TASK 2: Create a K-means clustering algorithm to group customers of a retail store based on their purchase history.

Importing Libraries

In [2]:
```
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")
```

Data Exploration

In [3]:
```
df = pd.read_csv('Mall_Customers.csv')
df.head()
```

Out[3]:

	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 [4]:
```
df.shape
```

Out[4]:
```
(200, 5)
```

In [5]:
```
df.describe()
```

Out[5]:

	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 [7]:
```
df.dtypes
```

Out[7]:
```
CustomerID                 int64
Gender                    object
Age                        int64
Annual Income (k$)         int64
Spending Score (1-100)     int64
dtype: object
```

In [10]:
```
df.isnull().sum()
```

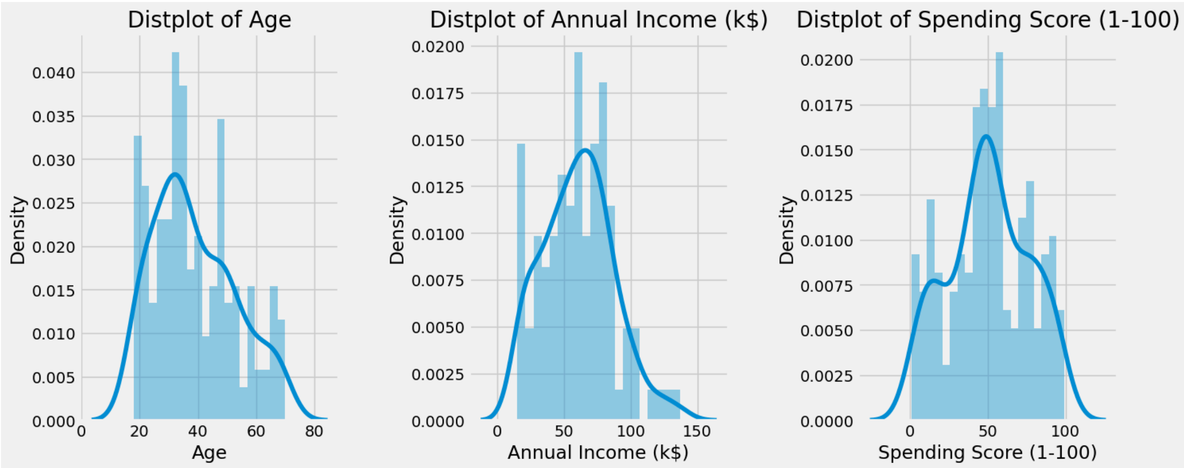
Out[10]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

Data Visualization

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

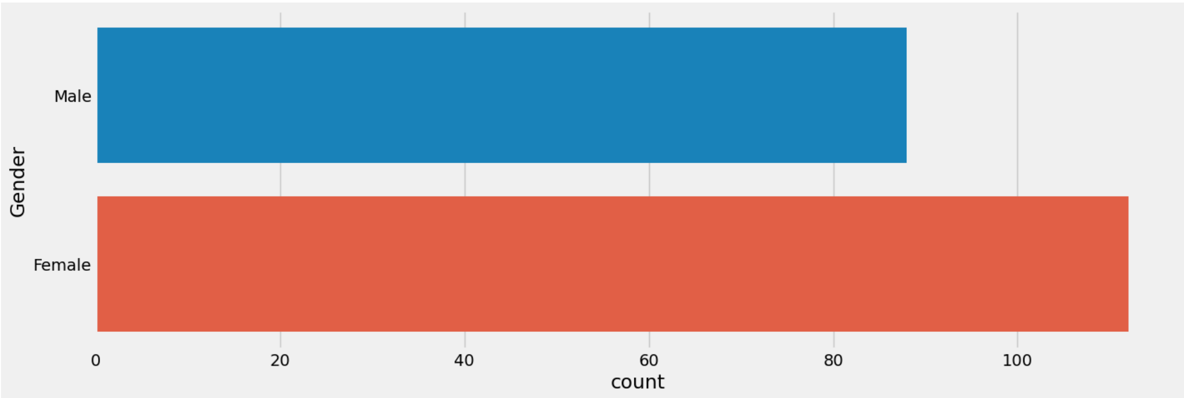
Histograms

In [12]:
```
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(df[x] , bins = 20)
    plt.title('Distplot of {}'.format(x))
plt.show()
```



