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DBSCAN CLUSTERING Python · Mall Customer Segmentation Data

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-p
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all f

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 5GB to the current directory (/kaggle/working/) that gets prese
# You can also write temporary files to /kaggle/temp/, but they won't be saved outsid
```

/kaggle/input/customer-segmentation-tutorial-in-python/Mall_Customers.csv

```
df=pd.read_csv("/content/Mall_Customers.xls")
```

```
df.head()
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   CustomerID              200 non-null    int64 
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64 
 3   Annual Income (k$)      200 non-null    int64 
 4   Spending Score (1-100)  200 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

```
df.describe()
```

	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

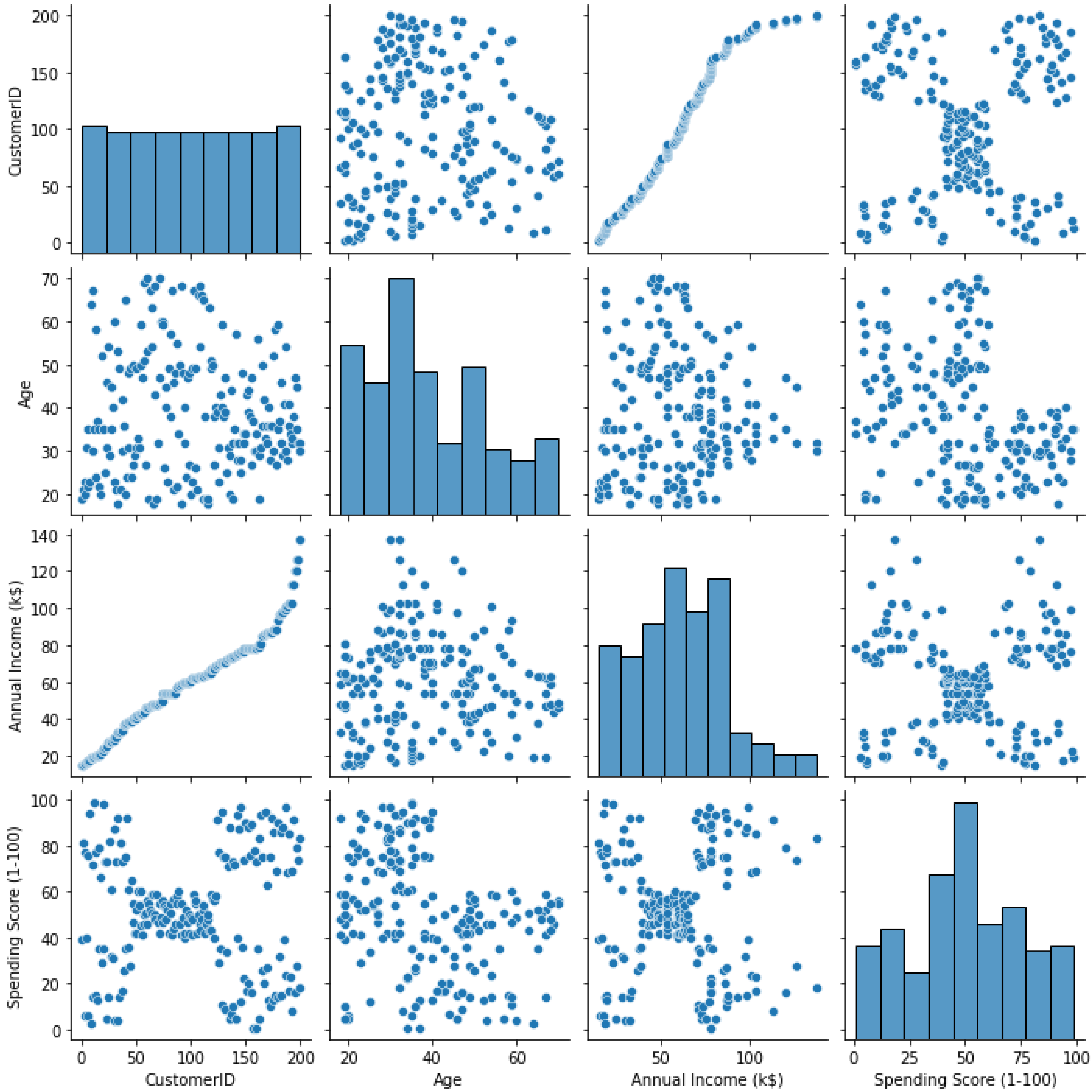
```
df.rename(columns={'Annual Income (k$)':'Income','Spending Score (1-100)':'SpendScore
```

```
df.head()
```

	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

```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7f1955ab9e50>
```



From the above diagram, we can say that the customer id is not correlated with income, it's not an useful feature so we can remove that.

