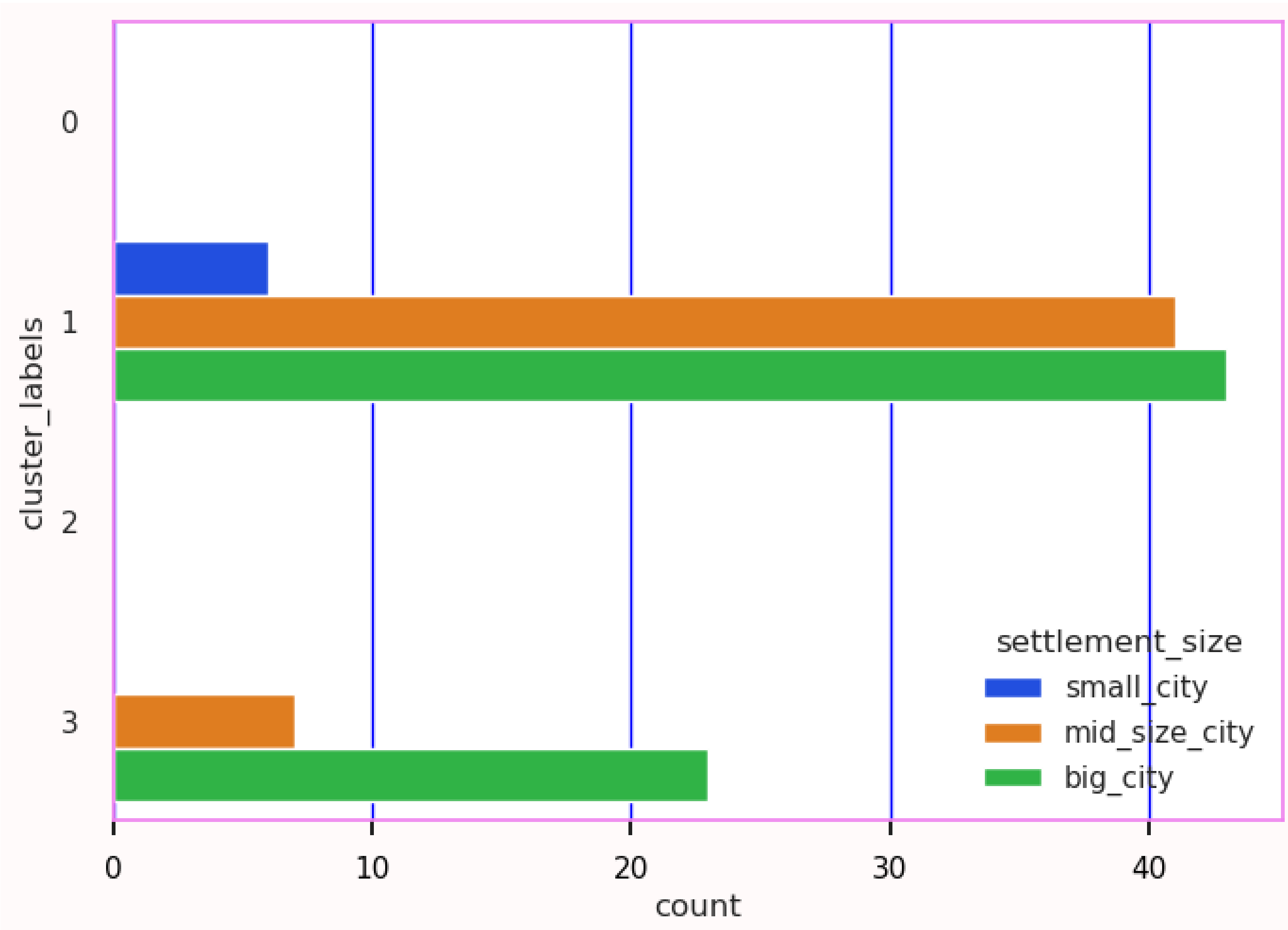
120 rows × 8 columns

In [137…

```
sns.countplot(
    data=cluster_anal[final_cond],
    y='cluster_labels',
    hue='settlement_size'
)
```

Out[137]:

```
<AxesSubplot:xlabel='count', ylabel='cluster_labels'>
```



So those between the ages of 30 and 50, in management and with high school diplomas are most likely to reside in big cities.

Clusters 3 and 1 satifies these conditions, while the others do not.

In [165…

```
cond = cluster_anal.settlement_size == 'small_city'
cluster_anal[final_cond & cond].settlement_size.value_counts()
```

Out[165]:

```
small_city       6
mid_size_city    0
big_city         0
Name: settlement_size, dtype: int64
```

- A total of 66 people in big cities
- A total of 48 people in mid size cities
- A total of 6 people in small cities

In [169…

```
# Saving for further analysis on PowerBi
cluster_anal.to_csv('../data/clustered.csv',index=False)
```