Question 2 - Section B

March 4, 2023

0.1 Question 2

[ ]:
```
%load_ext autoreload
%autoreload 2
```

[ ]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from utils import styled_print, download_data, read_and_clean_data, \
    plot_scatter_plot
```

0.1.1 Section B - Unsupervised Machine Learning

[ ]:
```
cleveland_url = "http://archive.ics.uci.edu/ml/machine-learning-databases/
↪heart-disease/processed.cleveland.data"
```

[ ]:
```
headers = {
    0: "age",
    1: "sex",
    2: "cp",
    3: "trestbps",
    4: "chol",
    5: "fbs",
    6: "restecg",
    7: "thalach",
    8: "exang",
    9: "oldpeak",
    10: "slope",
    11: "ca",
    12: "thal",
    13: "target"
}
```

[ ]:
```
styled_print(f"Heart Disease Data Analysis", header=True)
styled_print(f"Extracting Data From {cleveland_url}")
cleveland_file = download_data(cleveland_url, path_to_download="./data")
cleveland_df = read_and_clean_data(cleveland_file, header=headers.values())
```

```
> Heart Disease Data Analysis
    Extracting Data From http://archive.ics.uci.edu/ml/machine-learning-
databases/heart-disease/processed.cleveland.data
```

[ ]:
```
styled_print(f"Cleveland Dataframe Info", header=True)
cleveland_df.info()
```

```
> Cleveland Dataframe Info
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    float64
 1   sex       303 non-null    float64
 2   cp        303 non-null    float64
 3   trestbps  303 non-null    float64
 4   chol      303 non-null    float64
 5   fbs       303 non-null    float64
 6   restecg   303 non-null    float64
 7   thalach   303 non-null    float64
 8   exang     303 non-null    float64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    float64
 11  ca        299 non-null    float64
 12  thal      301 non-null    float64
 13  target    303 non-null    int64
dtypes: float64(13), int64(1)
memory usage: 33.3 KB
```

[ ]:
```
categorical_columns = ["cp", "restecg", "slope", "thal", "ca"]
binary_columns = ["sex", "fbs", "exang"]

continuous_columns = ["age", "trestbps", "chol", "thalach", "oldpeak"]
discrete_columns = categorical_columns + binary_columns
target_column = ["target"]
```

[ ]:
```
og_data_df = cleveland_df.copy()
og_data_df.head()
```

[ ]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	\
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	

```
1  67.0  1.0  4.0     160.0  286.0  0.0      2.0    108.0    1.0      1.5
2  67.0  1.0  4.0     120.0  229.0  0.0      2.0    129.0    1.0      2.6
3  37.0  1.0  3.0     130.0  250.0  0.0      0.0    187.0    0.0      3.5
4  41.0  0.0  2.0     130.0  204.0  0.0      2.0    172.0    0.0      1.4

   slope   ca  thal  target
0    3.0  0.0   6.0       0
1    2.0  3.0   3.0       2
2    2.0  2.0   7.0       1
3    3.0  0.0   3.0       0
4    1.0  0.0   3.0       0
```

[ ]:
```
og_data_df = og_data_df.dropna()
og_data_df.isnull().sum()
```

[ ]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

[ ]:
```
data_df = og_data_df.drop(target_column[0], axis=1)
```

[ ]:
```
scaler = StandardScaler()
data_scaled = pd.DataFrame(scaler.fit_transform(data_df), columns = data_df.
 ↪columns)
data_scaled.head()
```

[ ]:
```
        age       sex        cp  trestbps      chol       fbs   restecg  \
0  0.936181  0.691095 -2.240629  0.750380 -0.276443  2.430427  1.010199
1  1.378929  0.691095  0.873880  1.596266  0.744555 -0.411450  1.010199
2  1.378929  0.691095  0.873880 -0.659431 -0.353500 -0.411450  1.010199
3 -1.941680  0.691095 -0.164289 -0.095506  0.051047 -0.411450 -1.003419
4 -1.498933 -1.446980 -1.202459 -0.095506 -0.835103 -0.411450  1.010199

    thalach     exang   oldpeak     slope        ca      thal
0  0.017494 -0.696419  1.068965  2.264145 -0.721976  0.655877
```