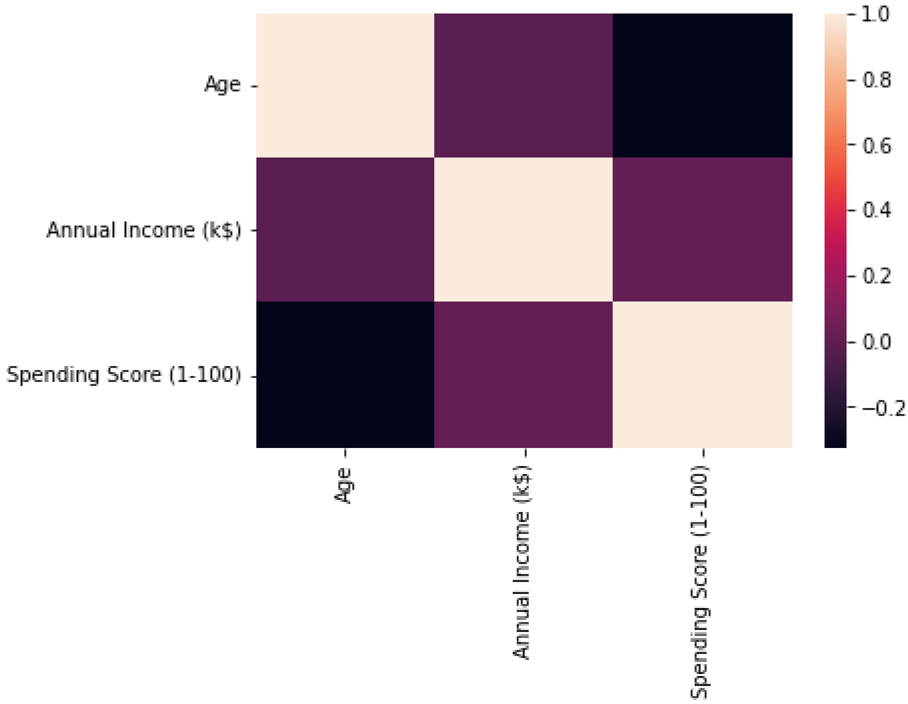
```
df=df.drop(['CustomerID'],axis=1)
```

```
df.head()
```

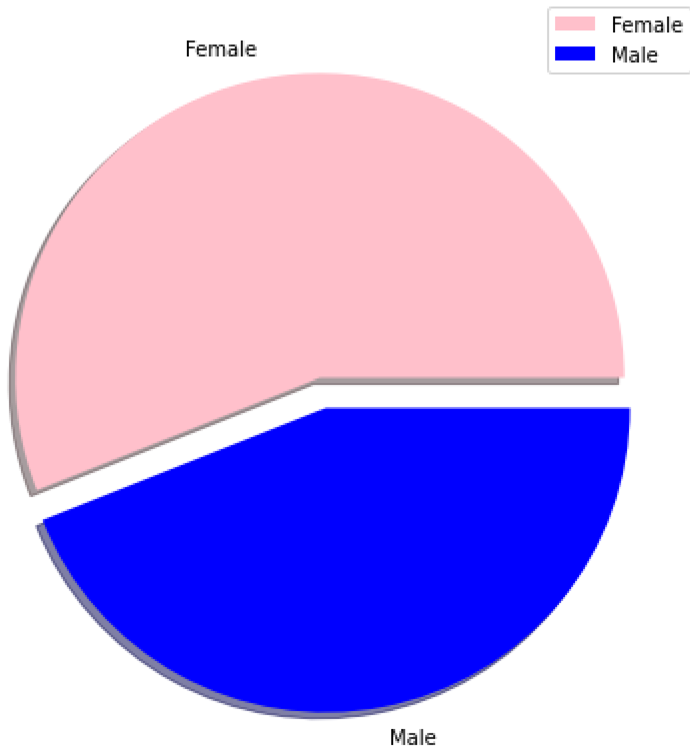
	Gender	Age	Income	SpendScore
0	Male	19	15	39
1	Male	21	15	81
2	Female	20	16	6
3	Female	23	16	77
4	Female	31	17	40

```
sns.heatmap(df.corr())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1950d56990>
```




```
plt.figure(figsize=(7,7))
size=df['Gender'].value_counts()
label=['Female','Male']
color=['Pink','Blue']
explode=[0,0.1]
plt.pie(size,explode=explode,labels=label,colors=color,shadow=True)
plt.legend()
plt.show()
```



