In [26]:
```
#unsupervised learning technique, called k-means clustering
#input: unlabelled customer data
#output: assign each data point to clusters
```

In [27]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from kneed import KneeLocator
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from mpl_toolkits.mplot3d import Axes3D

#reading the data frame
df_initial_mall_data = pd.read_csv('Mall_Customers.csv')
```

In [28]:
```
#taking a look at the data frame
df_initial_mall_data
```

Out[28]:

| | 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 [29]:
```
#taking a look of the first few rows of the data frame
df_initial_mall_data.head()
```

Out[29]:

| | 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 [30]:
```
#removing CustomerID as it doesn't provide us with any useful cluster information
df_initial_mall_data.drop('CustomerID', axis = 1, inplace = True)
```

In [31]:
```
df_initial_mall_data
```

Out[31]:

| | Gender | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|
| 0 | Male | 19 | 15 | 39 |
| 1 | Male | 21 | 15 | 81 |
| 2 | Female | 20 | 16 | 6 |
| 3 | Female | 23 | 16 | 77 |
| 4 | Female | 31 | 17 | 40 |
| ... | ... | ... | ... | ... |
| 195 | Female | 35 | 120 | 79 |
| 196 | Female | 45 | 126 | 28 |
| 197 | Male | 32 | 126 | 74 |
| 198 | Male | 32 | 137 | 18 |
| 199 | Male | 30 | 137 | 83 |

200 rows × 4 columns

In [32]:
```
#standardizing all variables in the dataset to get them around the same scale. We will standardize these variables to follow a normal distribution
col_names = ['Annual Income (k$)', 'Age', 'Spending Score (1-100)']
features = df_initial_mall_data[col_names]
scaler = StandardScaler().fit(features.values)
features = scaler.transform(features.values)
scaled_features = pd.DataFrame(features, columns = col_names)
scaled_features
```

Out[32]:

| | Annual Income (k$) | Age | Spending Score (1-100) |
|---|---|---|---|
| 0 | -1.738999 | -1.424569 | -0.434801 |
| 1 | -1.738999 | -1.281035 | 1.195704 |
| 2 | -1.700830 | -1.352802 | -1.715913 |
| 3 | -1.700830 | -1.137502 | 1.040418 |
| 4 | -1.662660 | -0.563369 | -0.395980 |
| ... | ... | ... | ... |
| 195 | 2.268791 | -0.276302 | 1.118061 |
| 196 | 2.497807 | 0.441365 | -0.861839 |
| 197 | 2.497807 | -0.491602 | 0.923953 |
| 198 | 2.917671 | -0.491602 | -1.250054 |
| 199 | 2.917671 | -0.635135 | 1.273347 |

200 rows × 3 columns

In [ ]:

In [33]:
```
#One hot encoding: The variable 'gender' is categorical, and we need to transform this into a numeric variable. This means that we need to substitu
gender = df_initial_mall_data['Gender']
df_new_mall_data = scaled_features.join(gender)

df_new_mall_data = pd.get_dummies(df_new_mall_data, prefix = None, prefix_sep = '_', dummy_na = False, columns = None, sparse = False, drop_first =

df_new_mall_data = df_new_mall_data.drop(['Gender_Male'], axis = 1)
df_new_mall_data
```

Out[33]:

| | Annual Income (k$) | Age | Spending Score (1-100) | Gender_Female |
|---|---|---|---|---|
| 0 | -1.738999 | -1.424569 | -0.434801 | 0 |
| 1 | -1.738999 | -1.281035 | 1.195704 | 0 |
| 2 | -1.700830 | -1.352802 | -1.715913 | 1 |
| 3 | -1.700830 | -1.137502 | 1.040418 | 1 |
| 4 | -1.662660 | -0.563369 | -0.395980 | 1 |
| ... | ... | ... | ... | ... |
| 195 | 2.268791 | -0.276302 | 1.118061 | 1 |
| 196 | 2.497807 | 0.441365 | -0.861839 | 1 |
| 197 | 2.497807 | -0.491602 | 0.923953 | 0 |
| 198 | 2.917671 | -0.491602 | -1.250054 | 0 |
| 199 | 2.917671 | -0.635135 | 1.273347 | 0 |

200 rows × 4 columns

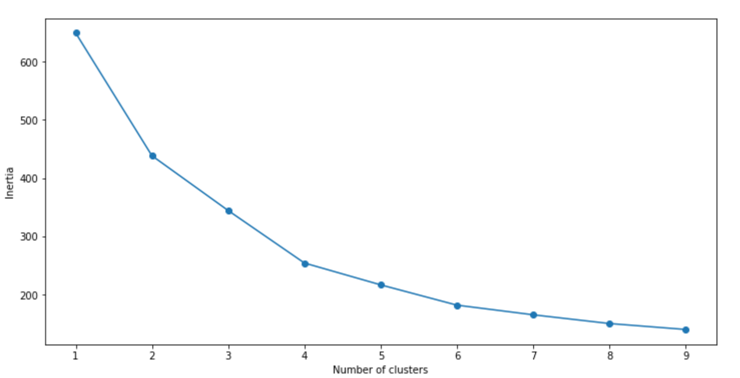
In [34]:
```
df_new_mall_data.head()
```

Out[34]:

| | Annual Income (k$) | Age | Spending Score (1-100) | Gender_Female |
|---|---|---|---|---|
| 0 | -1.738999 | -1.424569 | -0.434801 | 0 |
| 1 | -1.738999 | -1.281035 | 1.195704 | 0 |
| 2 | -1.700830 | -1.352802 | -1.715913 | 1 |
| 3 | -1.700830 | -1.137502 | 1.040418 | 1 |
| 4 | -1.662660 | -0.563369 | -0.395980 | 1 |

In [35]:
```
#Building a K-means clustering model and fitting it on all the variables in the dataset
#Then, visualizing the performance of the clustering model in an elbow plot
SSE = []

for cluster in range(1,10):
    kmeans = KMeans(n_clusters = cluster, init = 'k-means++')
    kmeans.fit(df_new_mall_data)
    SSE.append(kmeans.inertia_)

#Converting the results into a dataframe and plotting them
frame = pd.DataFrame({'Cluster':range(1,10), 'SSE':SSE})
plt.figure(figsize=(12,6))
plt.plot(frame['Cluster'], frame['SSE'], marker = 'o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

Out[35]: Text(0, 0.5, 'Inertia')

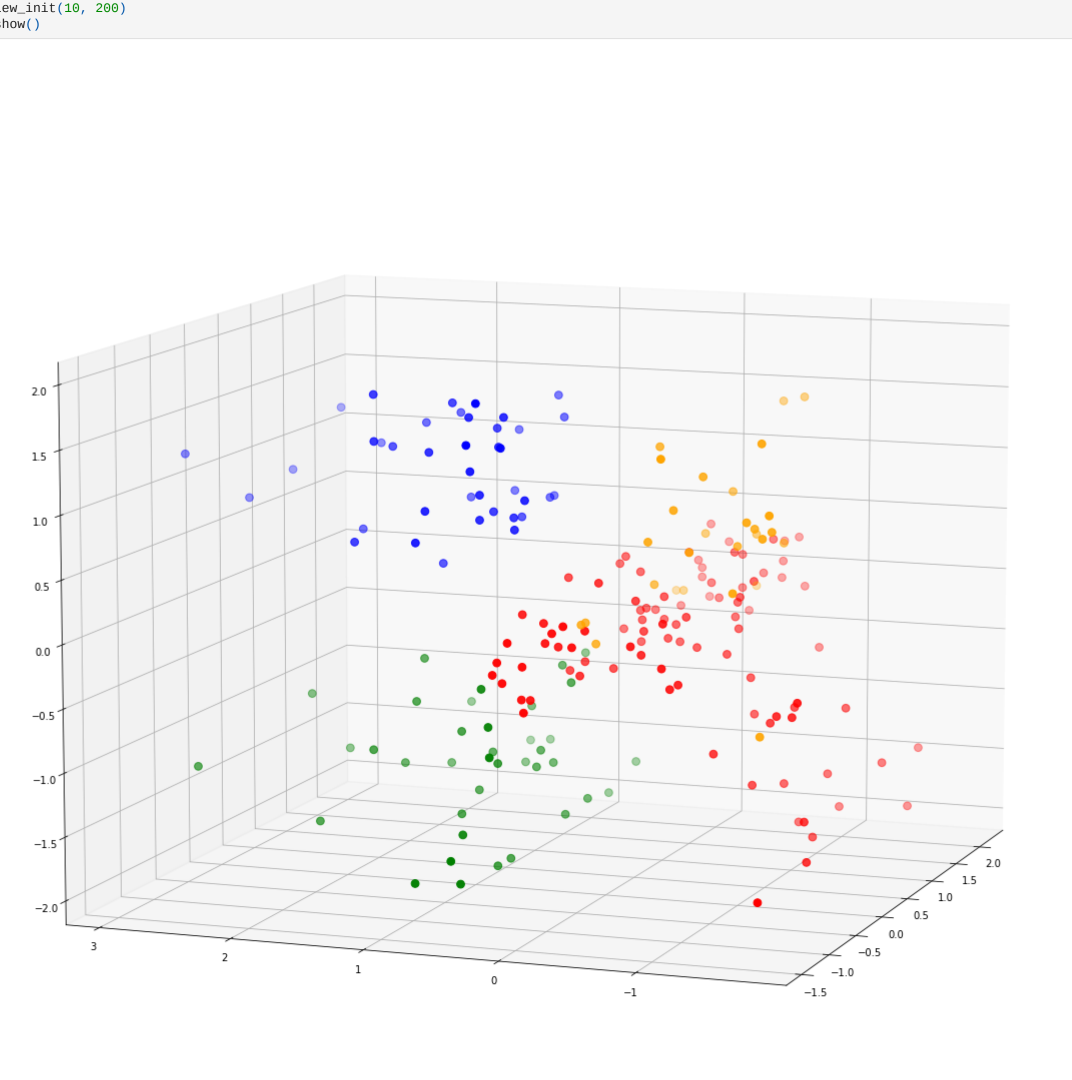



In [36]:
```
#Based on the elbow plot above, we can see that the optimal number of clusters is 4.
```

In [37]:
```
#A silhouette coefficient, or a silhouette score is a metric used to evaluate the quality of clusters created by the algorithm.
#It also measures the distance between an object and the data points in the nearest cluster. The higher this distance, the better.
#A silhouette score closer to +1 indicates good clustering performance, and a silhouette score closer to -1 indicates a poor clustering model.

# First, building a model with 4 clusters
kmeans = KMeans(n_clusters = 4, init = 'k-means++')
kmeans.fit(df_new_mall_data)

# Now, printing the silhouette score of this model
print(silhouette_score(df_new_mall_data, kmeans.labels_, metric = 'euclidean'))
```

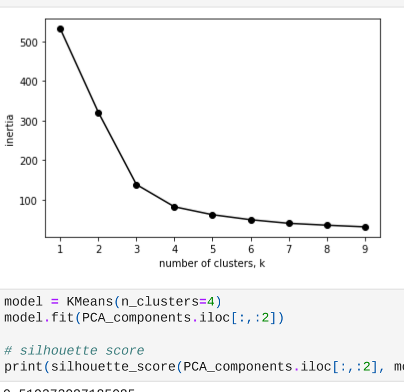
0.35027020434653977

In [38]:
```
#Silhouette score of this model is about 0.35, which isn't a bad model, but we can do better and try getting higher cluster separation.
#But before doing that, visualizing the clusters we just built to get an idea of how well the model is doing.

clusters = kmeans.fit_predict(df_initial_mall_data.iloc[:,1:])
df_new_mall_data["label"] = clusters

fig = plt.figure(figsize=(21,21))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 0], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 0], df_new_mall_data

ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 1], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 1], df_new_mall_data
ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 2], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 2], df_new_mall_data
ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 3], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 3], df_new_mall_data

ax.view_init(10, 200)
plt.show()
```




In [39]:
```
pca = PCA(n_components=4)
principalComponents = pca.fit_transform(df_new_mall_data)

features = range(pca.n_components_)
plt.bar(features, pca.explained_variance_ratio_, color='black')
plt.xlabel('PCA features')
plt.ylabel('variance %')
plt.xticks(features)

PCA_components = pd.DataFrame(principalComponents)
```

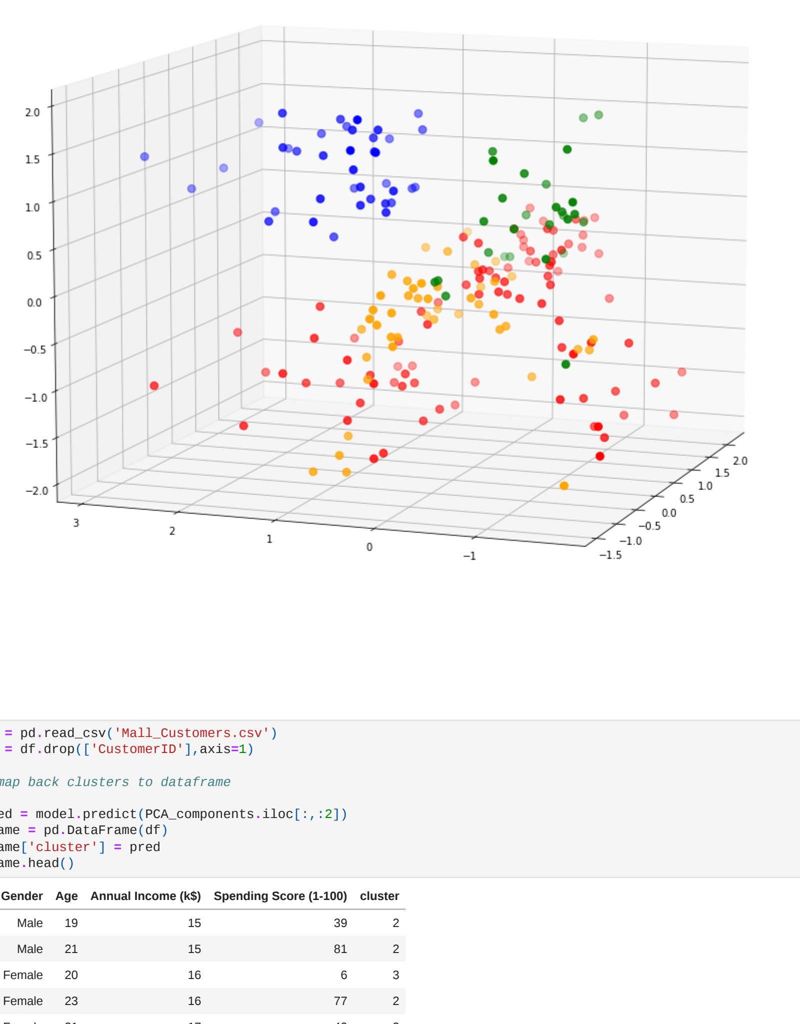

In [40]:
```
ks = range(1, 10)
inertias = []

for k in ks:
    model = KMeans(n_clusters=k)
    model.fit(PCA_components.iloc[:,:2])
    inertias.append(model.inertia_)

plt.plot(ks, inertias, '-o', color='black')
plt.xlabel('number of clusters, k')
plt.ylabel('inertia')
plt.xticks(ks)
plt.show()
```




In [41]:
```
model = KMeans(n_clusters=4)
model.fit(PCA_components.iloc[:,:2])

# silhouette score
print(silhouette_score(PCA_components.iloc[:,:2], model.labels_, metric='euclidean'))
```

0.519272987185085

In [42]:
```
model = KMeans(n_clusters=4)

clusters = model.fit_predict(PCA_components.iloc[:,:2])
df_new_mall_data["label"] = clusters

fig = plt.figure(figsize=(15,40))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 0], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 0], df_new_mall_data
ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 1], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 1], df_new_mall_data
ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 2], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 2], df_new_mall_data

ax.scatter(df_new_mall_data.Age[df_new_mall_data.label == 3], df_new_mall_data["Annual Income (k$)"][df_new_mall_data.label == 3], df_new_mall_data

ax.view_init(10, 200)
plt.show()
```




In [43]:
```
df = pd.read_csv('Mall_Customers.csv')
df = df.drop(['CustomerID'],axis=1)

# map back clusters to dataframe

pred = model.predict(PCA_components.iloc[:,:2])
frame = pd.DataFrame(df)
frame['cluster'] = pred
frame.head()
```

Out[43]:

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

In [44]:
```
avg_df = df.groupby(['cluster'], as_index=False).mean()
avg_df
```

Out[44]:

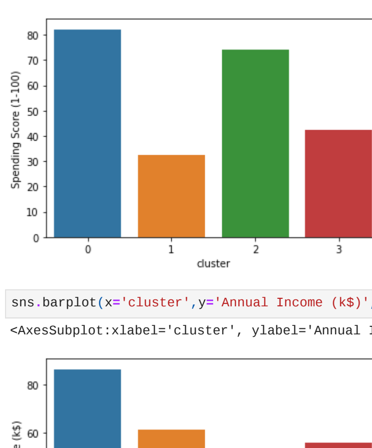
| | cluster | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|
| 0 | 0 | 32.692308 | 86.538462 | 82.128205 |
| 1 | 1 | 51.329545 | 61.545455 | 32.375000 |
| 2 | 2 | 24.821429 | 28.714286 | 74.250000 |
| 3 | 3 | 28.511111 | 55.933333 | 42.422222 |

In [45]:
```
sns.barplot(x='cluster',y='Age',data=avg_df)
```

Out[45]: <AxesSubplot:xlabel='cluster', ylabel='Age'>

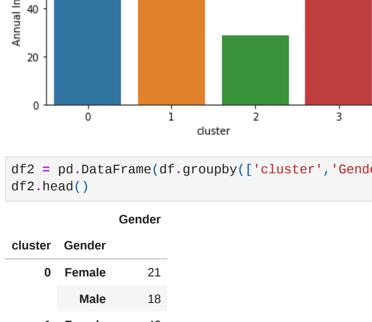

In [46]:
```
sns.barplot(x='cluster',y='Spending Score (1-100)',data=avg_df)
```

Out[46]: <AxesSubplot:xlabel='cluster', ylabel='Spending Score (1-100)'>




In [47]:
```
sns.barplot(x='cluster',y='Annual Income (k$)',data=avg_df)
```

Out[47]: <AxesSubplot:xlabel='cluster', ylabel='Annual Income (k$)'>




In [48]:
```
df2 = pd.DataFrame(df.groupby(['cluster','Gender'])['Gender'].count())
df2.head()
```

Out[48]:

| | | Gender |
|---|---|---|
| cluster | Gender | |
| 0 | Female | 21 |
| | Male | 18 |
| 1 | Female | 46 |
| | Male | 42 |
| 2 | Female | 14 |

In [49]:
```
#Cluster 0: The frugal spender
#Cluster 1: Almost retired
#Cluster 2: The careless buyer
#Cluster 3: Highly affluent individuals
```

In [ ]:

In [ ]: