1.Necessary Libraries

In [53]:

```
import numpy as np
import pandas as pd
import matplotlib as plt
import seaborn as sns
```

2.Load The Given Dataset into tool

In [54]:

```
df=pd.read_csv("Mall_Customers.csv")
```

In [55]:

```
df.head()
```

Out[55]:

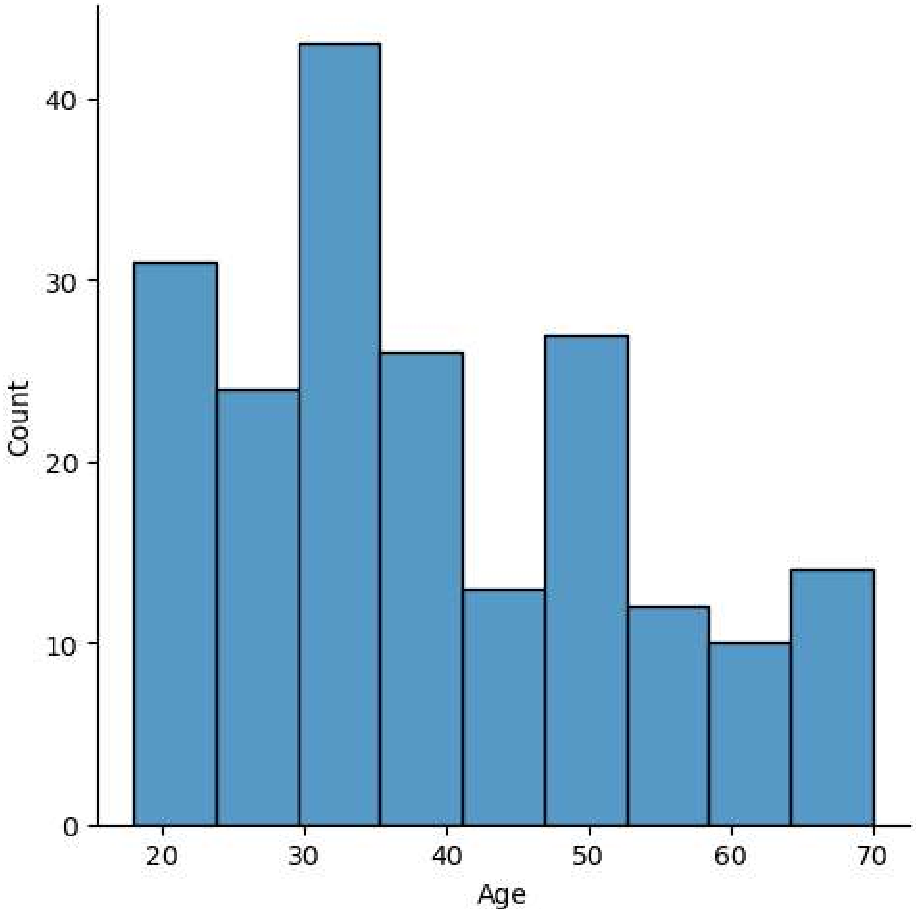
	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

3.Visualizations

3.1 Univariate Analysis

In [56]:

```
sns.displot(df['Age'])
```

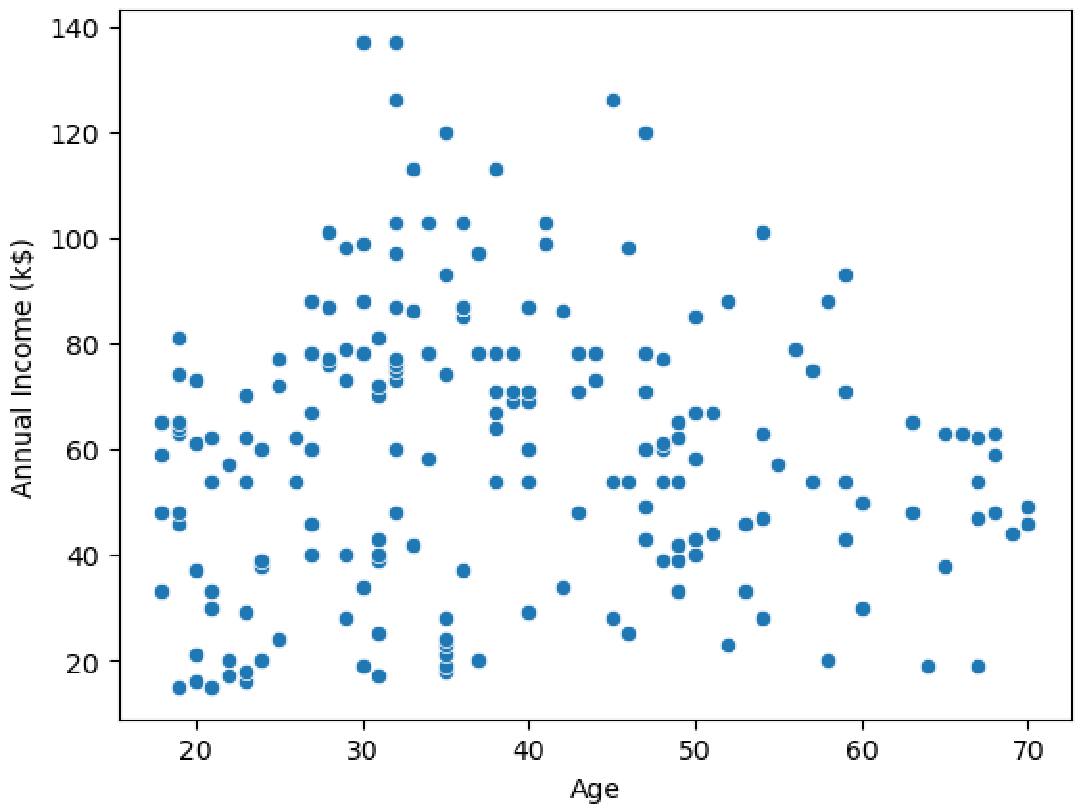


3.2 Bivariate Analysis

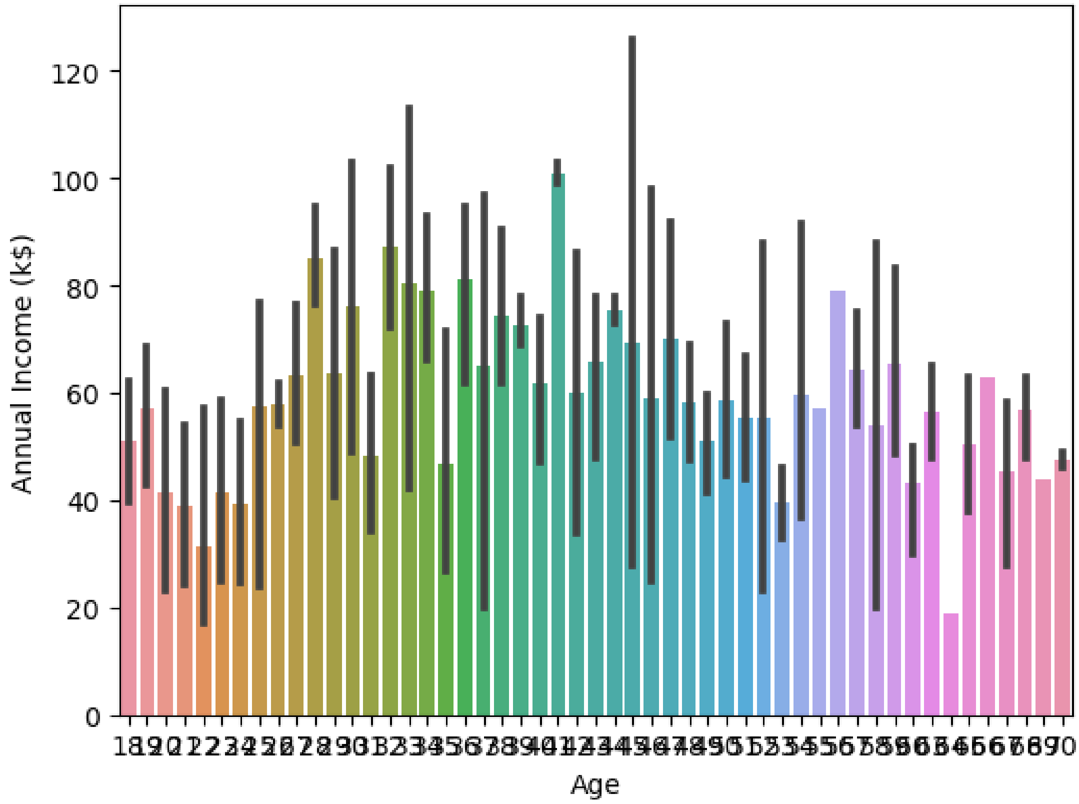
In [57]:

```
sns.scatterplot(df['Age'],df['Annual Income (k$)'])
```

```
C:\Users\Dhamu\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futur
eWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpr
etation.
  warnings.warn(
```



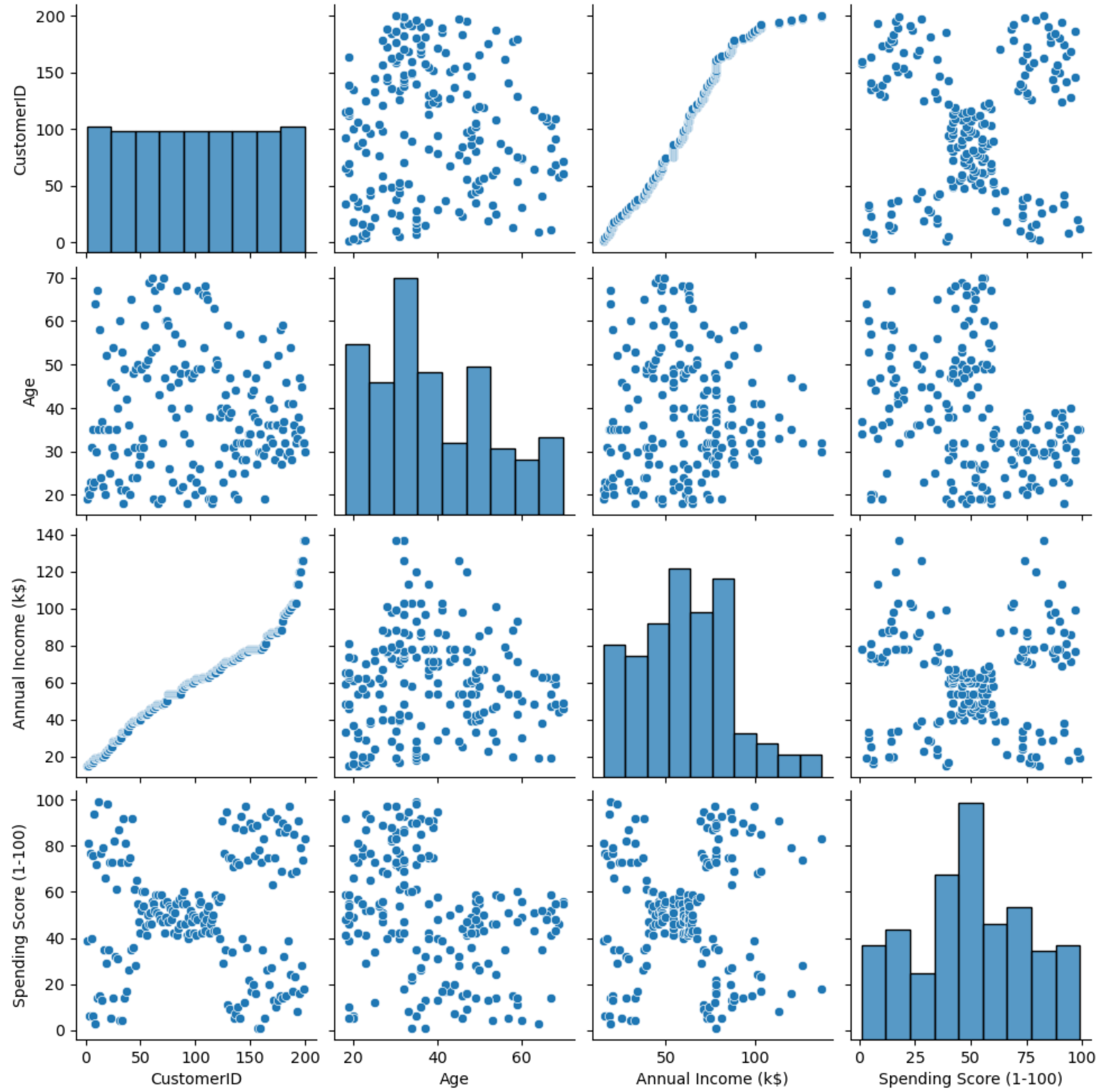

```
sns.barplot(df['Age'],df['Annual Income (k$)'])
C:\Users\Dhamu\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futur
eWarning: Pass the following variables as keyword args: x, y. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpr
etation.
  warnings.warn(
```



3.3 Multivariate Analysis

In [59]:

```
sns.pairplot(df)
```



4.Descriptive Statistics On The Dataset

In [60]:

```
df.describe()
```

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

5.Check For Missing Values

In [61]:

```
df.isnull()
```

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	False	False	False	False	False
1	False	False	False	False	False
2	False	False	False	False	False
3	False	False	False	False	False
4	False	False	False	False	False
...	...	...	...	...	...
195	False	False	False	False	False
196	False	False	False	False	False
197	False	False	False	False	False
198	False	False	False	False	False
199	False	False	False	False	False

200 rows × 5 columns

In [62]:

```
df.isnull().sum()
```

Out[62]:

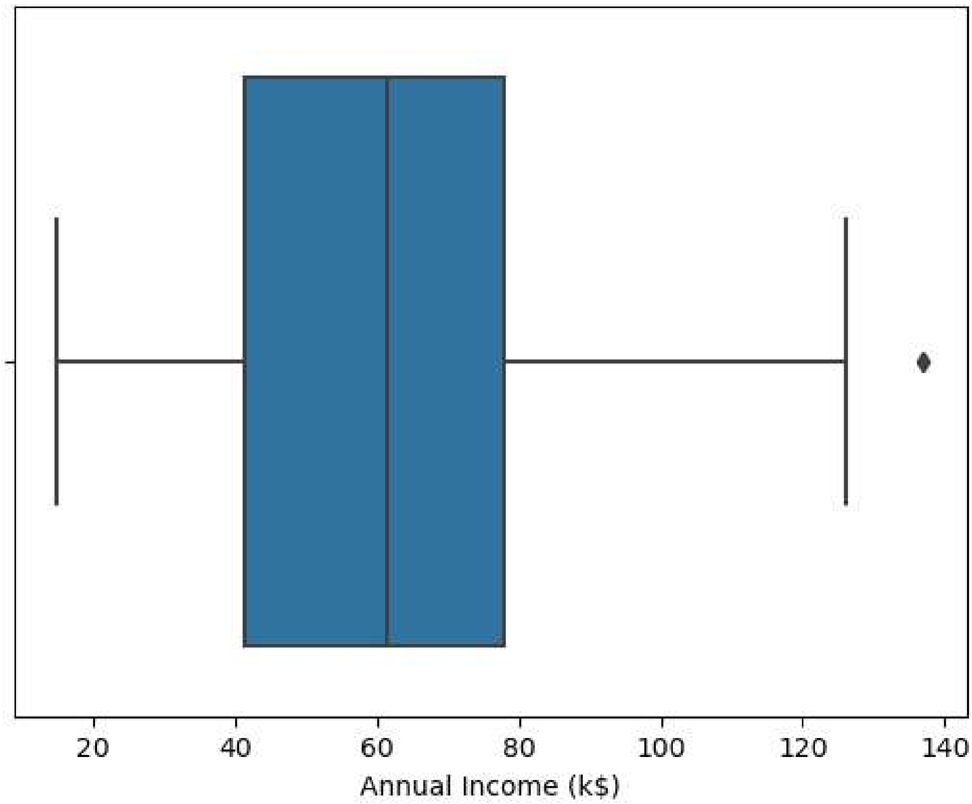
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

6.Find The Outliers And Replace The Outliers

```
sns.boxplot(df['Annual Income (k$)'])
```

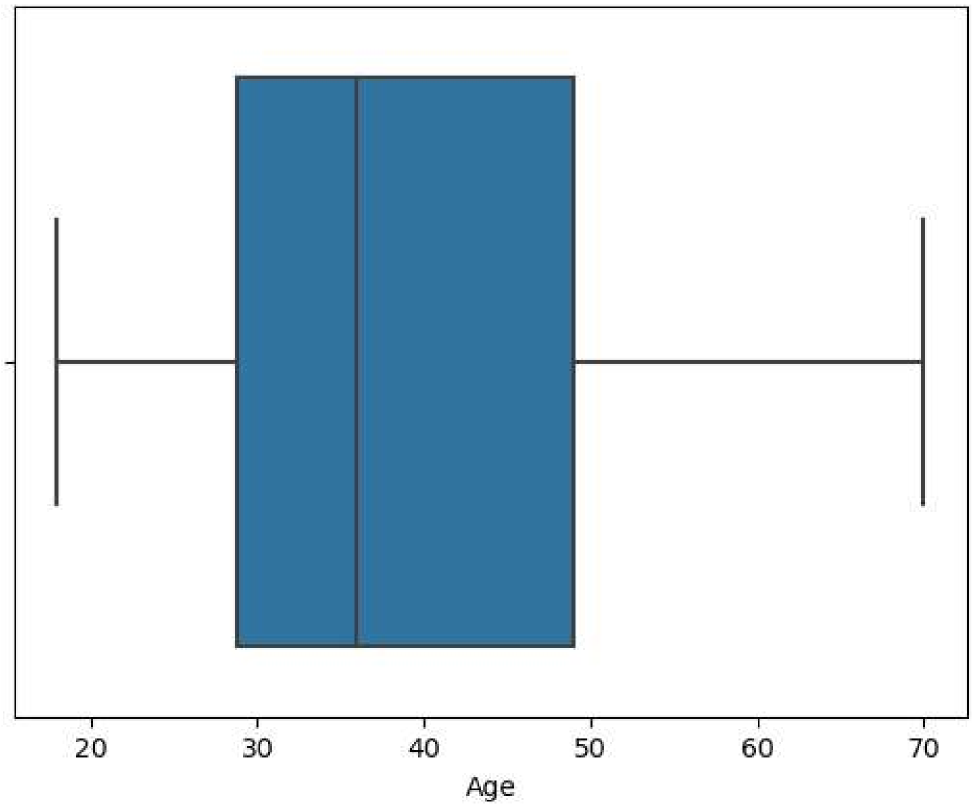
```
C:\Users\Dhamu\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futur
eWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arg
uments without an explicit keyword will result in an error or misinterpreta
tion.
  warnings.warn(
```

Out[63]:




```
sns.boxplot(df['Age'])
C:\Users\Dhamu\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Futur
eWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arg
uments without an explicit keyword will result in an error or misinterpreta
tion.
```

```
warnings.warn(
```



7.Check For Categorical Columns And Perform Encoding

In [65]:

```
df.head()
```

Out[65]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

Label Encoding

In [66]:

```
from sklearn.preprocessing import LabelEncoder
```

In [67]:

```
l=LabelEncoder()
```

In [68]:

```
df.Gender=l.fit_transform(df.Gender)
```

In [69]:

```
df.head()
```

Out[69]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	1	19	15	39
1	2	1	21	15	81
2	3	0	20	16	6
3	4	0	23	16	77
4	5	0	31	17	40

8.Scaling The Data

```
from sklearn.preprocessing import scale
```

In [71]:

```
df=pd.DataFrame(scale(df),columns=df.columns)
```

In [72]:

```
df.head()
```

Out[72]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	-1.723412	1.128152	-1.424569	-1.738999	-0.434801
1	-1.706091	1.128152	-1.281035	-1.738999	1.195704
2	-1.688771	-0.886405	-1.352802	-1.700830	-1.715913

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
3	-1.671450	-0.886405	-1.137502	-1.700830	1.040418
4	-1.654129	-0.886405	-0.563369	-1.662660	-0.395980

9.Perform any of the clustering algorithms

In [73]:

```
from sklearn import cluster
```

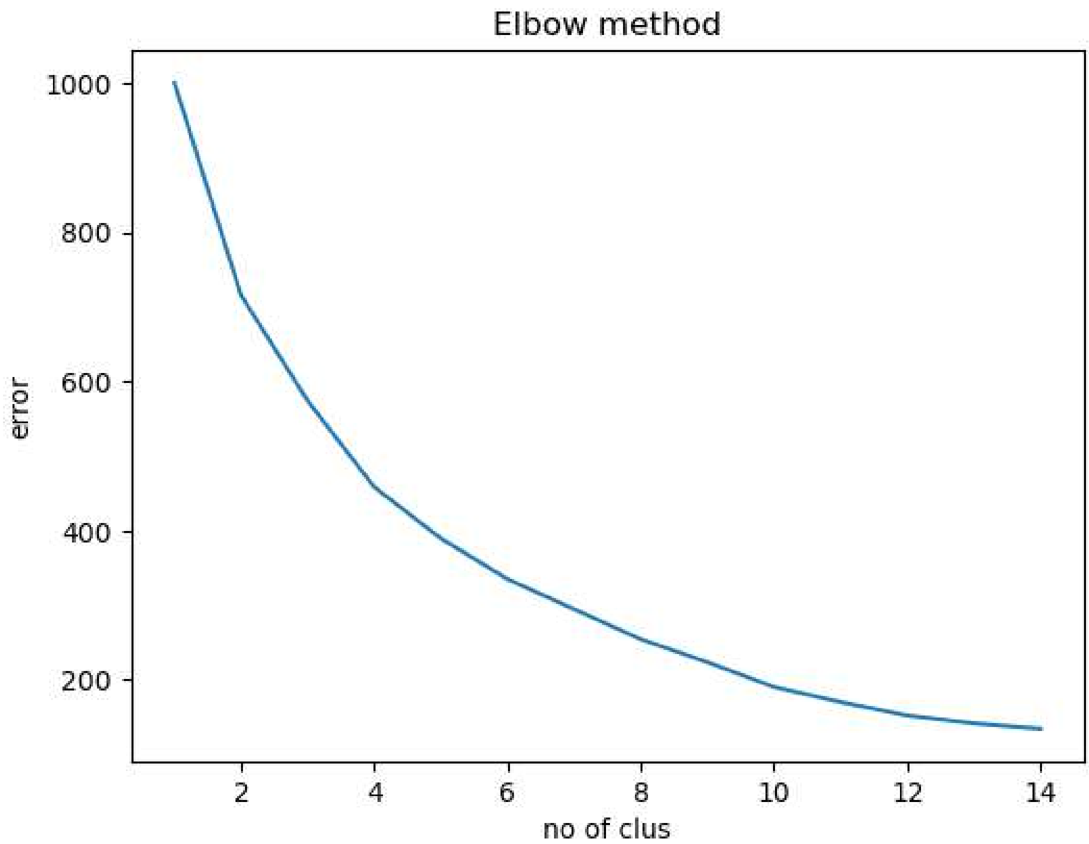
In [74]:

```
error=[]
for i in range(1,15):
    kmeans=cluster.KMeans(n_clusters=i,init='k-means++',random_state=0)
    kmeans.fit(df)
    error.append(kmeans.inertia_)
```

```
C:\Users\Dhamu\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036:
UserWarning: KMeans is known to have a memory leak on Windows with MKL, whe
n there are less chunks than available threads. You can avoid it by setting
the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [75]:

```
import matplotlib.pyplot as plt
plt.plot(range(1,15),error)
plt.title('Elbow method')
plt.xlabel('no of clus')
plt.ylabel('error')
plt.show()
```




```
km_model=cluster.KMeans(n_clusters=11,init='k-means++',random_state=2)
```

In [77]:

```
km_model.fit(df)
```

Out[77]:

```
KMeans(n_clusters=11, random_state=2)
```

In [78]:

```
target=km_model.predict(df)
target
```

Out[78]:

```
array([ 4,  4,  9, 10,  9, 10,  9, 10,  2, 10,  2, 10,  9, 10,  9,  4,  9,
        4,  2, 10,  4,  4,  9,  4,  9,  4,  9,  4,  9, 10,  2, 10,  2,  4,
        9, 10,  9, 10,  9, 10,  6,  4,  2, 10,  9, 10,  6,  0,  0,  0,  6,
        4,  0,  2,  6,  2,  6,  2,  0,  2,  2,  8,  6,  6,  2,  8,  6,  6,
        8,  0,  2,  6,  6,  6,  2,  8,  6,  8,  0,  6,  2,  8,  2,  6,  0,
        2,  6,  0,  0,  6,  6,  8,  2,  0,  0,  8,  6,  0,  2,  8,  0,  6,
        2,  8,  2,  0,  6,  2,  2,  2,  2,  0,  0,  8,  0,  0,  6,  6,  6,
        6,  8,  0,  0,  5,  0,  3,  1,  5,  1,  5,  1,  5,  0,  3,  1,  3,
        7,  5,  1,  3,  7,  5,  0,  3,  1,  5,  1,  3,  7,  5,  1,  5,  7,
        3,  7,  3,  1,  3,  1,  3,  7,  3,  1,  3,  1,  3,  1,  3,  7,  5,
        1,  5,  1,  5,  7,  3,  1,  5,  1,  5,  7,  3,  1,  3,  7,  5,  7,
        5,  7,  3,  7,  3,  1,  3,  7,  3,  7,  5,  1,  5])
```

10.Add The Cluster Data With The Primary Dataset

```
df['Target Customers']=target
```

In [80]:

```
df.head()
```

Out[80]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Target Customers
0	-1.723412	1.128152	-1.424569	-1.738999	-0.434801	4
1	-1.706091	1.128152	-1.281035	-1.738999	1.195704	4
2	-1.688771	-0.886405	-1.352802	-1.700830	-1.715913	9
3	-1.671450	-0.886405	-1.137502	-1.700830	1.040418	10
4	-1.654129	-0.886405	-0.563369	-1.662660	-0.395980	9

11.Split the data into Dependent and Independent Variables.

In [81]:

```
x=df.drop(columns=['Target Customers'],axis=1)
```

In [82]:

```
x
```

Out[82]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	-1.723412	1.128152	-1.424569	-1.738999	-0.434801
1	-1.706091	1.128152	-1.281035	-1.738999	1.195704
2	-1.688771	-0.886405	-1.352802	-1.700830	-1.715913
3	-1.671450	-0.886405	-1.137502	-1.700830	1.040418
4	-1.654129	-0.886405	-0.563369	-1.662660	-0.395980
...	...	...	...	...	...
195	1.654129	-0.886405	-0.276302	2.268791	1.118061

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
196	1.671450	-0.886405	0.441365	2.497807	-0.861839
197	1.688771	1.128152	-0.491602	2.497807	0.923953
198	1.706091	1.128152	-0.491602	2.917671	-1.250054
199	1.723412	1.128152	-0.635135	2.917671	1.273347

200 rows × 5 columns

In [83]:

```
y=df['Target Customers']
```

In [84]:

```
y
```

Out[84]:

```
0       4
1       4
2       9
3      10
4       9
       ..
195     3
196     7
197     5
198     1
199     5
Name: Target Customers, Length: 200, dtype: int32
```

12.Split the data into training and testing

In [85]:

```
from sklearn.model_selection import train_test_split
X_Train, X_Test, Y_Train, Y_Test = train_test_split(x, y, test_size=0.2, 
random_state=2)
```

```
X_Train.shape,X_Test.shape
```

Out[86]:

```
((160, 5), (40, 5))
```

In [87]:

```
X_Train.head()
```

Out[87]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
137	0.649527	1.128152	-0.491602	0.474828	0.885132

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
163	1.099866	-0.886405	-0.563369	0.780183	1.661563
111	0.199188	-0.886405	-1.424569	0.093133	0.147522
123	0.407037	1.128152	0.010765	0.322150	1.583920
109	0.164547	1.128152	1.948466	0.093133	-0.085407

```
X_Test.head()
```

Out[88]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
112	0.216509	-0.886405	-0.061002	0.131303	-0.318337
29	-1.221111	-0.886405	-1.137502	-1.204627	1.428633
182	1.428960	1.128152	0.513132	1.429063	-1.366519
199	1.723412	1.128152	-0.635135	2.917671	1.273347
193	1.619488	-0.886405	-0.061002	2.001605	1.583920

In [89]:

```
Y_Train.head()
```

Out[89]:

```
137    5
163    3
111    0
123    5
109    2
Name: Target Customers, dtype: int32
```

In [90]:

```
Y_Test.head()
```

Out[90]:

```
112     0
29     10
182     1
199     5
193     3
Name: Target Customers, dtype: int32
```

13.Build The Model

In [91]:

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10,criterion='entropy')
```

In [92]:

```
model.fit(X_Train,Y_Train)
```

Out[92]:

```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

In [93]:

```
y_pred_test=model.predict(X_Test)
```

In [94]:

```
y_pred_train=model.predict(X_Train)
```

14.Train The Model

In [95]:

```
from sklearn.metrics import
accuracy_score,confusion_matrix,classification_report
print('Training Accuracy',accuracy_score(Y_Train,y_pred_train))
Training Accuracy 1.0
```

15.Test The Model

In [97]:

```
print('Testing Accuracy',accuracy_score(Y_Test,y_pred_test))
Testing Accuracy 0.925
```

16.Measure the performance using Evaluation Metrics.

In [98]:

```
pd.crosstab(Y_Test,y_pred_test)
```

Out[98]:

col_0	0	1	2	3	4	5	6	7	8	9	10
Target Customers											
0	5	0	0	0	0	0	0	0	0	0	0
1	0	6	0	0	0	0	0	0	0	0	0
2	0	0	6	0	0	0	0	0	0	0	0

col_0	0	1	2	3	4	5	6	7	8	9	10
Target Customers											
3	0	0	0	2	0	0	0	0	0	0	0
4	0	0	0	0	2	0	0	0	0	0	0
5	0	0	0	0	0	3	0	0	0	0	0
6	0	0	0	0	0	0	2	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0	0
8	0	0	0	0	0	0	0	0	2	0	0
9	0	0	0	0	1	0	1	0	0	3	0
10	1	0	0	0	0	0	0	0	0	0	5

```
print(classification_report(Y_Test,y_pred_test))
              precision    recall  f1-score   support

           0       0.83      1.00      0.91         5
           1       1.00      1.00      1.00         6
           2       1.00      1.00      1.00         6
           3       1.00      1.00      1.00         2
           4       0.67      1.00      0.80         2
           5       1.00      1.00      1.00         3
           6       0.67      1.00      0.80         2
           7       1.00      1.00      1.00         1
           8       1.00      1.00      1.00         2
           9       1.00      0.60      0.75         5
          10       1.00      0.83      0.91         6

    accuracy                           0.93        40
   macro avg       0.92      0.95      0.92        40
weighted avg       0.95      0.93      0.92        40
```