From the diagram we can say that females are more visiting to mall than males

```
plt.figure(figsize=(10,5))
sns.countplot(df['Age'])
plt.xticks(rotation=90)
```

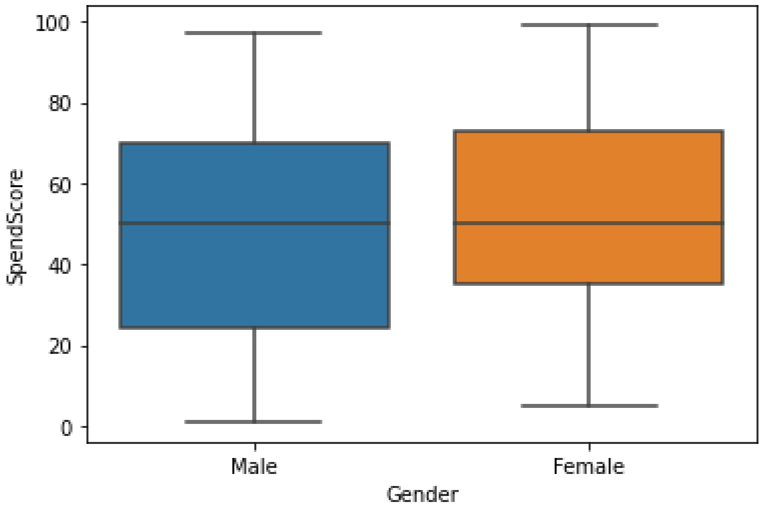
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWar
  FutureWarning
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15,
```

Peoples of age between 25 to 40 are mostly visiting mall than other age groups

```
33,
```

```
sns.boxplot(df['Gender'],df['SpendScore'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWar
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f1950b92c50>
```



This diagram shows the mean spendscore of female and male. we can observe that the mean average spend score of female is greater than male, they have higher spendscore than male,and their least spendscore is greater than males least spendscore

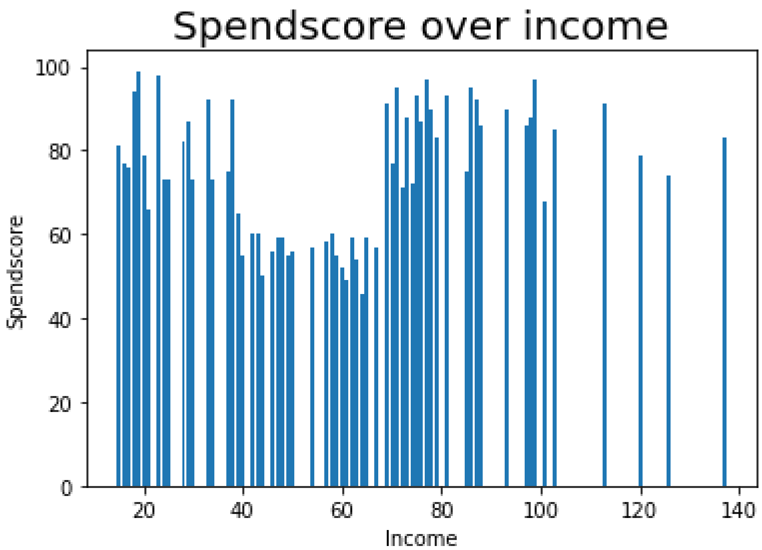
```
plt.figure(figsize=(15,5))
sns.countplot(df['Income'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWar
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f19508cf990>
```

Peoples of salary 54k and 78k are the mostly visited persons in mall.