```
1 -1.816334  1.435916  0.381773  0.643781  2.478425 -0.894220
2 -0.899420  1.435916  1.326662  0.643781  1.411625  1.172577
3  1.633010 -0.696419  2.099753  2.264145 -0.721976 -0.894220
4  0.978071 -0.696419  0.295874 -0.976583 -0.721976 -0.894220
```

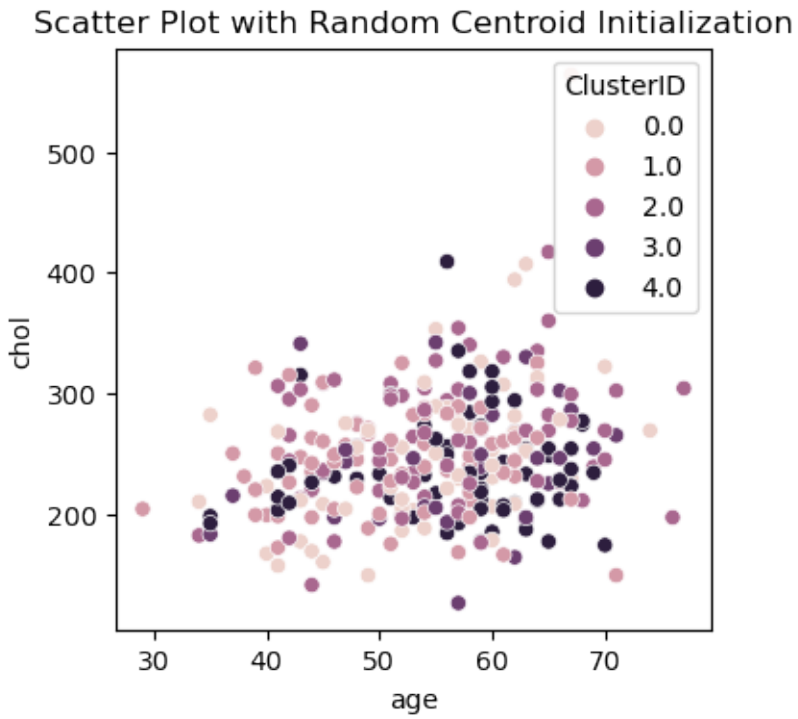
[ ]:
```
# Function to create Cluster Map for Better Visualization and Filtering
def create_cluster_map(data, model):
    cluster_map = pd.DataFrame()
    cluster_map['ClusterID'] = model.labels_
    cluster_map = pd.concat([data, cluster_map], axis=1)
    return cluster_map

def get_centroid(data, kmeans):
    centroids = pd.DataFrame(kmeans.cluster_centers_, columns=data.columns)
    return centroids
```

[ ]:
```
kmeans = KMeans(n_clusters=5, random_state=0, init='random', n_init='auto').
 ↪fit(data_scaled)
cluster_map = create_cluster_map(og_data_df, kmeans)

styled_print(f"Cluster Map from Kmeans with Random Cluster Initialization",␣
 ↪header=True)
print(cluster_map.head(10))

styled_print(f"Cluster Centroid from Kmeans with Random Cluster␣
 ↪Initialization", header=True)
print(get_centroid(data_df, kmeans).head(10))
```

```
› Cluster Map from Kmeans with Random Cluster Initialization
    age  sex   cp  trestbps   chol  fbs  restecg  thalach  exang  oldpeak  \
0  63.0  1.0  1.0     145.0  233.0  1.0      2.0    150.0    0.0      2.3
1  67.0  1.0  4.0     160.0  286.0  0.0      2.0    108.0    1.0      1.5
2  67.0  1.0  4.0     120.0  229.0  0.0      2.0    129.0    1.0      2.6
3  37.0  1.0  3.0     130.0  250.0  0.0      0.0    187.0    0.0      3.5
4  41.0  0.0  2.0     130.0  204.0  0.0      2.0    172.0    0.0      1.4
5  56.0  1.0  2.0     120.0  236.0  0.0      0.0    178.0    0.0      0.8
6  62.0  0.0  4.0     140.0  268.0  0.0      2.0    160.0    0.0      3.6
7  57.0  0.0  4.0     120.0  354.0  0.0      0.0    163.0    1.0      0.6
8  63.0  1.0  4.0     130.0  254.0  0.0      2.0    147.0    0.0      1.4
9  53.0  1.0  4.0     140.0  203.0  1.0      2.0    155.0    1.0      3.1