Count Plot of Gender

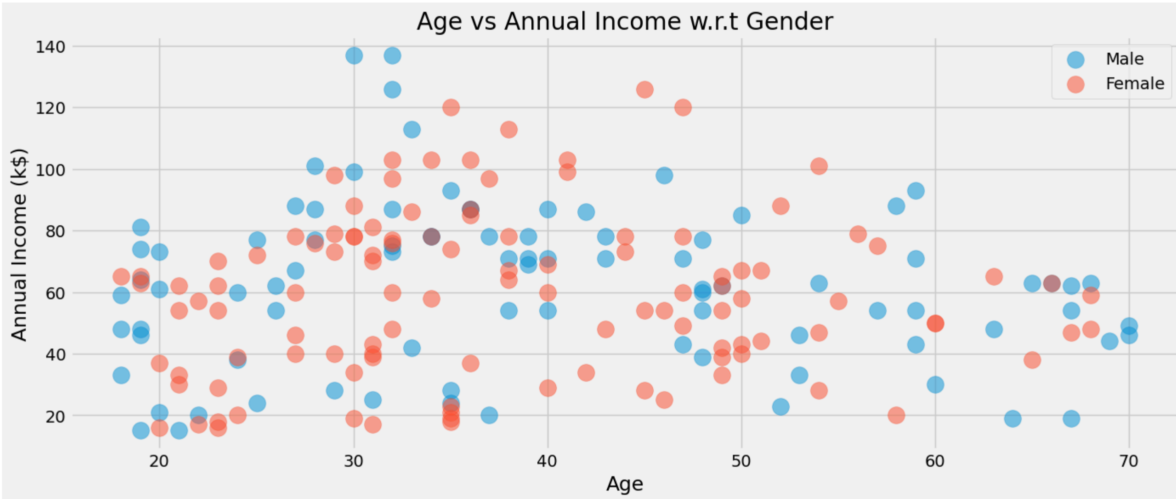
In [14]:
```
plt.figure(1 , figsize = (15 , 5))
sns.countplot(y = 'Gender' , data = df)
plt.show()
```



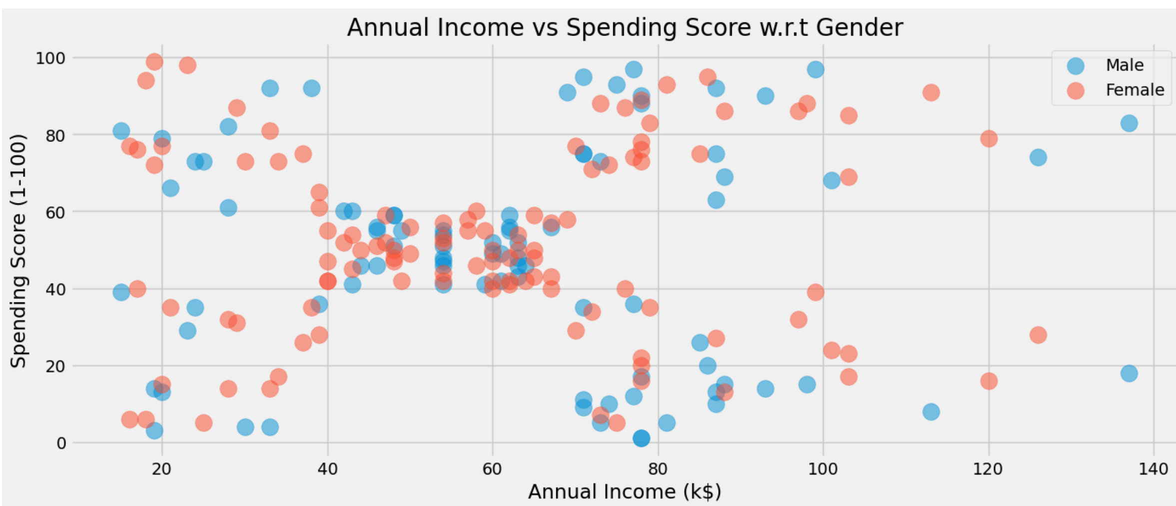
Ploting the Relation between Age , Annual Income and Spending Score