```
plt.bar(df['Income'],df['SpendScore'])
plt.title('Spendscore over income',fontsize=20)
plt.xlabel('Income')
plt.ylabel('Spendscore')
```

```
Text(0, 0.5, 'Spendscore')
```



Peoples of income in the range of 20k-40k and 70k-100k have the highest spend score

Density Based Spacial Clustering of Applications with noise (DBSCAN)

We are going to use the DBSCAN for algorithm for the purpose of clustering. It is an unsupervised machine learning algorithm. It is used for clusters of high density. It automatically predicts the outliers and removes it. It is better than hierarchical and k-means clustering algorithm. It makes the clusters based on the parameters like epsilon,min points and noise.It separately predicts the core points, border points and outliers efficiently.

```
df.head()
```

	Gender	Age	Income	SpendScore
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

```
x=df.iloc[:,[2,3]].values
```

```
x.shape
```

```
(200, 2)
```

```
from sklearn.cluster import DBSCAN
db=DBSCAN(eps=3,min_samples=4,metric='euclidean')
```

```
model=db.fit(x)
```

```
label=model.labels_
```

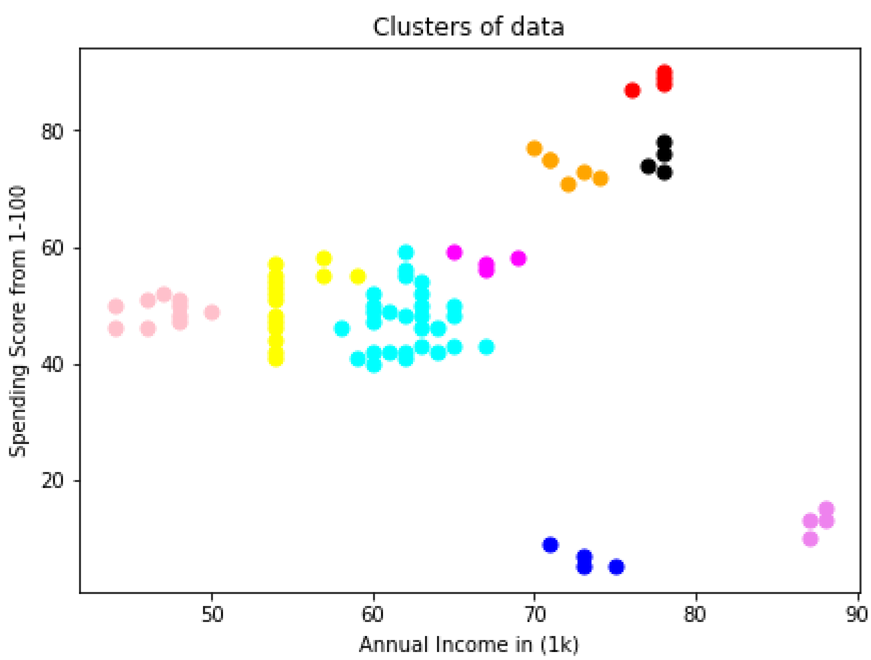
```
label
```

```
array([-1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1,
       -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1,
       -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1,
       -1, -1, -1, -1, -1,  0,  0,  0,  0, -1, -1,  0, -1,  0, -1,  0,  0,
       -1,  0, -1, -1,  0, -1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1, -1,  2,  1,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,
        2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  3,  2,
        3,  3, -1,  3, -1, -1,  4, -1, -1, -1,  4,  5,  4, -1,  4,  5, -1,
        5,  4, -1,  4,  5, -1, -1,  6, -1, -1, -1,  7, -1,  6, -1,  6, -1,
        7, -1,  6, -1,  7, -1,  7, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1,
        8, -1,  8, -1,  8, -1,  8, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1,
       -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1])
```

```
from sklearn import metrics

#identifying the points which makes up our core points
sample_cores=np.zeros_like(label,dtype=bool)

sample_cores[db.core_sample_indices_]=True

#Calculating the number of clusters

n_clusters=len(set(label))- (1 if -1 in label else 0)
print('No of clusters:',n_clusters)
```

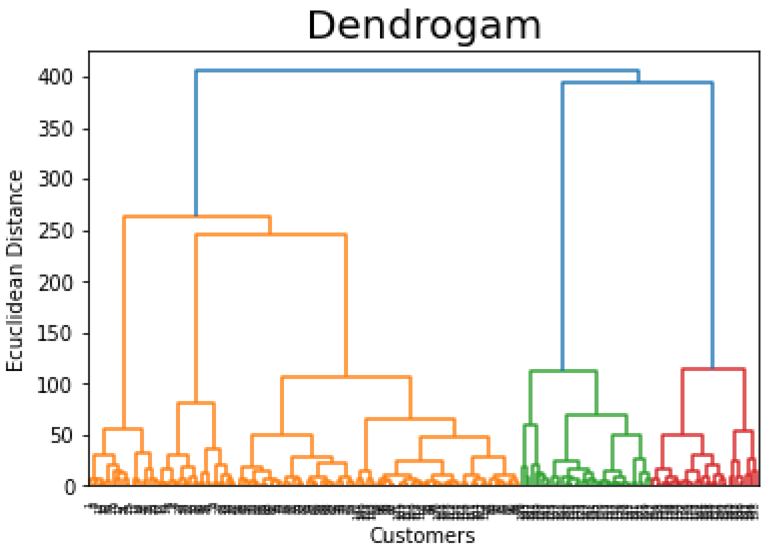
```
No of clusters: 9
```

```
y_means = db.fit_predict(x)
plt.figure(figsize=(7,5))
plt.scatter(x[y_means == 0, 0], x[y_means == 0, 1], s = 50, c = 'pink')
plt.scatter(x[y_means == 1, 0], x[y_means == 1, 1], s = 50, c = 'yellow')
plt.scatter(x[y_means == 2, 0], x[y_means == 2, 1], s = 50, c = 'cyan')
plt.scatter(x[y_means == 3, 0], x[y_means == 3, 1], s = 50, c = 'magenta')
plt.scatter(x[y_means == 4, 0], x[y_means == 4, 1], s = 50, c = 'orange')
plt.scatter(x[y_means == 5, 0], x[y_means == 5, 1], s = 50, c = 'blue')
plt.scatter(x[y_means == 6, 0], x[y_means == 6, 1], s = 50, c = 'red')
plt.scatter(x[y_means == 7, 0], x[y_means == 7, 1], s = 50, c = 'black')
plt.scatter(x[y_means == 8, 0], x[y_means == 8, 1], s = 50, c = 'violet')
plt.xlabel('Annual Income in (1k)')
plt.ylabel('Spending Score from 1-100')
plt.title('Clusters of data')
plt.show()
```



HIERARCHICAL CLUSTERING**

```
import scipy.cluster.hierarchy as sch

dendrogram = sch.dendrogram(sch.linkage(x, method = 'ward'))
plt.title('Dendrogam', fontsize = 20)
plt.xlabel('Customers')
plt.ylabel('Ecuclidean Distance')
plt.show()
```




```
from sklearn.cluster import AgglomerativeClustering

hc = AgglomerativeClustering(n_clusters = 9, affinity = 'euclidean', linkage = 'ward'
y_hc = hc.fit_predict(x)

plt.scatter(x[y_hc == 0, 0], x[y_hc == 0, 1], s = 50, c = 'pink')
plt.scatter(x[y_hc == 1, 0], x[y_hc == 1, 1], s = 50, c = 'yellow')
plt.scatter(x[y_hc == 2, 0], x[y_hc == 2, 1], s = 50, c = 'cyan')
plt.scatter(x[y_hc == 3, 0], x[y_hc == 3, 1], s = 50, c = 'magenta')
plt.scatter(x[y_hc == 4, 0], x[y_hc == 4, 1], s = 50, c = 'orange')
plt.scatter(x[y_hc == 5, 0], x[y_hc == 5, 1], s = 50, c = 'blue')
plt.scatter(x[y_hc == 6, 0], x[y_hc == 6, 1], s = 50, c = 'red')
plt.scatter(x[y_hc == 7, 0], x[y_hc == 7, 1], s = 50, c = 'black')
plt.scatter(x[y_hc == 8, 0], x[y_hc == 8, 1], s = 50, c = 'violet')


plt.title('Hierarchial Clustering', fontsize = 20)
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend()
plt.grid()
plt.show()
```

```
WARNING:matplotlib.legend:No handles with labels found to put in legend.
```