   slope   ca  thal  target  ClusterID
0    3.0  0.0   6.0     0.0        4.0
1    2.0  3.0   3.0     2.0        3.0
2    2.0  2.0   7.0     1.0        0.0
3    3.0  0.0   3.0     0.0        1.0
4    1.0  0.0   3.0     0.0        1.0
```

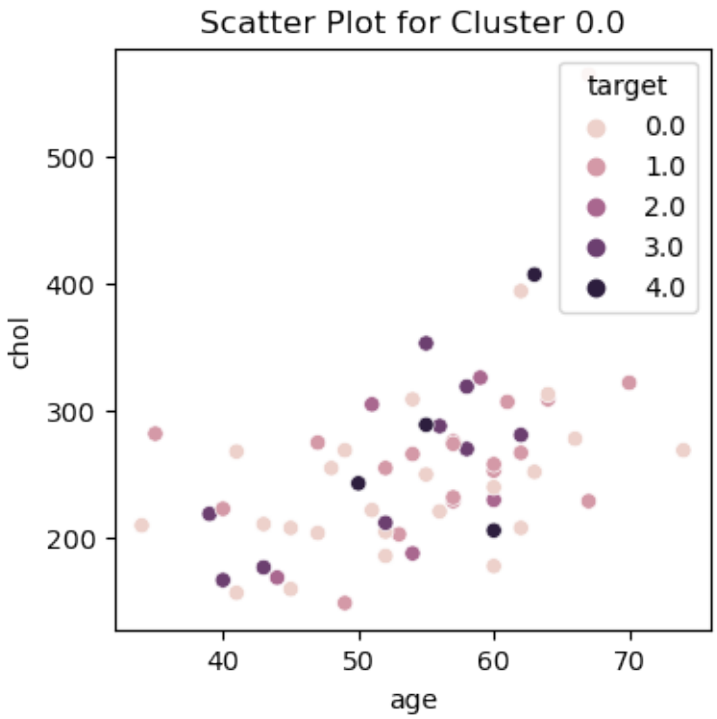
```
5    1.0  0.0   3.0     0.0        1.0
6    3.0  2.0   3.0     3.0        3.0
7    1.0  0.0   3.0     0.0        2.0
8    2.0  1.0   7.0     2.0        4.0
9    3.0  0.0   7.0     1.0        0.0
> Cluster Centroid from Kmeans with Random Cluster Initialization
        age       sex        cp  trestbps      chol       fbs   restecg  \
0  0.152587  0.521406  0.807965 -0.149213 -0.076158 -0.185904  0.035352
1 -1.096155  0.275358 -0.322899 -0.443260 -0.307748 -0.332509 -0.416114
2  0.429704 -1.382189 -0.117100  0.035222  0.437205 -0.110039  0.018645
3  0.739019 -0.177498  0.679223  0.797961  0.448369  0.299019  0.380943
4  0.270329  0.691095 -0.650932  0.210246 -0.253868  0.521041  0.223629

    thalach     exang   oldpeak     slope        ca      thal
0 -0.956250  1.300530  0.635380  0.540901  0.073891  0.770699
1  0.816156 -0.489109 -0.606065 -0.706522 -0.544176 -0.556930
2  0.114743 -0.341030 -0.422554 -0.240054 -0.334049 -0.831590
3 -0.672920  0.169842  1.028700  0.745054  1.845012  0.639731
4  0.241265 -0.463195 -0.022220  0.137417 -0.038557  0.405601
```

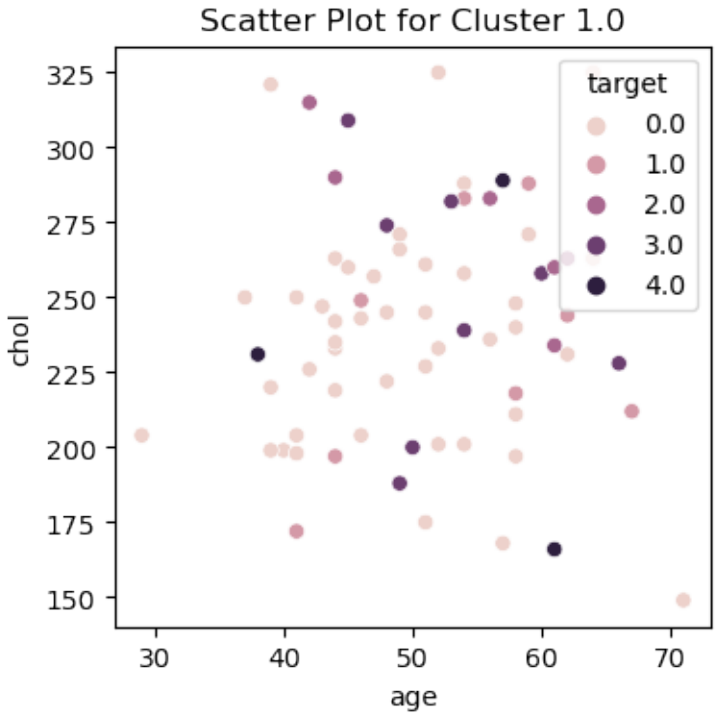
[ ]:
```
plot_scatter_plot(
    df=cluster_map,
    x="age",
    y="chol",
    hue='ClusterID',
    title="Scatter Plot with Random Centroid Initialization",
    figsize=(4, 4),
    dpi=100)
```

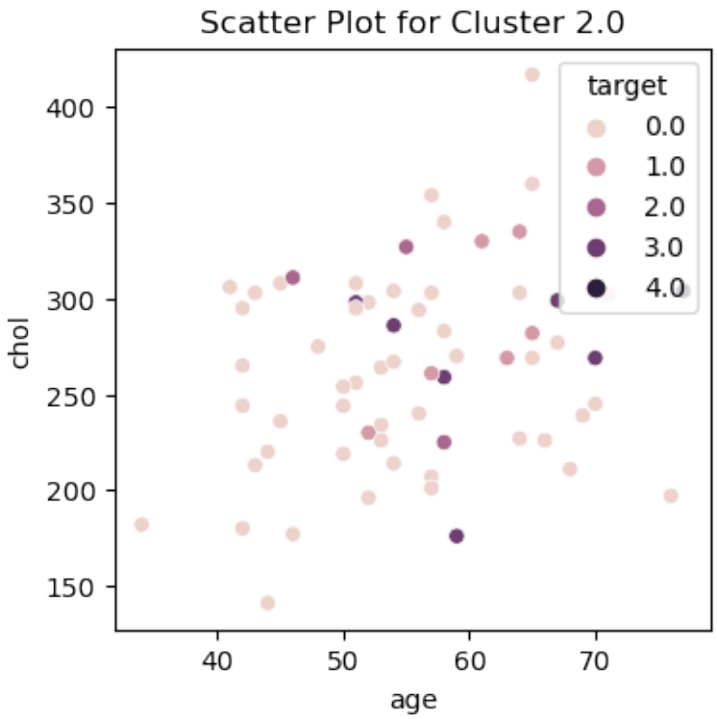


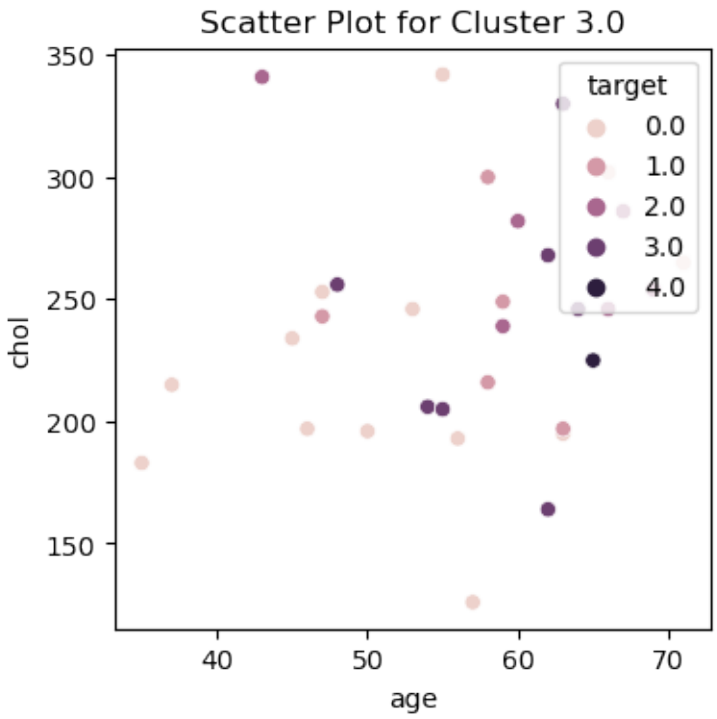
When we us k=5, we don't see andy clear patterns. Let's try to visualize each cluster along with target variable.

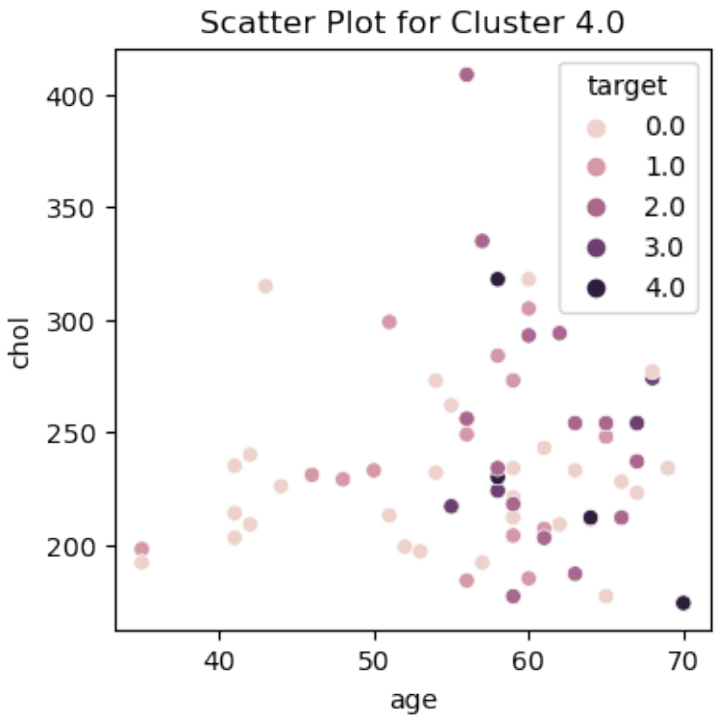
[ ]:
```
grouped = cluster_map.groupby('ClusterID')
for name, group in grouped:
    plot_scatter_plot(
        df=group,
        x="age",
        y="chol",
        hue='target',
        title=f"Scatter Plot for Cluster {name}",
        figsize=(4, 4),
        dpi=100
    )
```


Scatter Plot for Cluster 0.0
target
0.0
1.0
2.0
3.0
4.0
chol
500
400
300
200
40
50
60
70
age


Scatter Plot for Cluster 1.0
target
0.0
1.0
2.0
3.0
4.0
chol
325
300
275
250
225
200
175
150
30
40
50
60
70
age

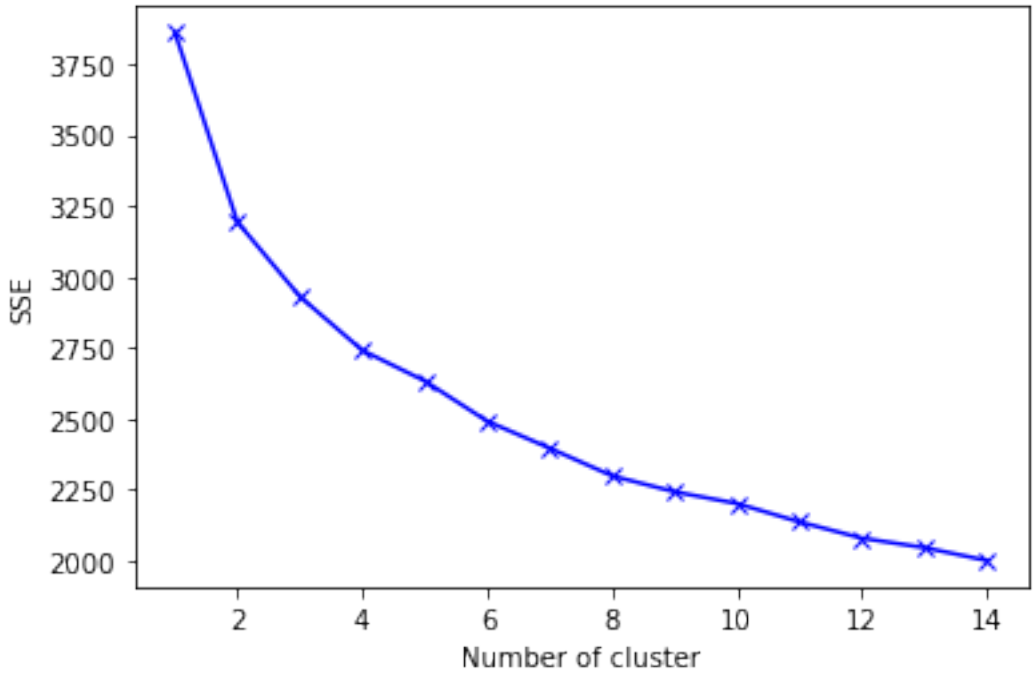

Scatter Plot for Cluster 2.0
target
0.0
1.0
2.0
3.0
4.0
chol
400
350
300
250
200
150
40
50
60
70
age


Scatter Plot for Cluster 3.0
target
0.0
1.0
2.0
3.0
4.0
chol
350
300
250
200
150
40
50
60
70
age

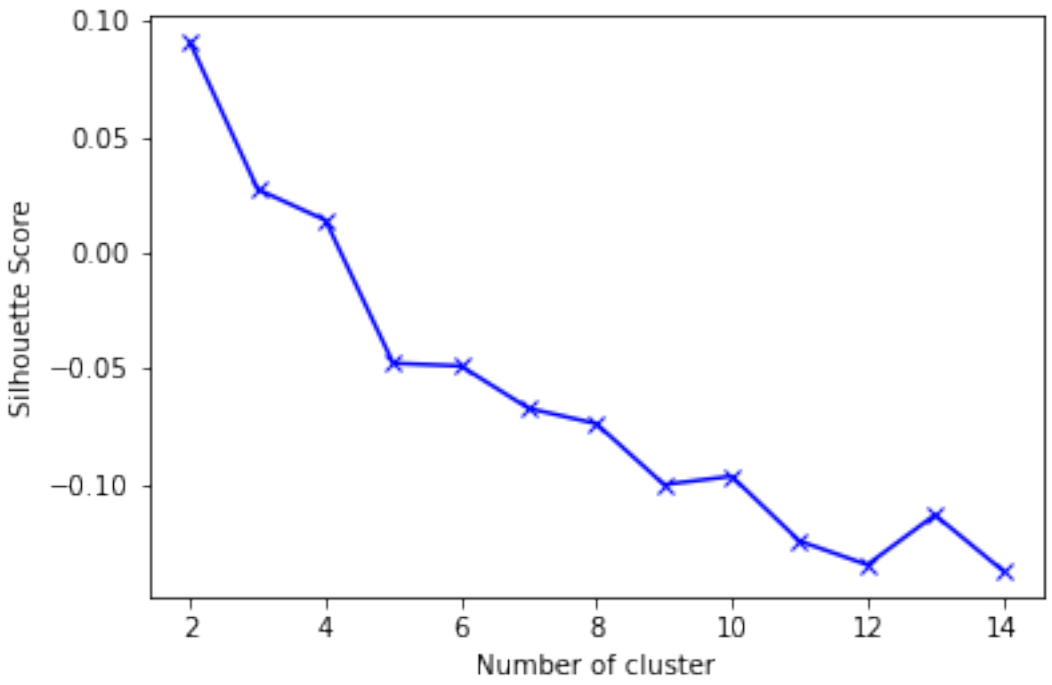


Observations - Cluster 0 - Most of the samples are in the range of 40-60 years of age and has significantly higher number of heart dieses patients. - Cluster 4 - Most of the samples are in the range of 50-70 years of age and has significantly higher number of heart dieses patients.
- Cluster 1 and 2 - Most of the samples are of non-heart dieses patients.

[ ]:
```
sse = {}
for k in range(1, 15):
    kmeans = KMeans(n_clusters=k, random_state=0, init='random', n_init='auto').
 ↪fit(data_scaled)
    sse[k] = kmeans.inertia_

# Elbow plot
plt.figure()
plt.plot(list(sse.keys()), list(sse.values()), 'bx-')
plt.xlabel("Number of cluster")
plt.ylabel("SSE")
plt.show()
```



[ ]:
```
sc = {}
for k in range(2, 15):
    kmeans = KMeans(n_init='auto', n_clusters=k, init='random', random_state=0).
 ↪fit(data_scaled)
    labels = kmeans.predict(data_scaled)
    sc[k] = silhouette_score(data_df, labels)

# Elbow plot
plt.figure()
plt.plot(list(sc.keys()), list(sc.values()), 'bx-')
plt.xlabel("Number of cluster")
plt.ylabel("Silhouette Score")
plt.show()
```



k = 2 has significantly higher amount of silhouette score. Let's use k=2 for clustering.

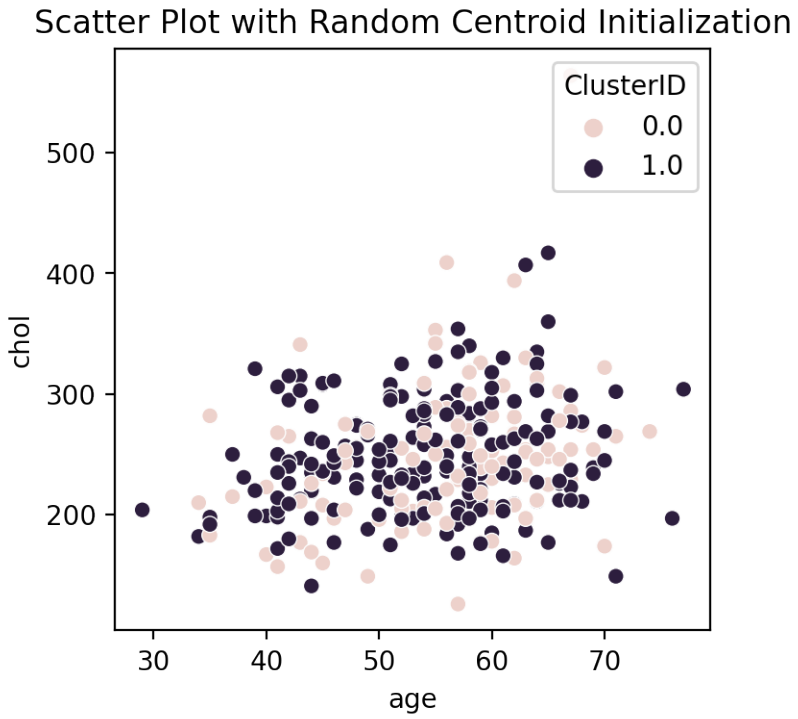
[ ]:
```
kmeans = KMeans(n_clusters=2, random_state=0, init='random', n_init='auto').
 ↪fit(data_scaled)
cluster_map = create_cluster_map(og_data_df, kmeans)

styled_print(f"Cluster Map from Kmeans with Random Cluster Initialization",␣
 ↪header=True)
print(cluster_map.head(10))

styled_print(f"Cluster Centroid from Kmeans with Random Cluster␣
 ↪Initialization", header=True)
print(get_centroid(data_df, kmeans).head(10))
```

› Cluster Map from Kmeans with Random Cluster Initialization

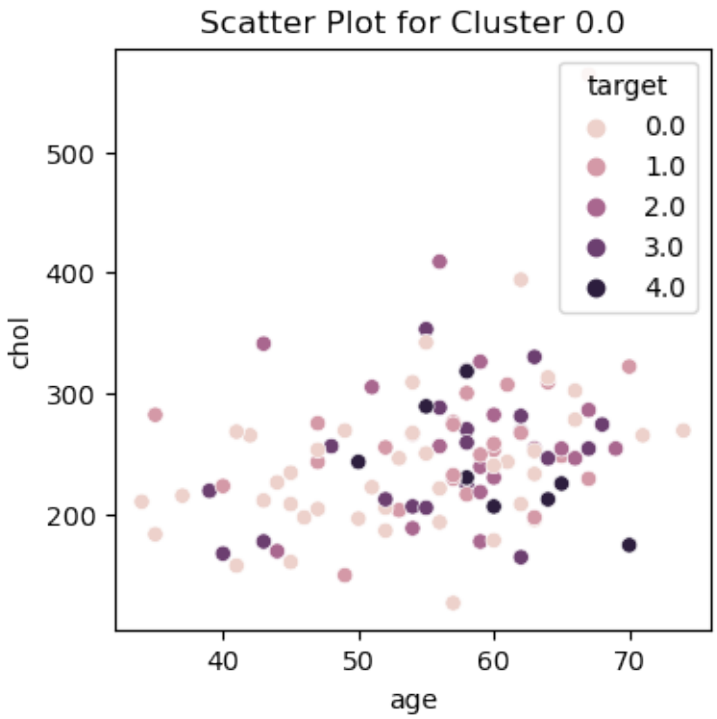
	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	\
0	63.0	1.0	1.0	145.0	233.0	1.0	2.0	150.0	0.0	2.3	
1	67.0	1.0	4.0	160.0	286.0	0.0	2.0	108.0	1.0	1.5	
2	67.0	1.0	4.0	120.0	229.0	0.0	2.0	129.0	1.0	2.6	
3	37.0	1.0	3.0	130.0	250.0	0.0	0.0	187.0	0.0	3.5	
4	41.0	0.0	2.0	130.0	204.0	0.0	2.0	172.0	0.0	1.4	
5	56.0	1.0	2.0	120.0	236.0	0.0	0.0	178.0	0.0	0.8	
6	62.0	0.0	4.0	140.0	268.0	0.0	2.0	160.0	0.0	3.6	
7	57.0	0.0	4.0	120.0	354.0	0.0	0.0	163.0	1.0	0.6	
8	63.0	1.0	4.0	130.0	254.0	0.0	2.0	147.0	0.0	1.4	

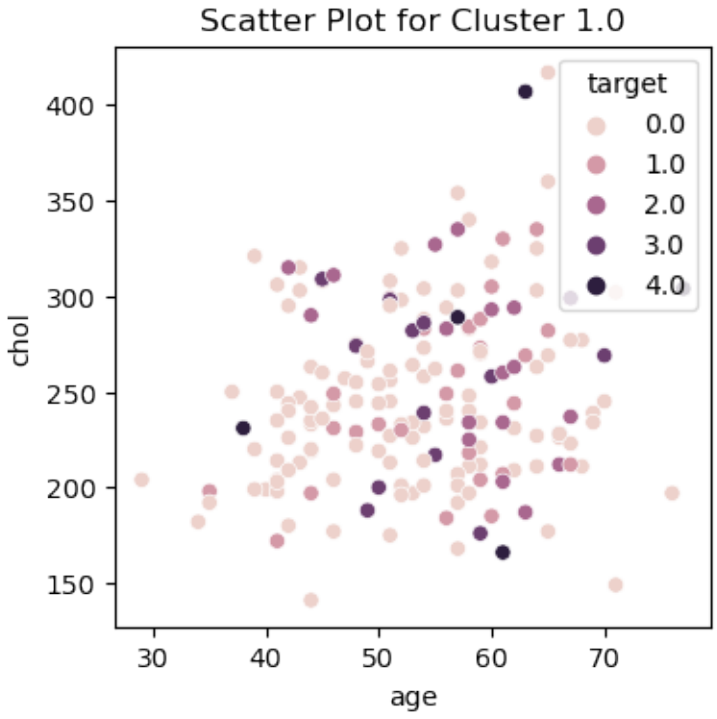
```
9  53.0  1.0  4.0     140.0  203.0  1.0      2.0    155.0    1.0      3.1

   slope   ca  thal  target  ClusterID
0    3.0  0.0   6.0     0.0        0.0
1    2.0  3.0   3.0     2.0        0.0
2    2.0  2.0   7.0     1.0        0.0
3    3.0  0.0   3.0     0.0        1.0
4    1.0  0.0   3.0     0.0        1.0
5    1.0  0.0   3.0     0.0        1.0
6    3.0  2.0   3.0     3.0        0.0
7    1.0  0.0   3.0     0.0        1.0
8    2.0  1.0   7.0     2.0        0.0
9    3.0  0.0   7.0     1.0        0.0
> Cluster Centroid from Kmeans with Random Cluster Initialization
        age       sex        cp  trestbps      chol       fbs   restecg  \
0  0.422907  0.293753  0.635009  0.185957  0.142253  0.116686  0.217225
1 -0.259720 -0.180403 -0.389979 -0.114202 -0.087362 -0.071661 -0.133405

    thalach     exang   oldpeak     slope        ca      thal
0 -0.730952  0.737718  0.717007  0.586423  0.628046  0.738183
1  0.448900 -0.453055 -0.440336 -0.360140 -0.385702 -0.453341
```

[ ]:
```
plot_scatter_plot(
    df=cluster_map,
    x="age",
    y="chol",
    hue='ClusterID',
    title="Scatter Plot with Random Centroid Initialization",
    figsize=(4, 4),
    dpi=200)
```



[ ]:
```
grouped = cluster_map.groupby('ClusterID')
for name, group in grouped:
    plot_scatter_plot(
        df=group,
        x="age",
        y="chol",
        hue='target',
        title=f"Scatter Plot for Cluster {name}",
        figsize=(4, 4),
        dpi=100
    )
```


Scatter Plot for Cluster 0.0
target
0.0
1.0
2.0
3.0
4.0
chol
500
400
300
200
40
50
60
70
age


Scatter Plot for Cluster 1.0
target
0.0
1.0
2.0
3.0
4.0
chol
400
350
300
250
200
150
30
40
50
60
70
age

Observations

- Cluster 0 has mostly patient with high severity of heart dieses. Large number of samples in this group are very dark in color which indicates target label 2, 3 and 4.
- Cluster 1 contains lower severity of samples.
- Using clustering helps us to see that instead of 5 categories in targets, if we choose 2 categories in target variable, it would be much better distribution of data.
- Using only `age` and `chol` might not be good enough features. That means that other features are also very important and useful to predict the heart dieses.