In [16]:
```
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 = df)
        plt.ylabel(y.split()[0]+' '+y.split()[1] if len(y.split()) > 1 else y
plt.show()
```

In [18]:
```
plt.figure(1 , figsize = (15 , 6))
for gender in ['Male' , 'Female']:
    plt.scatter(x = 'Age' , y = 'Annual Income (k$)' , data = df[df['Gender']
                s = 200 , alpha = 0.5 , label = gender)
plt.xlabel('Age'), plt.ylabel('Annual Income (k$)')
plt.title('Age vs Annual Income w.r.t Gender')
plt.legend()
plt.show()
```

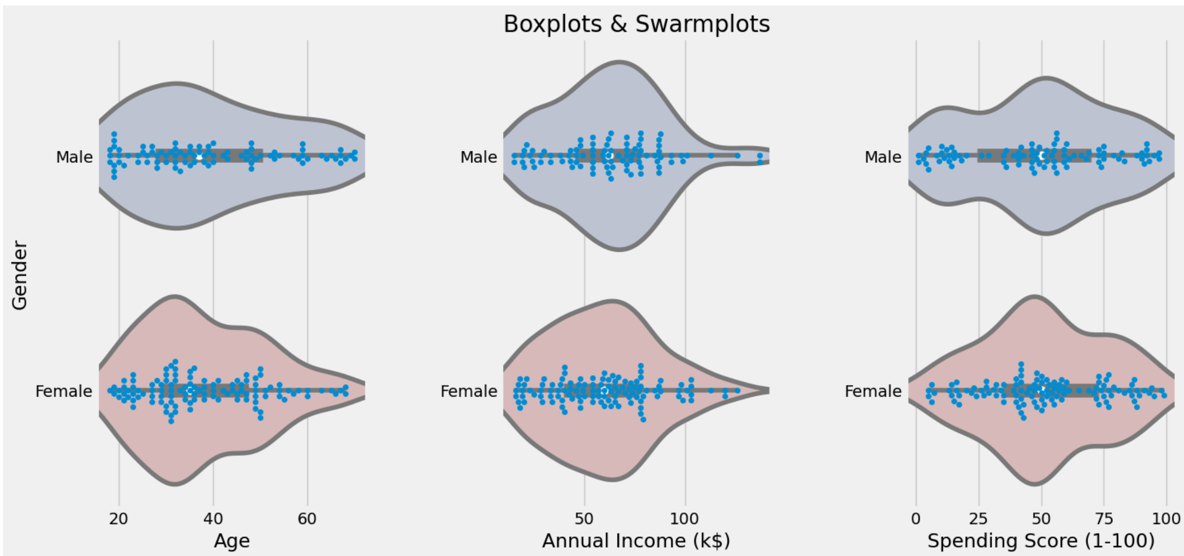


In [22]:
```
plt.figure(1 , figsize = (15 , 6))
for gender in ['Male' , 'Female']:
    plt.scatter(x = 'Annual Income (k$)',y = 'Spending Score (1-100)' ,
                data = df[df['Gender'] == gender] ,s = 200 , alpha = 0.5 , lab
plt.xlabel('Annual Income (k$)'), plt.ylabel('Spending Score (1-100)')
plt.title('Annual Income vs Spending Score w.r.t Gender')
plt.legend()
plt.show()
```



Distribution of values in Age , Annual Income and Spending Score according to Gender\

In [24]:
```
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 = df , palette = 'vlag')
    sns.swarmplot(x = cols , y = 'Gender' , data = df)
    plt.ylabel('Gender' if n == 1 else '')
    plt.title('Boxplots & Swarmplots' if n == 2 else '')
plt.show()
```



