In [ ]:
```
TASK 1:Customer Segmentation Using KMeans
      Create a K-means clustering algorithm to group customers of a retail store base
```

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly as py
import plotly.graph_objs as go
from sklearn.cluster import KMeans
import warnings
import os
warnings.filterwarnings("ignore")
```

In [2]:
```
data=pd.read_csv("C:\\Users\\abhis\\Downloads//Mall_Customers.csv")
data
```

Out[2]:

	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
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

In [4]:
```
data.head()
```

Out[4]:

	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

In [6]:
```
data.shape
```
Out[6]:
```
(200, 5)
```

In [7]:
```
data.describe()
```
Out[7]:

	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
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

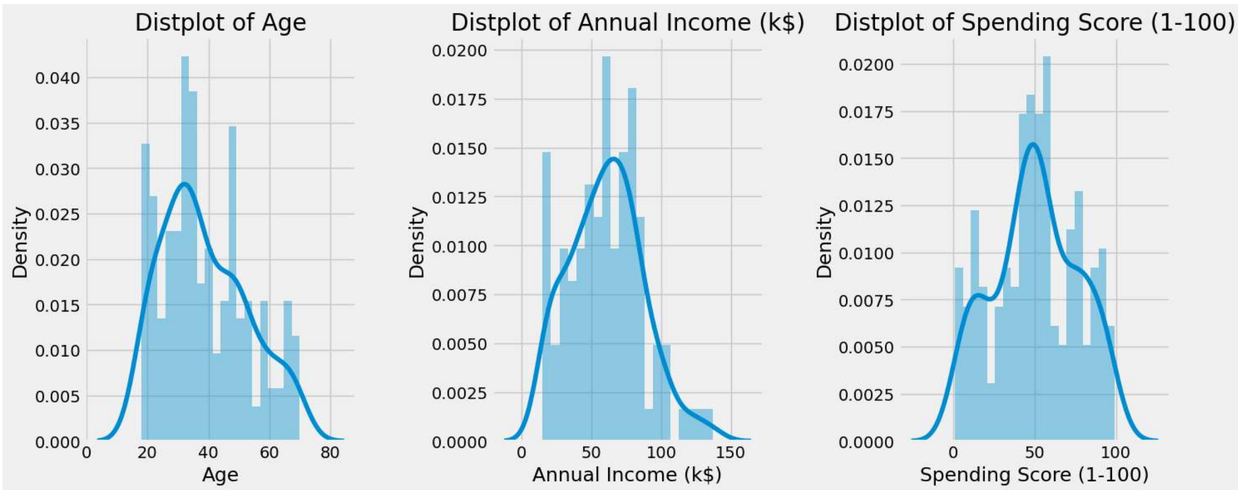
In [9]:
```
data.dtypes
```
Out[9]:
```
CustomerID                 int64
Gender                    object
Age                        int64
Annual Income (k$)         int64
Spending Score (1-100)     int64
dtype: object
```

In [10]:
```
data.isnull().sum()
```
Out[10]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

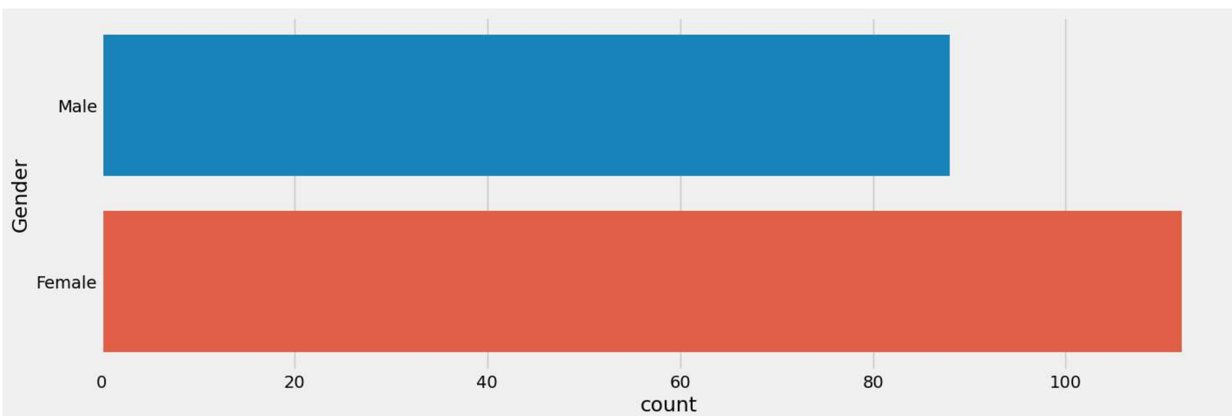
In [ ]:
```
# Data VIsualization
```

In [11]:
```
plt.style.use('fivethirtyeight')
```

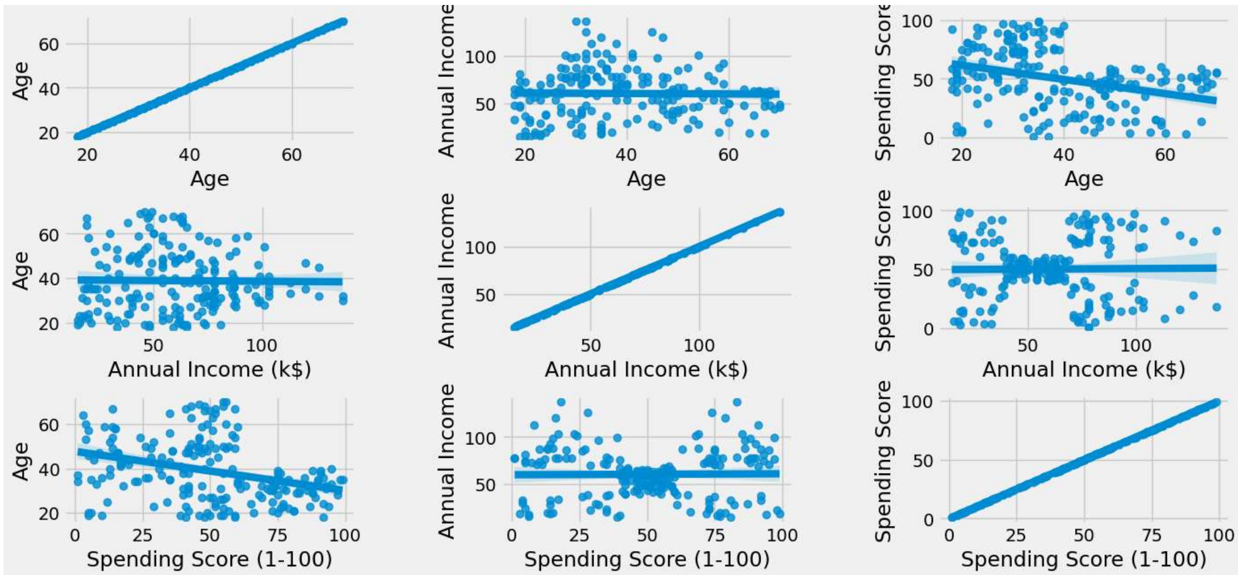
In [13]:
```
plt.figure(1 , figsize = (15 , 6))
n = 0
for x in ['Age' , 'Annual Income (k$)' , 'Spending Score (1-100)']:
    n += 1
    plt.subplot(1 , 3 , n)
    plt.subplots_adjust(hspace =0.5 , wspace = 0.5)
    sns.distplot(data[x] , bins = 20)
    plt.title('Distplot of {}'.format(x))
plt.show()
```



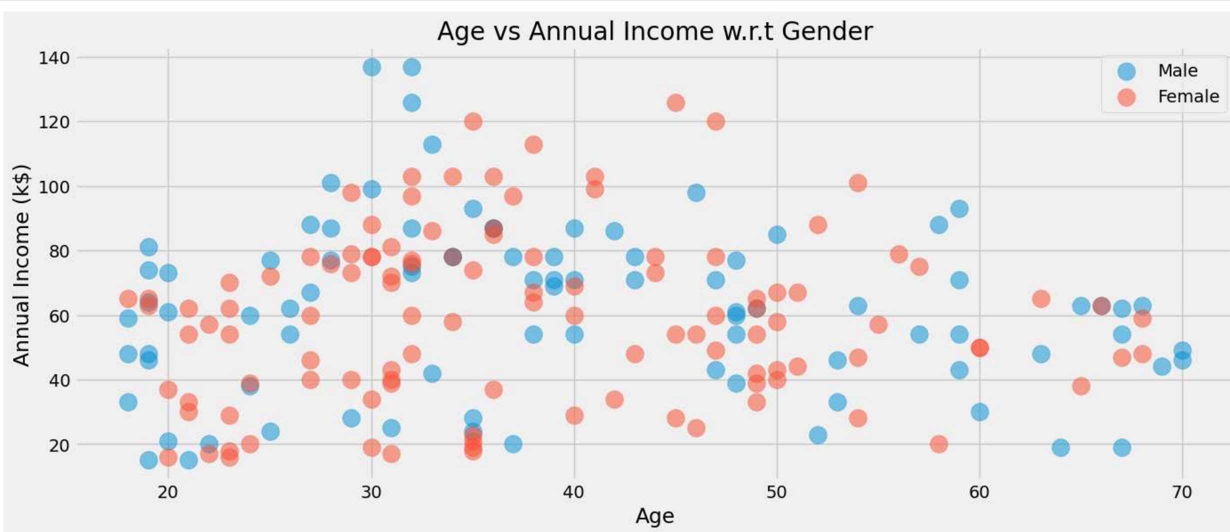
In [14]:
```
plt.figure(1 , figsize = (15 , 5))
sns.countplot(y = 'Gender' , data = data)
plt.show()
```



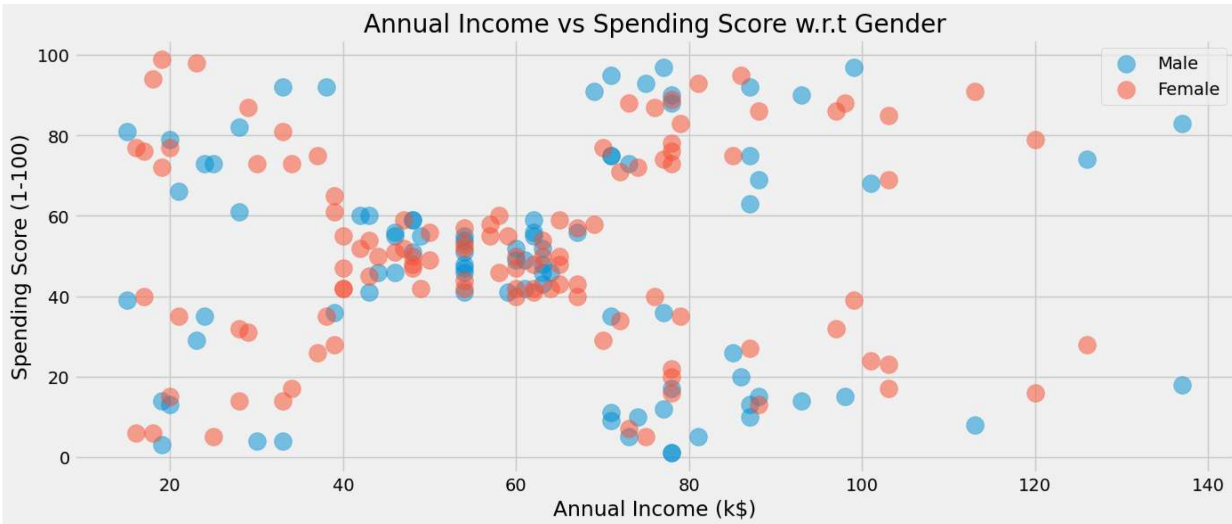
In [15]:
```
plt.figure(1 , figsize = (15 , 7))
n = 0
for x in ['Age' , 'Annual Income (k$)' , 'Spending Score (1-100)']:
    for y in ['Age' , 'Annual Income (k$)' , 'Spending Score (1-100)']:
        n += 1
        plt.subplot(3 , 3 , n)
        plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
        sns.regplot(x = x , y = y , data = data)
        plt.ylabel(y.split()[0]+' '+y.split()[1] if len(y.split()) > 1 else y )
plt.show()
```



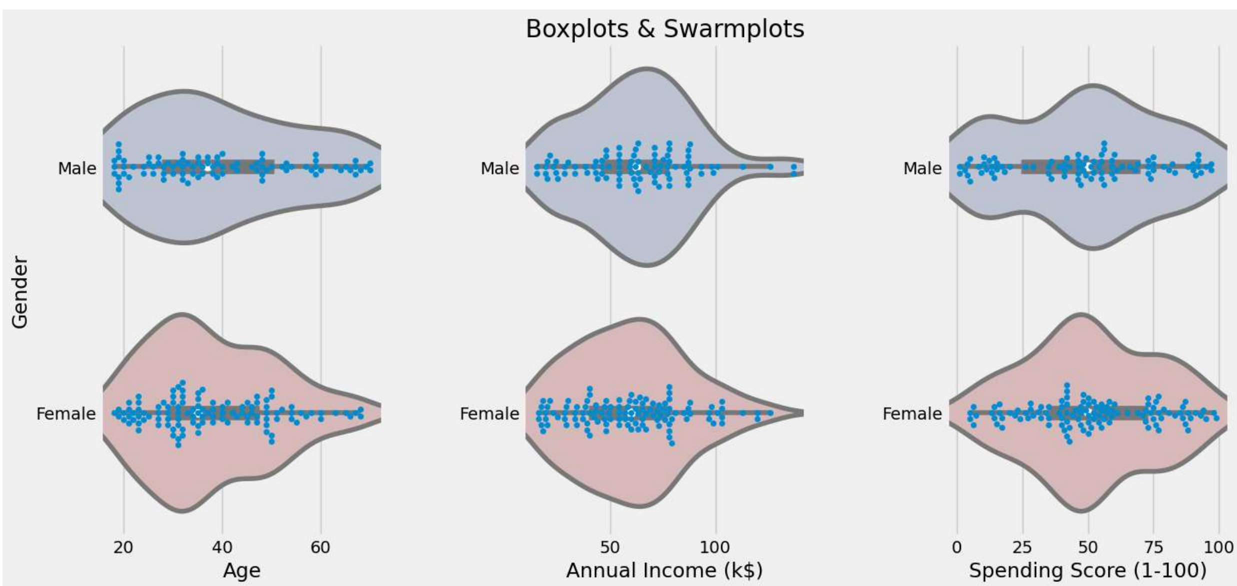
In [16]:
```
plt.figure(1 , figsize = (15 , 6))
for gender in ['Male' , 'Female']:
    plt.scatter(x = 'Age' , y = 'Annual Income (k$)' , data = data[data['Gender'] ==
                s = 200 , alpha = 0.5 , label = gender)
plt.xlabel('Age'), plt.ylabel('Annual Income (k$)')
plt.title('Age vs Annual Income w.r.t Gender')
plt.legend()
plt.show()
```



In [17]:
```
plt.figure(1 , figsize = (15 , 6))
for gender in ['Male' , 'Female']:
    plt.scatter(x = 'Annual Income (k$)',y = 'Spending Score (1-100)' ,
                data = data[data['Gender'] == gender] ,s = 200 , alpha = 0.5 , label
plt.xlabel('Annual Income (k$)'), plt.ylabel('Spending Score (1-100)')
plt.title('Annual Income vs Spending Score w.r.t Gender')
plt.legend()
plt.show()
```

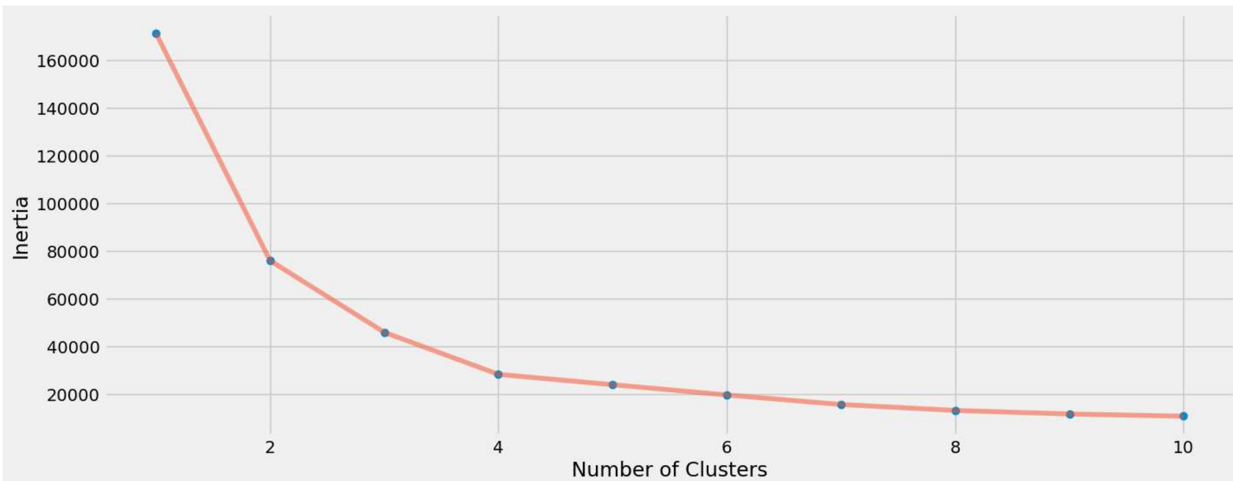


In [18]:
```
plt.figure(1 , figsize = (15 , 7))
n = 0
for cols in ['Age' , 'Annual Income (k$)' , 'Spending Score (1-100)']:
    n += 1
    plt.subplot(1 , 3 , n)
    plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
    sns.violinplot(x = cols , y = 'Gender' , data = data , palette = 'vlag')
    sns.swarmplot(x = cols , y = 'Gender' , data = data)
    plt.ylabel('Gender' if n == 1 else '')
    plt.title('Boxplots & Swarmplots' if n == 2 else '')
plt.show()
```



In [20]:
```python
X1 = data[['Age' , 'Spending Score (1-100)']].iloc[: , :].values
inertia = []
for n in range(1 , 11):
    algorithm = (KMeans(n_clusters = n ,init='k-means++', n_init = 10 ,max_iter=300,
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
    algorithm.fit(X1)
    inertia.append(algorithm.inertia_)
```

In [21]:
```python
plt.figure(1 , figsize = (15 ,6))
plt.plot(np.arange(1 , 11) , inertia , 'o')
plt.plot(np.arange(1 , 11) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```

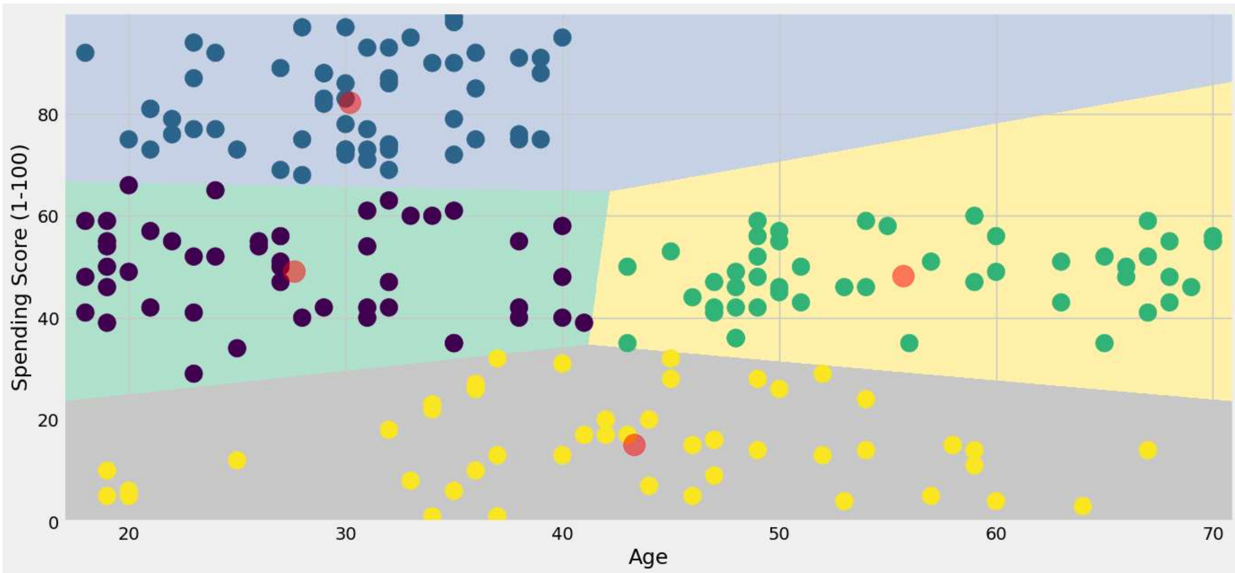


In [22]:
```python
algorithm = (KMeans(n_clusters = 4 ,init='k-means++', n_init = 10 ,max_iter=300,
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
algorithm.fit(X1)
labels1 = algorithm.labels_
centroids1 = algorithm.cluster_centers_
```

In [23]:
```python
h = 0.02
x_min, x_max = X1[:, 0].min() - 1, X1[:, 0].max() + 1
y_min, y_max = X1[:, 1].min() - 1, X1[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
Z = algorithm.predict(np.c_[xx.ravel(), yy.ravel()])
```

In [24]:

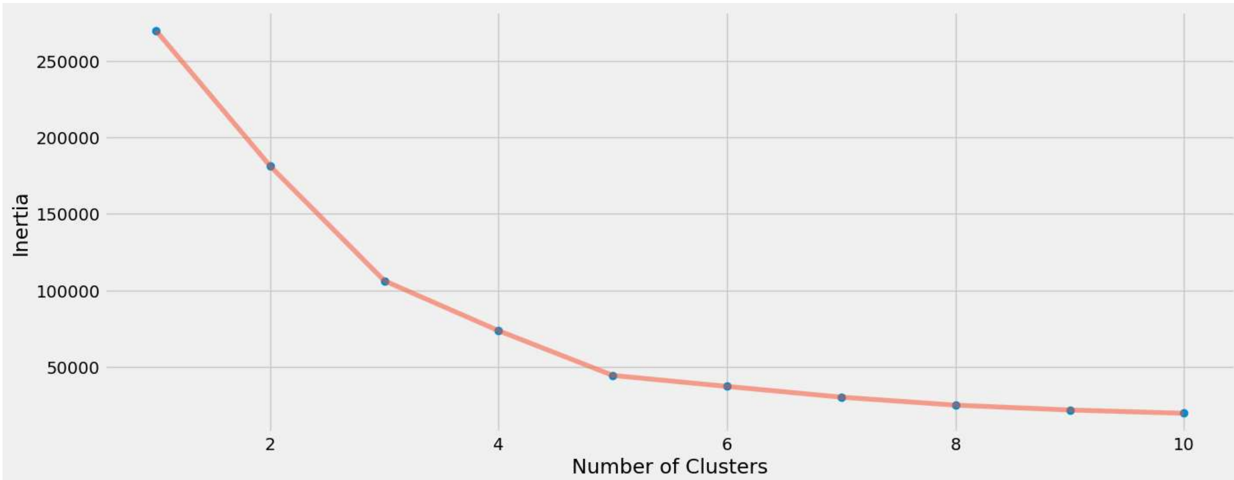
```
plt.figure(1 , figsize = (15 , 7) )
plt.clf()
Z = Z.reshape(xx.shape)
plt.imshow(Z , interpolation='nearest',
           extent=(xx.min(), xx.max(), yy.min(), yy.max()),
           cmap = plt.cm.Pastel2, aspect = 'auto', origin='lower')

plt.scatter( x = 'Age' ,y = 'Spending Score (1-100)' , data = data , c = labels1 ,
            s = 200 )
plt.scatter(x = centroids1[: , 0] , y =  centroids1[: , 1] , s = 300 , c = 'red' , al
plt.ylabel('Spending Score (1-100)') , plt.xlabel('Age')
plt.show()
```



In [26]:

```
X2 = data[['Annual Income (k$)' , 'Spending Score (1-100)']].iloc[: , :].values
inertia = []
for n in range(1 , 11):
    algorithm = (KMeans(n_clusters = n ,init='k-means++', n_init = 10 ,max_iter=300,
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
    algorithm.fit(X2)
    inertia.append(algorithm.inertia_)
```

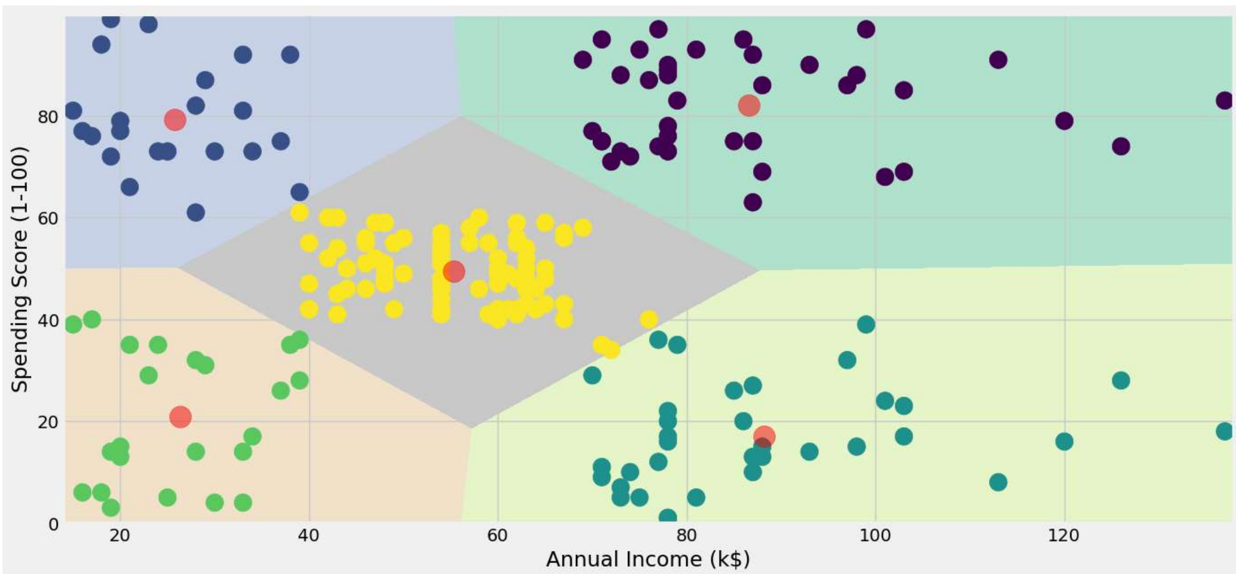
In [27]:
```
plt.figure(1 , figsize = (15 ,6))
plt.plot(np.arange(1 , 11) , inertia , 'o')
plt.plot(np.arange(1 , 11) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```



In [28]:
```
algorithm = (KMeans(n_clusters = 5 ,init='k-means++', n_init = 10 ,max_iter=300,
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
algorithm.fit(X2)
labels2 = algorithm.labels_
centroids2 = algorithm.cluster_centers_
```

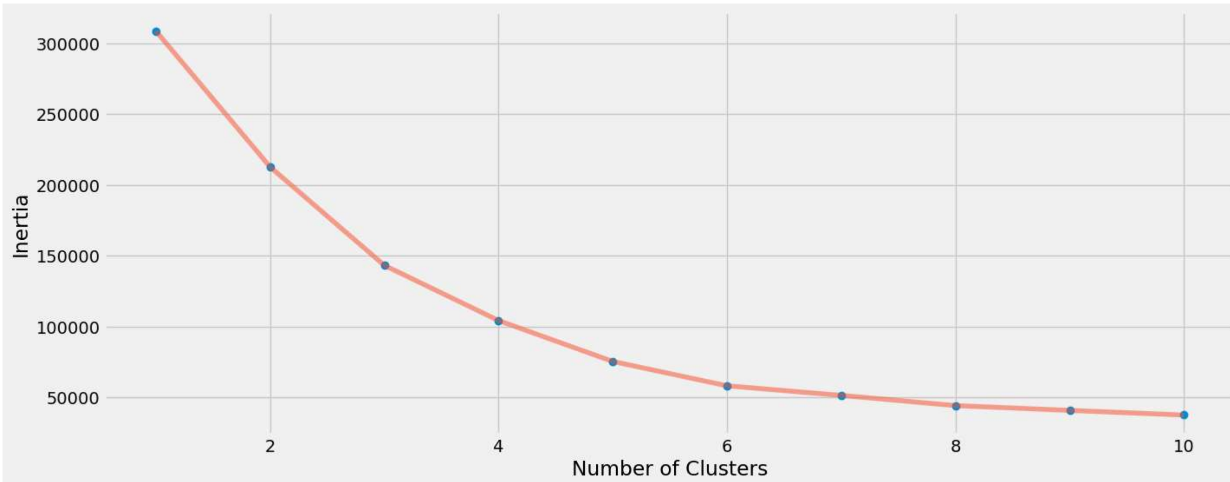
In [29]:
```
h = 0.02
x_min, x_max = X2[:, 0].min() - 1, X2[:, 0].max() + 1
y_min, y_max = X2[:, 1].min() - 1, X2[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
Z2 = algorithm.predict(np.c_[xx.ravel(), yy.ravel()])
```

In [31]:
```
plt.figure(1 , figsize = (15 , 7) )
plt.clf()
Z2 = Z2.reshape(xx.shape)
plt.imshow(Z2 , interpolation='nearest',
           extent=(xx.min(), xx.max(), yy.min(), yy.max()),
           cmap = plt.cm.Pastel2, aspect = 'auto', origin='lower')

plt.scatter( x = 'Annual Income (k$)' ,y = 'Spending Score (1-100)' , data = data , c
            s = 200 )
plt.scatter(x = centroids2[: , 0] , y =  centroids2[: , 1] , s = 300 , c = 'red' , al
plt.ylabel('Spending Score (1-100)') , plt.xlabel('Annual Income (k$)')
plt.show()
```



In [33]:
```
X3 = data[['Age' , 'Annual Income (k$)' ,'Spending Score (1-100)']].iloc[: , :].value
inertia = []
for n in range(1 , 11):
    algorithm = (KMeans(n_clusters = n ,init='k-means++', n_init = 10 ,max_iter=300,
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
    algorithm.fit(X3)
    inertia.append(algorithm.inertia_)
```

In [34]:
```
plt.figure(1 , figsize = (15 ,6))
plt.plot(np.arange(1 , 11) , inertia , 'o')
plt.plot(np.arange(1 , 11) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```

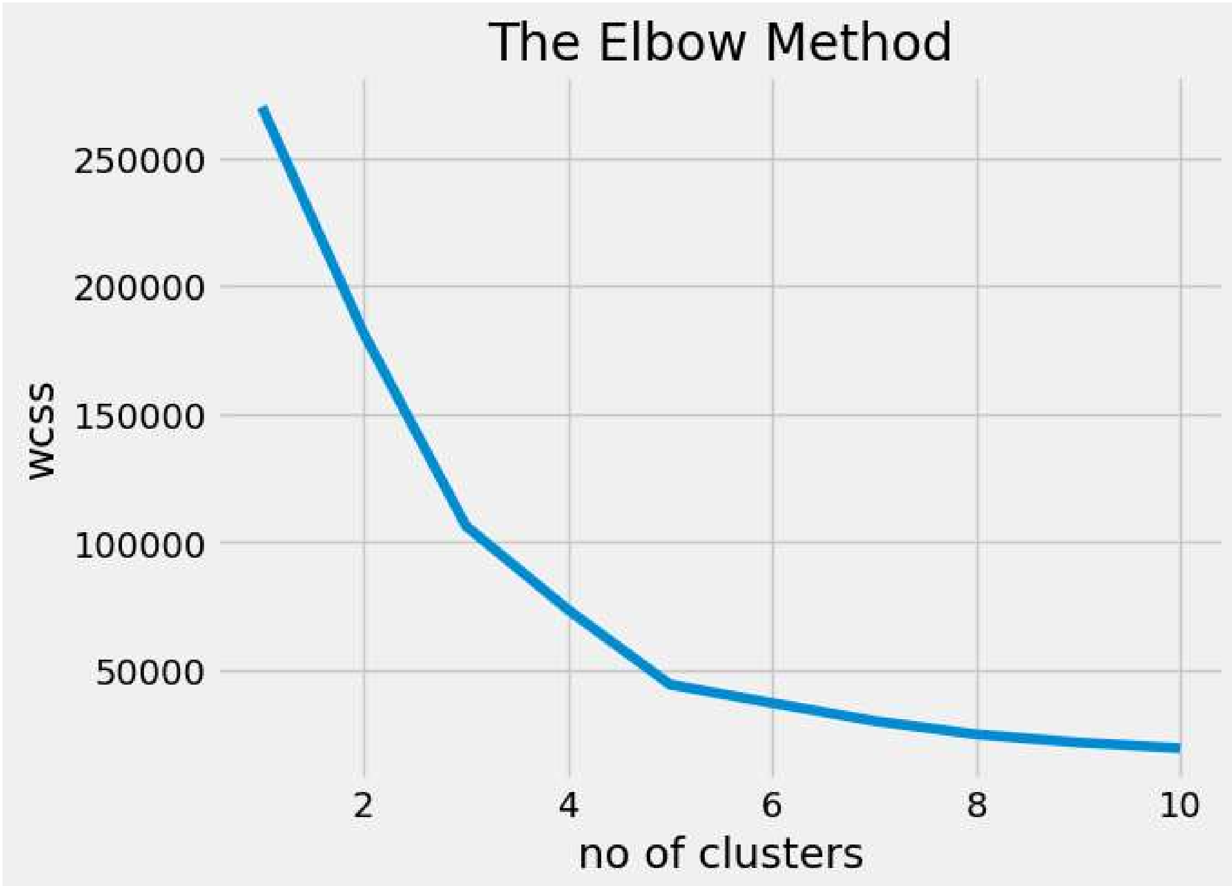


In [ ]:
```
# KMeans Algorithm to decide the optimum cluster number , KMeans++ using Elbow Mmethoc
```

In [38]:
```
X= data.iloc[:, [3,4]].values
```

In [39]:
```
from sklearn.cluster import KMeans
wcss=[]

for i in range(1,11):
    kmeans = KMeans(n_clusters= i, init='k-means++', random_state=0)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
```

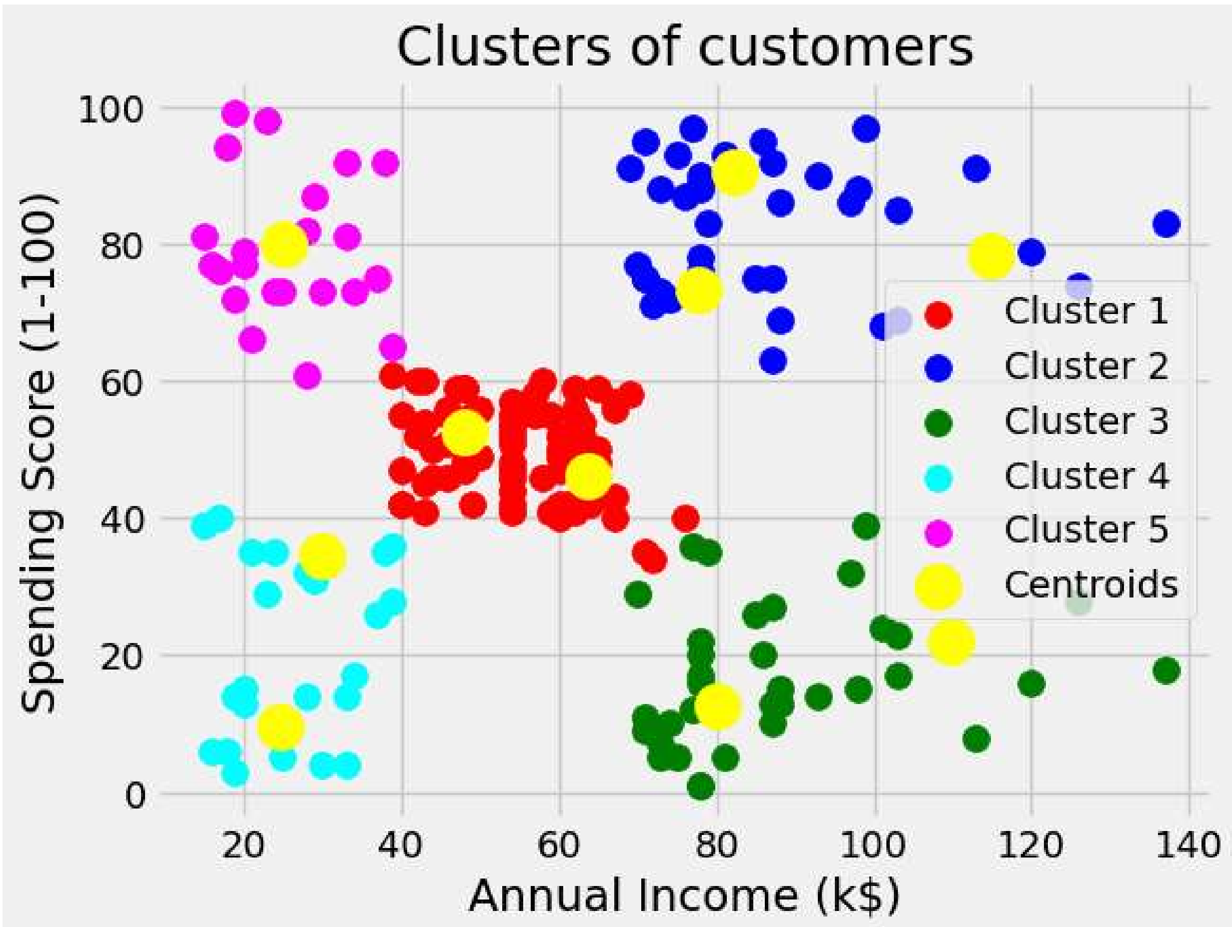
In [40]:
```
plt.plot(range(1,11), wcss)
plt.title('The Elbow Method')
plt.xlabel('no of clusters')
plt.ylabel('wcss')
plt.show()
```



In [41]:
```
kmeansmodel = KMeans(n_clusters= 5, init='k-means++', random_state=0)
y_kmeans= kmeansmodel.fit_predict(X)
```

In [42]:

```
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Cl
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'C
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 100, c = 'green', label = '
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 100, c = 'cyan', label = 'C
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 100, c = 'magenta', label =
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



In [ ]: