Практическая работа №7

Машинное обучение. K-Means Clustering

Теоретические сведения

There are many models for **clustering** out there. In this notebook, we will be presenting the model that is considered one of the simplest models amongst them. Despite its simplicity, the **K-means** is vastly used for clustering in many data science applications, especially useful if you need to quickly discover insights from **unlabeled data**. In this notebook, you will learn how to use k-Means for customer segmentation.

Some real-world applications of k-means:

- Customer segmentation
- Understand what the visitors of a website are trying to accomplish
- Pattern recognition
- Machine learning
- Data compression

In this notebook we practice k-means clustering with 2 examples:

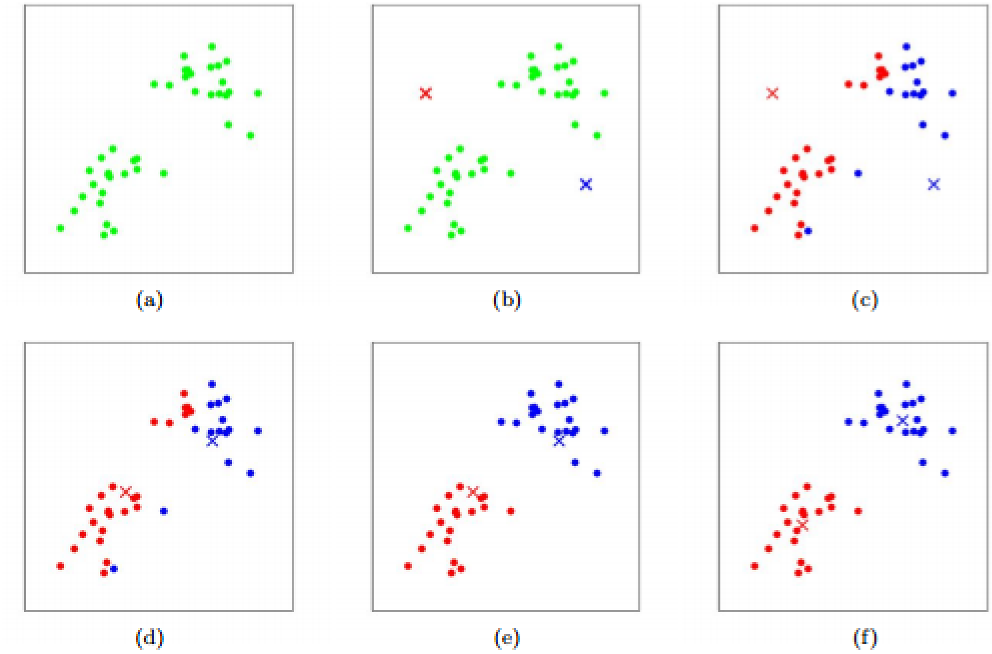
- k-means on a random generated dataset
- Using k-means for customer segmentation

Существует множество моделей кластеризации. В этом лабораторной работе мы представим модель, которая считается одной из самых простых среди них. Несмотря на свою простоту, метод K-средних широко используется для кластеризации во многих приложениях по обработке и анализу данных, что особенно полезно, если вам нужно быстро извлечь ценную информацию из неразмеченных данных. В этой лабораторной работе вы узнаете, как использовать k-Means для сегментации клиентов.

Действие алгоритма таково, что он стремится минимизировать суммарное квадратичное отклонение точек кластеров от центров этих кластеров. Он разбивает множество элементов векторного пространства на заранее известное число кластеров k.

Основная идея заключается в том, что на каждой итерации перевычисляется центр масс для каждого кластера, полученного на предыдущем шаге, затем векторы разбиваются на кластеры вновь в соответствии с тем, какой из новых центров оказался ближе по выбранной метрике.

Алгоритм завершается, когда на какой-то итерации не происходит изменения внутрикластерного расстояния. Это происходит за конечное число итераций, так как количество возможных разбиений конечного множества конечно, а на каждом шаге суммарное квадратичное отклонение V уменьшается, поэтому зацикливание невозможно.



Некоторые реальные приложения k-средних:

- Сегментация клиентов
- Распознавание образов
- Машинное обучение
- Сжатие данных

В этой лабораторной работе мы используем кластеризацию методом k-средних на двух примерах:

```
k–средних для случайно сгенерированного набора данных
Использование k–средних для сегментации клиентов
```

Программа работы

Import libraries

Lets first import the required libraries. Also run **%matplotlib inline** since we will be plotting in this section.

In [1]:
```
import random
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.datasets.samples_generator import make_blobs
%matplotlib inline
```

k-Means on a randomly generated dataset

Lets create our own dataset for this lab!

First we need to set up a random seed. Use **numpy's random.seed()** function, where the seed will be set to **0**

In [2]:
```
np.random.seed(0)
```

Next we will be making *random clusters* of points by using the **make_blobs** class. The **make_blobs** class can take in many inputs, but we will be using these specific ones.

Input

- **n_samples**: The total number of points equally divided among clusters.
  - Value will be: 5000
- **centers**: The number of centers to generate, or the fixed center locations.
  - Value will be: [[4, 4], [-2, -1], [2, -3],[1,1]]
- **cluster_std**: The standard deviation of the clusters.
  - Value will be: 0.9

Output

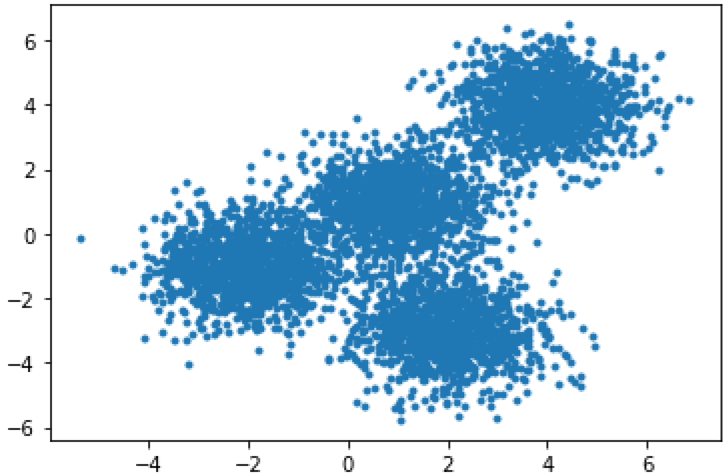
- **X**: Array of shape [n_samples, n_features]. (Feature Matrix)
  - The generated samples.
- **y**: Array of shape [n_samples]. (Response Vector)
  - The integer labels for cluster membership of each sample.

In [3]:
```
X, y = make_blobs(n_samples=5000, centers=[[4,4], [-2, -1], [2, -3], [1, 1]],
                  cluster_std=0.9)
```

Display the scatter plot of the randomly generated data.

In [4]:
```
plt.scatter(X[:, 0], X[:, 1], marker='.')
```

Out[4]:
```
<matplotlib.collections.PathCollection at 0x2c062270148>
```



Setting up K-Means

Now that we have our random data, let's set up our K-Means Clustering.

The KMeans class has many parameters that can be used, but we will be using these three:

- **init**: Initialization method of the centroids.
  - Value will be: "k-means++"
  - k-means++: Selects initial cluster centers for k-mean clustering in a smart way to speed up convergence.
- **n_clusters**: The number of clusters to form as well as the number of centroids to generate.
  - Value will be: 4 (since we have 4 centers)
- **n_init**: Number of time the k-means algorithm will be run with different centroid seeds. The final results will be the best output of n_init consecutive runs in terms of inertia.
  - Value will be: 12

Initialize KMeans with these parameters, where the output parameter is called **k_means**.

In [5]:
```
k_means = KMeans(init = "k-means++", n_clusters = 4, n_init = 12)
```

Now let's fit the KMeans model with the feature matrix we created above, **X**

In [6]:
```
k_means.fit(X)
```

Out[6]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=12, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

Now let's grab the labels for each point in the model using KMeans' **.labels_** attribute and save it as **k_means_labels**

In [7]:
```
k_means_labels = k_means.labels_
k_means_labels
```

Out[7]:
```
array([0, 3, 3, ..., 1, 0, 0])
```

We will also get the coordinates of the cluster centers using KMeans' **.cluster_centers_** and save it as **k_means_cluster_centers**

In [8]:
```
k_means_cluster_centers = k_means.cluster_centers_
k_means_cluster_centers
```

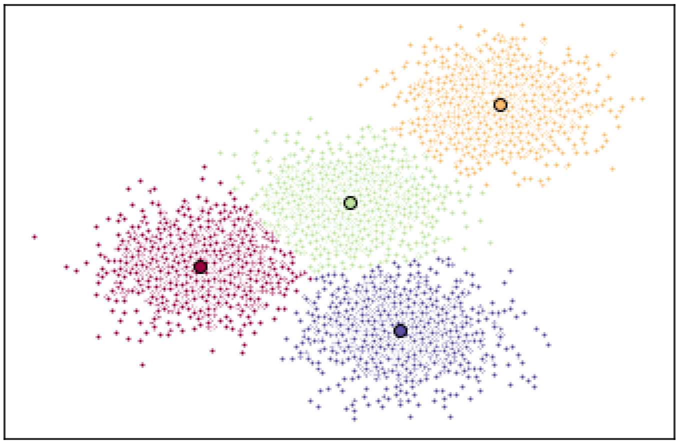
Out[8]:
```
array([[-2.03743147, -0.99782524],
       [ 3.97334234,  3.98758687],
       [ 0.96900523,  0.98370298],
       [ 1.99741008, -3.01666822]])
```

Creating the Visual Plot

So now that we have the random data generated and the KMeans model initialized, let's plot them and see what it looks like!

Please read through the code and comments to understand how to plot the model.

In [9]:
```
# Initialize the plot with the specified dimensions.
fig = plt.figure(figsize=(6, 4))

# Colors uses a color map, which will produce an array of colors based on
# the number of labels there are. We use set(k_means_labels) to get the
# unique labels.
colors = plt.cm.Spectral(np.linspace(0, 1, len(set(k_means_labels))))

# Create a plot
ax = fig.add_subplot(1, 1, 1)

# For loop that plots the data points and centroids.
# k will range from 0-3, which will match the possible clusters that each
# data point is in.
for k, col in zip(range(len([[4,4], [-2, -1], [2, -3], [1, 1]])), colors):

    # Create a list of all data points, where the data poitns that are
    # in the cluster (ex. cluster 0) are labeled as true, else they are
    # labeled as false.
    my_members = (k_means_labels == k)

    # Define the centroid, or cluster center.
    cluster_center = k_means_cluster_centers[k]

    # Plots the datapoints with color col.
    ax.plot(X[my_members, 0], X[my_members, 1], 'w',
            markerfacecolor=col, marker='.')

    # Plots the centroids with specified color, but with a darker outline
    ax.plot(cluster_center[0], cluster_center[1], 'o', markerfacecolor=col,
            markeredgecolor='k', markersize=6)

# Title of the plot
ax.set_title('KMeans')

# Remove x-axis ticks
ax.set_xticks(())

# Remove y-axis ticks
ax.set_yticks(())

# Show the plot
plt.show()
```



Practice

Try to cluster the above dataset into 3 clusters.
Notice: do not generate data again, use the same dataset as above.

In [ ]:
```
# write your code here
```

Double-click **here** for the solution.

Customer Segmentation with K-Means

Imagine that you have a customer dataset, and you need to apply customer segmentation on this historical data. Customer segmentation is the practice of partitioning a customer base into groups of individuals that have similar characteristics. It is a significant strategy as a business can target these specific groups of customers and effectively allocate marketing resources. For example, one group might contain customers who are high-profit and low-risk, that is, more likely to purchase products, or subscribe for a service. A business task is to retaining those customers. Another group might include customers from non-profit organizations. And so on.

Представьте, что у вас есть набор данных о клиентах, и вам нужно применить сегментацию клиентов к этим историческим данным. Сегментация клиентов — это практика разделения клиентской базы на группы лиц со схожими характеристиками. Это важная стратегия, поскольку бизнес может ориентироваться на эти конкретные группы клиентов и эффективно распределять маркетинговые ресурсы. Например, одна группа может содержать клиентов с высокой прибылью и низким уровнем риска, то есть с большей вероятностью купят продукты или подпишутся на услугу. Бизнес-задача состоит в том, чтобы удержать этих клиентов. Другая группа может включать клиентов из некоммерческих организаций. И так далее.

Load Data From CSV File

Before you can work with the data, you must use the URL to get the Cust_Segmentation.csv.

In [10]:
```
import pandas as pd
cust_df = pd.read_csv("Cust_Segmentation.csv")
cust_df.head()
```

Out[10]:

	Customer Id	Age	Edu	Years Employed	Income	Card Debt	Other Debt	Defaulted	Address	DebtIncomeRatio
0	1	41	2	6	19	0.124	1.073	0.0	NBA001	6.3
1	2	47	1	26	100	4.582	8.218	0.0	NBA021	12.8
2	3	33	2	10	57	6.111	5.802	1.0	NBA013	20.9
3	4	29	2	4	19	0.681	0.516	0.0	NBA009	6.3
4	5	47	1	31	253	9.308	8.908	0.0	NBA008	7.2

Pre-processing</h2>

As you can see, **Address** in this dataset is a categorical variable. k-means algorithm isn't directly applicable to categorical variables because Euclidean distance function isn't really meaningful for discrete variables. So, lets drop this feature and run clustering.

In [11]:

```
df = cust_df.drop('Address', axis=1)
df.head()
```

Out[11]:

	Customer Id	Age	Edu	Years Employed	Income	Card Debt	Other Debt	Defaulted	DebtIncomeRatio
0	1	41	2	6	19	0.124	1.073	0.0	6.3
1	2	47	1	26	100	4.582	8.218	0.0	12.8
2	3	33	2	10	57	6.111	5.802	1.0	20.9
3	4	29	2	4	19	0.681	0.516	0.0	6.3
4	5	47	1	31	253	9.308	8.908	0.0	7.2

Normalizing over the standard deviation

Now let's normalize the dataset. But why do we need normalization in the first place? Normalization is a statistical method that helps mathematical-based algorithms to interpret features with different magnitudes and distributions equally. We use **StandardScaler()** to normalize our dataset.

In [12]:

```
from sklearn.preprocessing import StandardScaler
X = df.values[:,1:]
X = np.nan_to_num(X)
Clus_dataSet = StandardScaler().fit_transform(X)
Clus_dataSet
```

Out[12]:

```
array([[ 0.74291541,  0.31212243, -0.37878978, ..., -0.59048916,
        -0.52379654, -0.57652509],
       [ 1.48949049, -0.76634938,  2.5737211 , ...,  1.51296181,
        -0.52379654,  0.39138677],
       [-0.25251804,  0.31212243,  0.2117124 , ...,  0.80170393,
         1.90913822,  1.59755385],
       ...,
       [-1.24795149,  2.46906604, -1.26454304, ...,  0.03863257,
         1.90913822,  3.45892281],
       [-0.37694723, -0.76634938,  0.50696349, ..., -0.70147601,
        -0.52379654, -1.08281745],
       [ 2.1116364 , -0.76634938,  1.09746566, ...,  0.16463355,
        -0.52379654, -0.2340332 ]])
```

Modeling

In our example (if we didn't have access to the k-means algorithm), it would be the same as guessing that each customer group would have certain age, income, education, etc, with multiple tests and experiments. However, using the K-means clustering we can do all this process much easier.

Lets apply k-means on our dataset, and take look at cluster labels.

In [13]:
```
clusterNum = 3
k_means = KMeans(init = "k-means++", n_clusters = clusterNum, n_init = 12)
k_means.fit(X)
labels = k_means.labels_
print(labels)
```

```
[1 2 1 1 0 2 1 2 1 2 2 1 1 1 1 1 1 1 2 1 1 1 1 2 2 2 1 1 2 1 2 1 1 1 1 1 1
 1 1 2 1 2 1 0 1 2 1 1 1 2 2 1 1 2 2 1 1 1 2 1 2 1 2 2 1 1 2 1 1 1 2 2 2 1
 1 1 1 1 2 1 2 2 0 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 2 2 1 1 1 1 1 1 2 1
 1 1 1 1 1 1 1 2 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 2 1 2 1
 1 1 1 1 1 1 2 1 2 2 1 2 1 1 2 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 2 1 1 1 2 1
 1 1 1 1 2 1 1 2 1 2 1 1 2 0 1 2 1 1 1 1 1 1 0 2 1 1 1 1 2 1 1 2 2 1 2 1 2
 1 1 1 1 2 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 0 2 1 1 1 1 1 1 1 2 1 1 1 1
 1 1 2 1 1 2 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 1 2 1 2 1 2 2 1 1 1 1 1 1
 1 1 1 2 2 2 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 1 1 1 1 1 2 1 2 2 1
 1 1 1 1 2 1 1 1 1 1 1 2 1 1 2 1 1 2 1 1 1 1 1 2 1 1 1 0 1 1 1 2 1 2 2 2 1
 1 1 2 1 1 1 1 1 1 1 1 1 1 1 2 1 2 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1
 1 2 1 1 2 1 1 1 1 2 1 1 1 1 2 1 1 2 1 1 1 1 1 1 1 1 1 2 1 1 1 2 1 1 1 1 0
 1 1 1 1 1 1 2 1 1 1 0 1 1 1 1 2 1 0 1 1 1 1 2 1 2 2 2 1 1 2 2 1 1 1 1 1 1
 1 2 1 1 1 1 2 1 1 1 2 1 2 1 1 1 2 1 1 1 1 2 2 1 1 1 1 2 1 1 1 1 2 1 1 1 1
 1 2 2 1 1 1 1 1 1 1 1 1 1 1 0 2 1 1 1 1 1 1 2 1 1 1 1 2 1 1 2 1 1 0 1 0 1
 1 0 1 1 1 1 1 1 1 1 1 2 1 2 1 1 0 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 2 1 2
 1 1 1 1 1 1 2 1 1 1 1 2 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 2
 2 1 1 2 1 2 1 1 2 1 2 1 1 0 1 2 1 2 1 1 1 1 1 2 2 1 1 1 1 2 1 1 1 2 2 1 1
 2 1 1 1 2 1 0 1 1 2 1 1 1 1 1 1 1 2 1 1 1 2 1 1 1 1 1 2 1 1 2 1 1 1 1 1 1
 1 1 2 1 1 2 1 2 1 2 2 1 1 1 2 1 2 1 1 1 1 1 2 1 1 1 1 2 2 1 1 2 2 1 1 1 1
 1 2 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 2 1 2 2 1 2 1 2 2 1 1 2 1 1 1 1 1 2 2
 1 1 1 1 1 1 1 2 1 1 1 1 1 1 0 2 2 1 1 1 1 1 1 1 2 1 1 1 1 1 1 2 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 2]
```

Insights

We assign the labels to each row in dataframe.

In [14]:
```
df["Clus_km"] = labels
df.head(5)
```

Out[14]:

	Customer Id	Age	Edu	Years Employed	Income	Card Debt	Other Debt	Defaulted	DebtIncomeRatio	Clus_km
0	1	41	2	6	19	0.124	1.073	0.0	6.3	1
1	2	47	1	26	100	4.582	8.218	0.0	12.8	2
2	3	33	2	10	57	6.111	5.802	1.0	20.9	1
3	4	29	2	4	19	0.681	0.516	0.0	6.3	1
4	5	47	1	31	253	9.308	8.908	0.0	7.2	0

We can easily check the centroid values by averaging the features in each cluster.

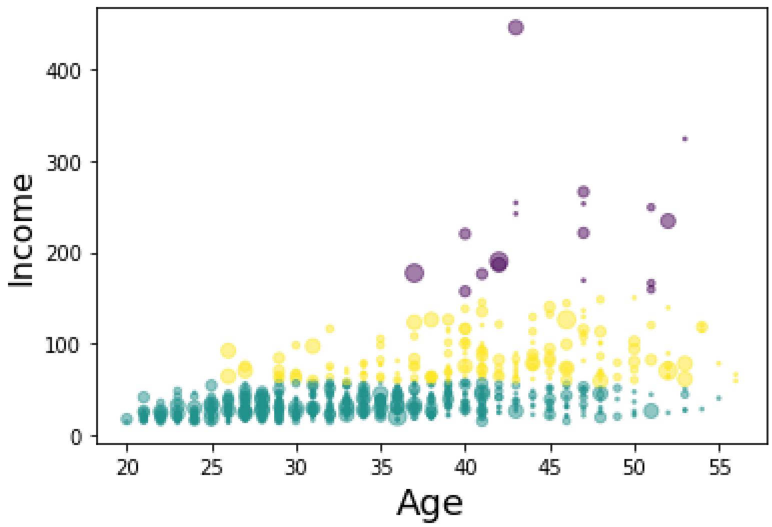
In [15]:
```
df.groupby('Clus_km').mean()
```

Out[15]:

Clus_km	Customer Id	Age	Edu	Years Employed	Income	Card Debt	Other Debt	Defaulted	Debtl
0	410.166667	45.388889	2.666667	19.555556	227.166667	5.678444	10.907167	0.285714	
1	432.006154	32.967692	1.613846	6.389231	31.204615	1.032711	2.108345	0.284658	
2	403.780220	41.368132	1.961538	15.252747	84.076923	3.114412	5.770352	0.172414	

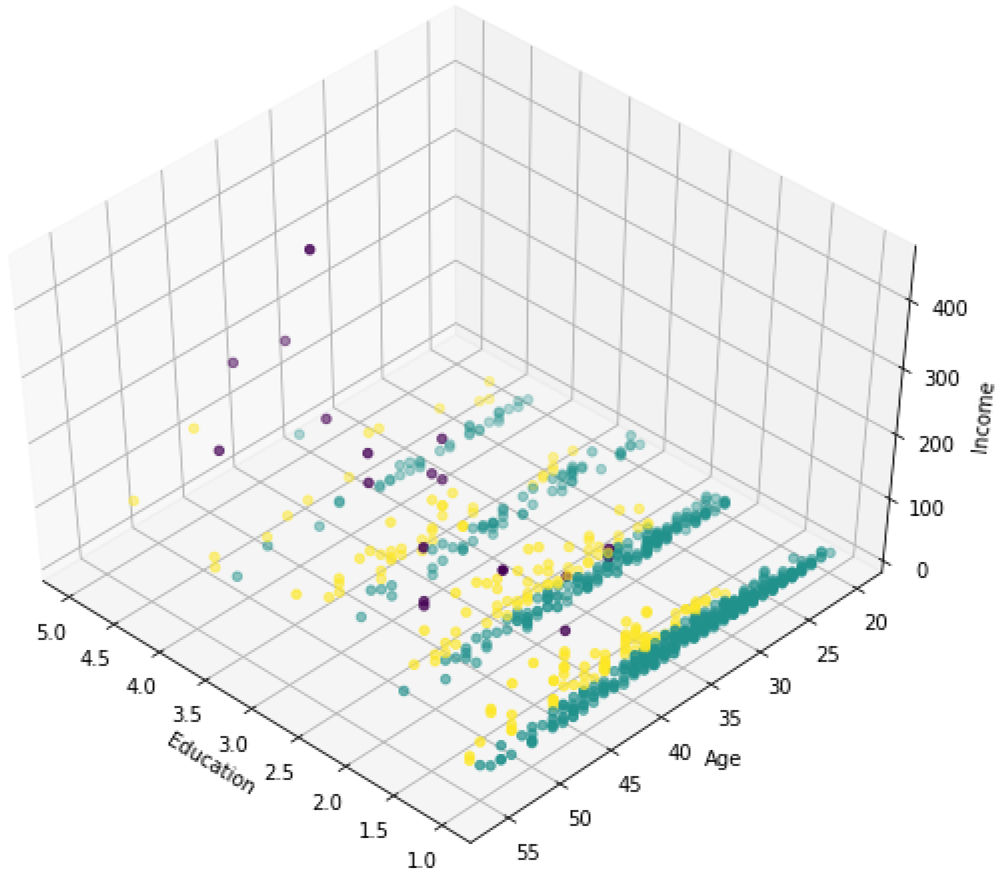
Now, lets look at the distribution of customers based on their age and income:

In [16]:
```
area = np.pi * ( X[:, 1])**2
plt.scatter(X[:, 0], X[:, 3], s=area, c=labels.astype(np.float), alpha=0.5)
plt.xlabel('Age', fontsize=18)
plt.ylabel('Income', fontsize=16)

plt.show()
```



In [17]:
```
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure(1, figsize=(8, 6))
plt.clf()
ax = Axes3D(fig, rect=[0, 0, .95, 1], elev=48, azim=134)

plt.cla()
# plt.ylabel('Age', fontsize=18)
# plt.xlabel('Income', fontsize=16)
# plt.zlabel('Education', fontsize=16)
ax.set_xlabel('Education')
ax.set_ylabel('Age')
ax.set_zlabel('Income')

ax.scatter(X[:, 1], X[:, 0], X[:, 3], c= labels.astype(np.float))
```

Out[17]:
```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x2c064970288>
```



k-means will partition your customers into mutually exclusive groups, for example, into 3 clusters. The customers in each cluster are similar to each other demographically. Now we can create a profile for each group, considering the common characteristics of each cluster. For example, the 3 clusters can be:

- AFFLUENT, EDUCATED AND OLD AGED
- MIDDLE AGED AND MIDDLE INCOME
- YOUNG AND LOW INCOME