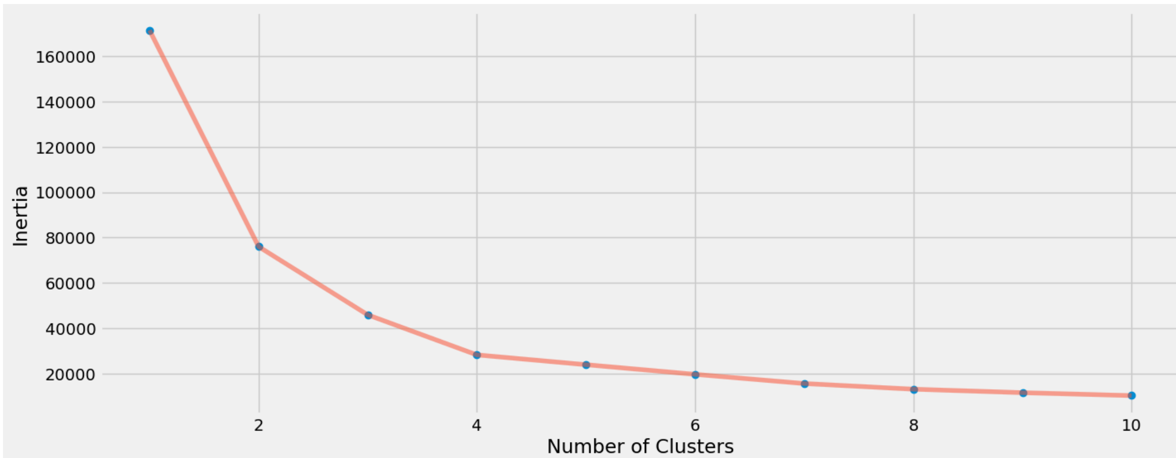
Clustering using K- means

1.Segmentation using Age and Spending Score

In [27]:
```
'''Age and spending Score'''
X1 = df[['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_ite
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
    algorithm.fit(X1)
    inertia.append(algorithm.inertia_)
```

Selecting N Clusters based in Inertia (Squared Distance between Centroids and data points, should be less)

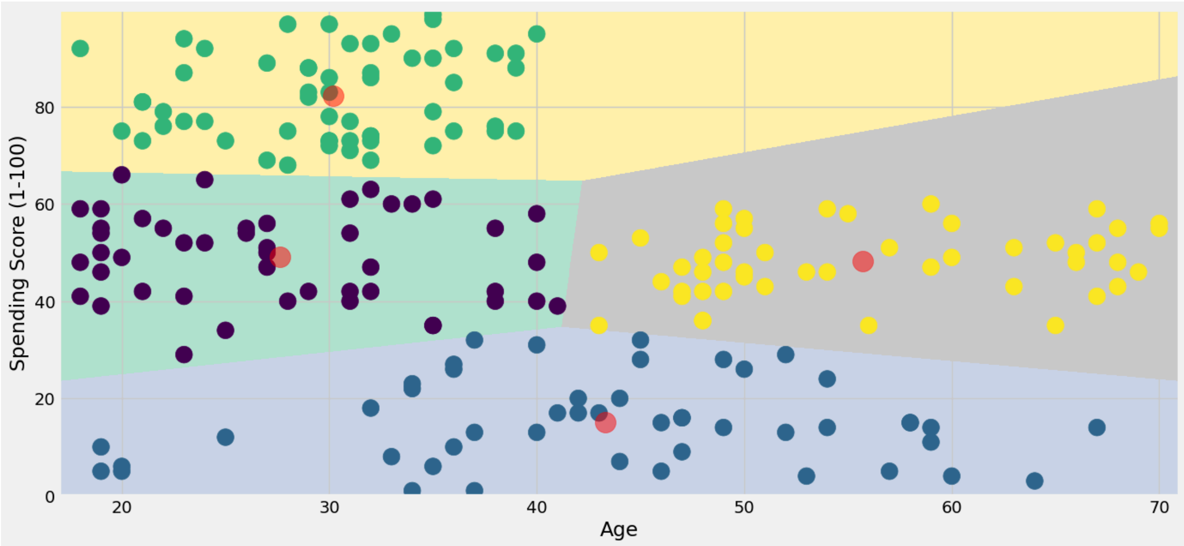
In [30]:
```
plt.figure(1 , figsize = (15 ,6))
plt.plot(np.arange(1 , 11) , inertia , 'o')
plt.plot(np.arange(1 , 11) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```



In [32]:
```
algorithm = (KMeans(n_clusters = 4 ,init='k-means++', n_init = 10 ,max_iter=30
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
algorithm.fit(X1)
labels1 = algorithm.labels_
centroids1 = algorithm.cluster_centers_
```

In [34]:
```
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()])
```

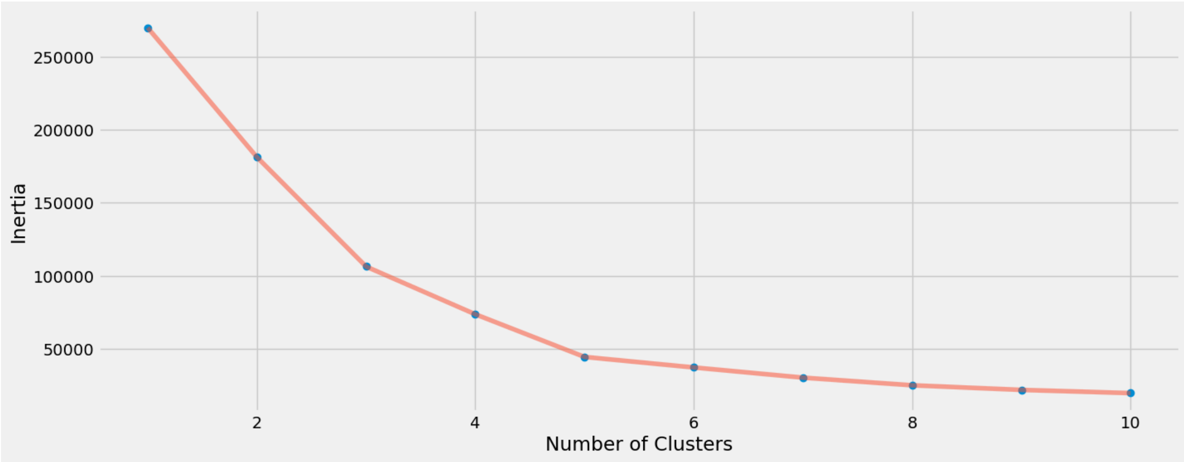
In [42]:
```
plt.figure(1 , figsize = (15 , 7) )
plt.clf()
Z = Z.reshape(xx.shape)
plt.imshow(Z , interpolation='nearest',
           extent=(xx.min(), xx.max(), yy.min(), yy.max()),
           cmap = plt.cm.Pastel2, aspect = 'auto', origin='lower')

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



2. Segmentation using Annual Income and Spending Score

In [43]:
```
'''Annual Income and spending Score'''
X2 = df[['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_ite
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
    algorithm.fit(X2)
    inertia.append(algorithm.inertia_)
```

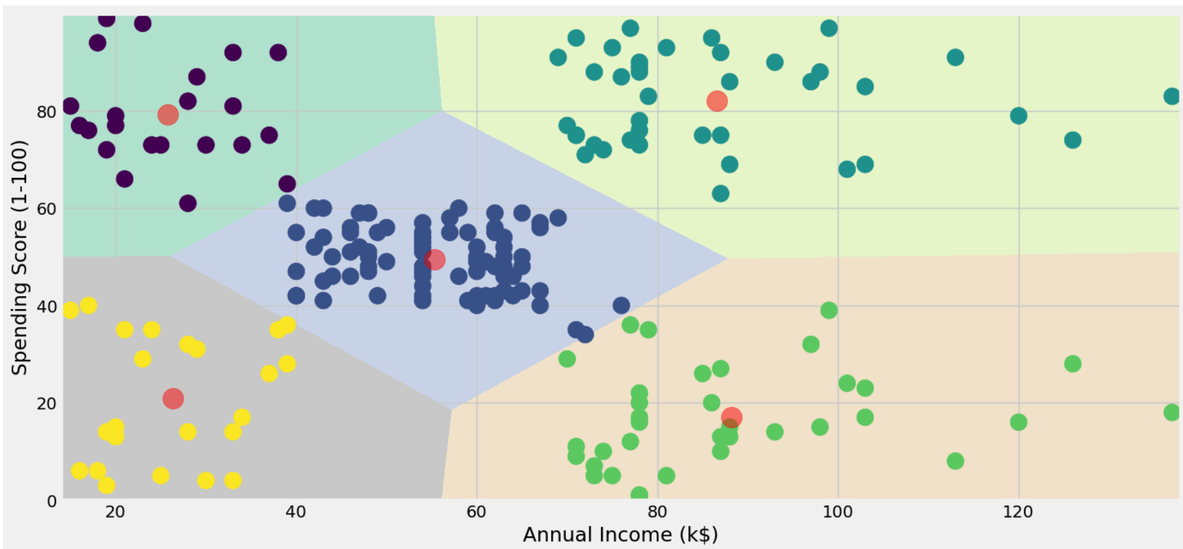
In [45]:
```
plt.figure(1 , figsize = (15 ,6))
plt.plot(np.arange(1 , 11) , inertia , 'o')
plt.plot(np.arange(1 , 11) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```



In [47]:
```
algorithm = (KMeans(n_clusters = 5 ,init='k-means++', n_init = 10 ,max_iter=30
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
algorithm.fit(X2)
labels2 = algorithm.labels_
centroids2 = algorithm.cluster_centers_
```

In [49]:
```
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()])
```

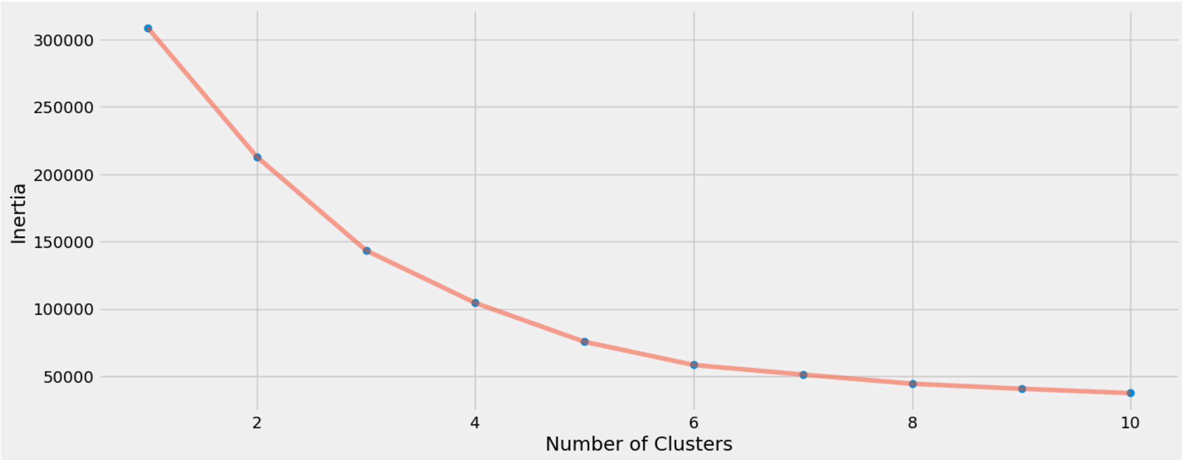
In [50]:
```
plt.figure(1 , figsize = (15 , 7) )
plt.clf()
Z2 = Z2.reshape(xx.shape)
plt.imshow(Z2 , interpolation='nearest',
           extent=(xx.min(), xx.max(), yy.min(), yy.max()),
           cmap = plt.cm.Pastel2, aspect = 'auto', origin='lower')

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



3.Segmentation using Age , Annual Income and Spending Score

In [52]:
```
X3 = df[['Age' , 'Annual Income (k$)' ,'Spending Score (1-100)']].iloc[: , :].
inertia = []
for n in range(1 , 11):
    algorithm = (KMeans(n_clusters = n ,init='k-means++', n_init = 10 ,max_ite
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
    algorithm.fit(X3)
    inertia.append(algorithm.inertia_)
```

In [53]:
```
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 [55]:
```
algorithm = (KMeans(n_clusters = 6 ,init='k-means++', n_init = 10 ,max_iter=30
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
algorithm.fit(X3)
labels3 = algorithm.labels_
centroids3 = algorithm.cluster_centers_
```

In [60]:
```
df['label3'] =  labels3
trace1 = go.Scatter3d(
    x= df['Age'],
    y= df['Spending Score (1-100)'],
    z= df['Annual Income (k$)'],
    mode='markers',
     marker=dict(
        color = df['label3'],
        size= 20,
        line=dict(
            color= df['label3'],
            width= 12
        ),
        opacity=0.8
     )
)
data = [trace1]
layout = go.Layout(

    title= 'Clusters',
    scene = dict(
            xaxis = dict(title  = 'Age'),
            yaxis = dict(title  = 'Spending Score'),
            zaxis = dict(title  = 'Annual Income')
        )
)
fig = go.Figure(data=data, layout=layout)
py.offline.iplot(fig)
```

Feature Selection For The Model

- Annual income and Spending Score

In [61]:
```
df.head(10)
```

Out[61]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)	label3
0	1	Male	19	15	39	4
1	2	Male	21	15	81	5
2	3	Female	20	16	6	4
3	4	Female	23	16	77	5
4	5	Female	31	17	40	4
5	6	Female	22	17	76	5
6	7	Female	35	18	6	4
7	8	Female	23	18	94	5
8	9	Male	64	19	3	4
9	10	Female	30	19	72	5

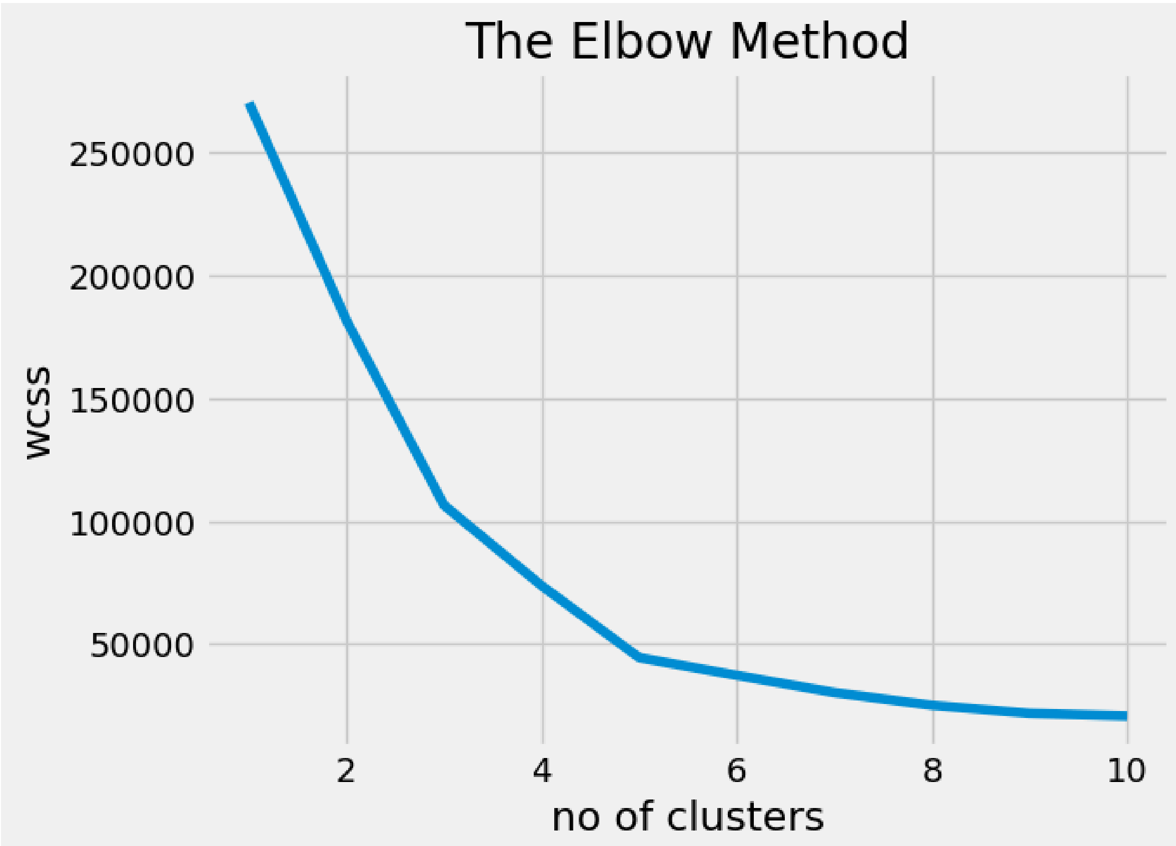
In [63]:
```
X= df.iloc[:, [3,4]].values
```

Building the Model

KMeans Algorithm to decide the optimum cluster number , KMeans++ using Elbow method

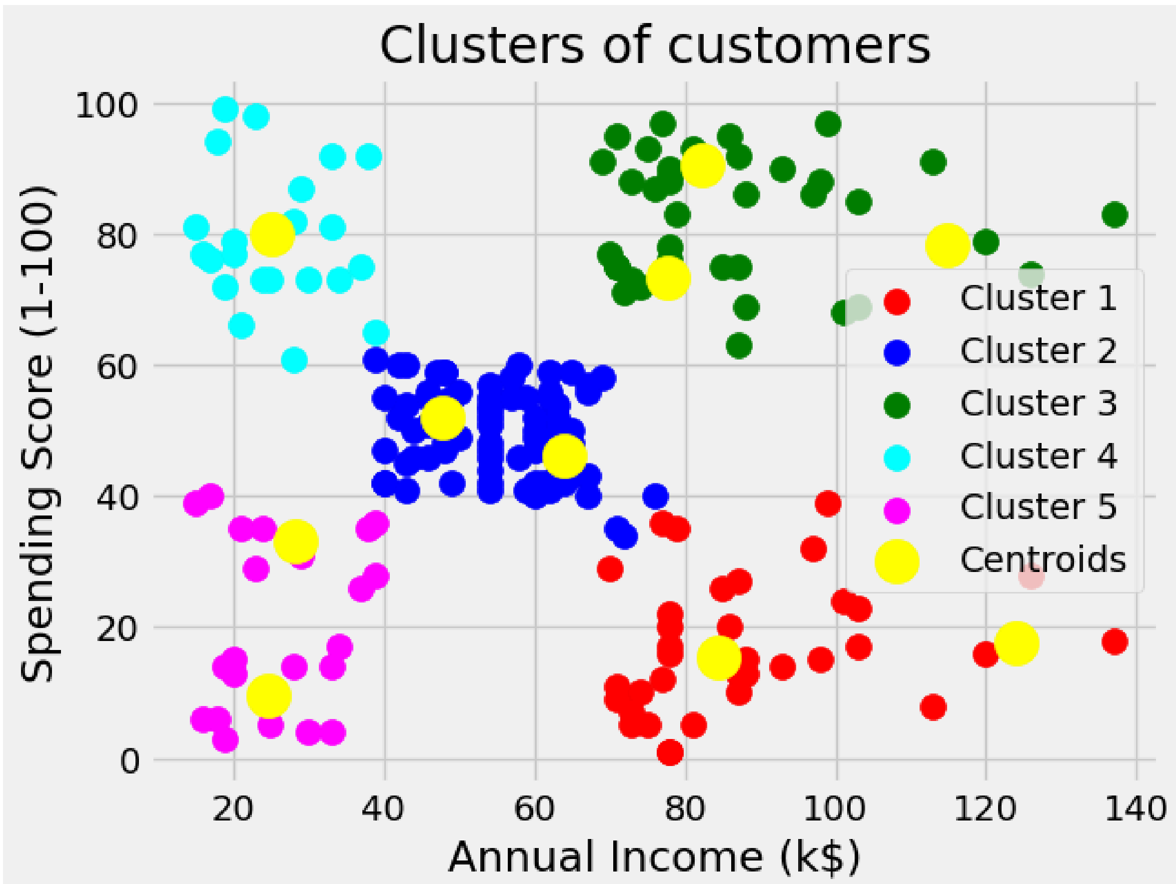
In [65]:
```
from sklearn.cluster import KMeans
wcss=[]

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 [66]:
```
#Visualizing the ELBOW method to get the optimal value of K
plt.plot(range(1,11), wcss)
plt.title('The Elbow Method')
plt.xlabel('no of clusters')
plt.ylabel('wcss')
plt.show()
```



In [69]:
```
#If you zoom out this curve then you will see that last elbow comes at k=5
#no matter what range we select ex- (1,21) also i will see the same behaviour
#that is why we usually prefer range (1,11)
##Finally we got that k=5

#Model Build
kmeansmodel = KMeans(n_clusters= 5, init='k-means++', random_state=0)
y_kmeans= kmeansmodel.fit_predict(X)

#For unsupervised learning we use "fit_predict()" wherein for supervised learn
#y_kmeans is the final model . Now how and where we will deploy this model in
#This use case is very common and it is used in BFS industry(credit card) and
```

In [72]:
```
#Visualizing all the clusters

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



""# Model Interpretation

- **Cluster 1: Earning high but spending less**
- **Cluster 2 : Average in terms of earning and spending**
- **Cluster 3 : Earning high and also spending high (TARGET SET)**
- **Cluster 4 : Earning less but spending more**
- **Cluster 5 : Earning less , spending less**

In [ ]: