COMP-4448

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Mall Market Segmentation via KNN

In [57]:
```python
import sklearn # PCA, clustering
import pandas as pd # used as ETE data structure, EDA/profiling
import seaborn as sns # used for data import, 2d plots
import matplotlib.pyplot as plt # used for 3d plots
import matplotlib as mpl # used for 3d plots
import numpy as np # used for typing
from dataclasses import dataclass # used for profiling
from pandas_profiling import ProfileReport

import warnings

from typing import NoReturn, Optional, Union # typing
from mpl_toolkits.mplot3d import Axes3D # used for 3d plots
from sklearn.compose import make_column_transformer

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler

sns.set_style('whitegrid')
```

Question 1

• Data cleaning where necessary

In [58]:
```python
df = pd.read_csv('Mall_Customers.csv').drop(['CustomerID'], 1)
```

In [59]:
```python
df.head()
```

Out[59]:

	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

In [60]:
```python
df.isna().sum()
```

Out[60]:
```
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [61]:
```python
df.describe()
```

Out[61]:

	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

• Scale the data using an appropriate scaler

In [62]:
```python
ct = make_column_transformer((MinMaxScaler(), ['Age', 'Annual Income (k$)', 'Spending Score (1-100)']),
                             (OneHotEncoder(), ['Gender']))
```

In [63]:
```python
X = pd.DataFrame(ct.fit_transform(df), columns = ['age', 'income', 'spendscore', 'gender_f', 'gender_m'
])
```

In [64]:
```python
X
```

Out[64]:

	age	income	spendscore	gender_f	gender_m
0	0.019231	0.000000	0.387755	0.0	1.0
1	0.057692	0.000000	0.816327	0.0	1.0
2	0.038462	0.008197	0.051020	1.0	0.0
3	0.096154	0.008197	0.775510	1.0	0.0
4	0.250000	0.016393	0.397959	1.0	0.0
...	...	...	...	...	...
195	0.326923	0.860656	0.795918	1.0	0.0
196	0.519231	0.909836	0.275510	1.0	0.0
197	0.269231	0.909836	0.744898	0.0	1.0
198	0.269231	1.000000	0.173469	0.0	1.0
199	0.230769	1.000000	0.836735	0.0	1.0

200 rows × 5 columns

• Conduct a principal component analysis

In [65]:
```python
from sklearn.decomposition import PCA
```

In [66]:
```python
pcask = list(map(lambda x: PCA(n_components=x, random_state=42), [2, 3, .95]))
```

In [67]:
```python
list(map(lambda x: x.fit(X), pcask))
```

Out[67]:
```
[PCA(n_components=2, random_state=42),
 PCA(n_components=3, random_state=42),
 PCA(n_components=0.95, random_state=42)]
```

2 comps:

In [68]:
```python
pcask[0].explained_variance_
```

Out[68]:
```
array([0.49605563, 0.09341752])
```

In [69]:
```python
sum(pcask[0].explained_variance_)
```

Out[69]:
```
0.5894731518544857
```

3 comps:

In [70]:
```python
pcask[1].explained_variance_
```

Out[70]:
```
array([0.49605563, 0.09341752, 0.04760125])
```

In [71]:
```python
sum(pcask[1].explained_variance_)
```

Out[71]:
```
0.637074404376449
```

.95 variance:

In [72]:
```python
len(pcask[2].components_)
```

Out[72]:
```
4
```

In [73]:
```python
len(X.columns)
```

Out[73]:
```
5
```

In [74]:
```python
pd.DataFrame(pcask[2].components_,columns=X.columns,index = [f'PC-{x+1}' for x in range(0, len(pcask[2]
.components_))])
```

Out[74]:

	age	income	spendscore	gender_f	gender_m
PC-1	0.028551	0.018908	-0.026760	-0.706439	0.706439
PC-2	0.726813	-0.026264	-0.685245	0.027315	-0.027315
PC-3	-0.683757	0.058010	-0.727399	0.000736	-0.000736
PC-4	0.058343	0.997791	0.024760	0.014063	-0.014063

The data must retain 4 components to achieve .95 variance explainability. At 2 and 3 components, 58% and 63% explainability is achieved, respectively.

• Construct a dendrogram using agglomerative clustering to see how many clusters will be optimal to specify in the kmeans clustering.

In [75]:
```python
from scipy.cluster.hierarchy import dendrogram, linkage
```

In [76]:
```python
Z = linkage(X, 'ward')
```

In [77]:
```python
Z_table = pd.DataFrame(Z, columns=['merge_index1', 'merge_index2', 'distance', 'sample_count'])
Z_table
```

Out[77]:

	merge_index1	merge_index2	distance	sample_count
0	129.0	131.0	0.019231	2.0
1	65.0	68.0	0.019231	2.0
2	3.0	5.0	0.023262	2.0
3	60.0	70.0	0.026623	2.0
4	114.0	115.0	0.028041	2.0
...	...	...	...	...
194	376.0	390.0	2.145281	59.0
195	387.0	389.0	2.531713	52.0
196	393.0	394.0	3.721188	112.0
197	392.0	395.0	3.803026	88.0
198	396.0	397.0	14.049143	200.0

199 rows × 4 columns

Dendrogram

In [78]:
```python
plt.figure(figsize=(25, 10))
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('sample index')
plt.ylabel('distance')
dendrogram(
    Z,
    leaf_rotation=90.,  # rotates the x axis labels
    leaf_font_size=8.,  # font size for the x axis labels
)
plt.show()
```

Setting a cutoff at d=3 appears reasonable, leaving 4 clusters. Alterantively, 2 clusters could be set at d>=4.

• Implement a kmeans clustering to find the clusters in the data

In [23]:
```python
from sklearn.cluster import KMeans
```

In [79]:
```python
km = KMeans(n_clusters=4, random_state=42)
```

In [80]:
```python
km.fit(X)
```

Out[80]:
```
KMeans(n_clusters=4, random_state=42)
```

• Predict the clusters

In [81]:
```python
dat = X.copy()
```

In [82]:
```python
dat['y'] = km.predict(X)
```

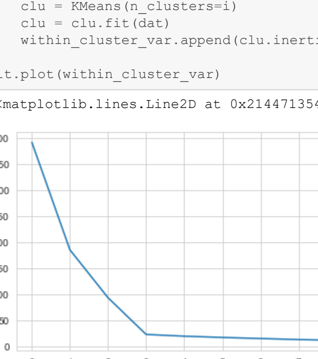
In [83]:
```python
dat['y']
```

Out[83]:
```
0      2
1      2
2      3
3      1
4      1
      ..
195    1
196    3
197    2
198    0
199    2
Name: y, Length: 200, dtype: int32
```

• Visualize the clusters

Using gender, age, and spend_score to visualize.

In [84]:
```python
fig = plt.figure()
ax = Axes3D(fig)
ax.scatter(xs = dat['gender_m'], ys = dat['age'], zs = dat['spendscore'], c=dat['y'], cmap=mpl.colors.L
istedColormap(['red', 'green', 'blue', 'yellow']))
ax.set_xlabel('gender_m')
ax.set_ylabel('age')
ax.set_zlabel('spendscore')
plt.show()
```

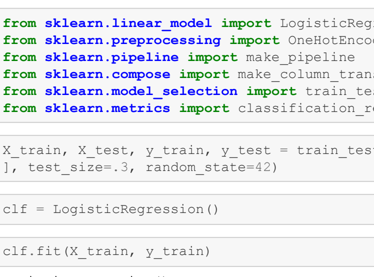


• Also use a loop and a plot to tune the number of clusters. Does the number of clusters obtain parallel the number of clusters obtained using the dendrogram?

In [85]:
```python
n_clusters = list(range(1, 10))
within_cluster_var = []
for i in n_clusters:
    clu = KMeans(n_clusters=i)
    clu = clu.fit(dat)
    within_cluster_var.append(clu.inertia_)

plt.plot(within_cluster_var)
```

Out[85]:
```
[<matplotlib.lines.Line2D at 0x21447135460>]
```



This method appears to suggest 3 clusters.

• Add the cluster values to your original dataset to be the labels

See above

• Using tools in sklearn, run a logistic regression on the original dataset with new labels to classify cases into the clusters or labels.

In [86]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import make_pipeline
from sklearn.compose import make_column_transformer
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
```

In [87]:
```python
X_train, X_test, y_train, y_test = train_test_split(dat[dat.columns[~dat.columns.isin(['y'])]], dat['y'
], test_size=.3, random_state=42)
```

In [88]:
```python
clf = LogisticRegression()
```

In [89]:
```python
clf.fit(X_train, y_train)
```

Out[89]:
```
LogisticRegression()
```

In [90]:
```python
print(classification_report(y_test, clf.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       1.00      1.00      1.00        18
           2       1.00      1.00      1.00         9
           3       1.00      1.00      1.00        18

    accuracy                           1.00        60
   macro avg       1.00      1.00      1.00        60
weighted avg       1.00      1.00      1.00        60
```

In [91]:
```python
accuracy_score(y_test, clf.predict(X_test), normalize=True)
```

Out[91]:
```
1.0
```

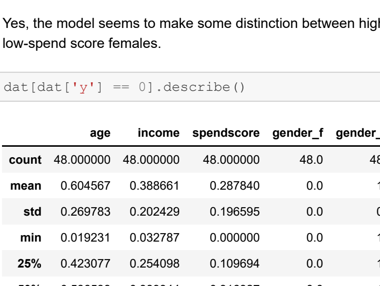
• Tune the cutoff value, c, of the logistic regression constructor in sklearn and plot the error rates and the corresponding settings of c. note that the cutoff c ranges from 0 to 1.

In [92]:
```python
from sklearn import metrics
```

In [93]:
```python
cs = np.linspace(0, 1, 101)[1:]
accs = []
preds = clf.predict_proba(X_test)
accs = list(map(lambda c: accuracy_score(y_test, np.where(preds[:, 1]>c, 1, 0), normalize=True), cs))
```

In [94]:
```python
sns.lineplot(x=cs, y=accs)
```

Out[94]:
```
<AxesSubplot:>
```



• Use the optimal cut off to compute the accuracy of your logistic regression.

In [95]:
```python
print(f'Optimal accuracy: {accs[np.argmax(accs)]} at c = {cs[np.argmax(accs)]}')
```

```
Optimal accuracy: 0.55 at c = 0.02
```

• Do you think the clustering algorithm found good clusters that can be used for classification?

Yes, the model seems to make some distinction between high-spend score males, low-spend score males, high-spend score females, and low-spend score females.

In [96]:
```python
dat[dat['y'] == 0].describe()
```

Out[96]:

	age	income	spendscore	gender_f	gender_m	y
count	48.000000	48.000000	48.000000	48.0	48.0	48.0
mean	0.604567	0.388661	0.287840	0.0	1.0	0.0
std	0.269783	0.202429	0.196595	0.0	0.0	0.0
min	0.019231	0.032787	0.000000	0.0	1.0	0.0
25%	0.423077	0.254098	0.109694	0.0	1.0	0.0
50%	0.586538	0.389344	0.316327	0.0	1.0	0.0
75%	0.793269	0.516393	0.461735	0.0	1.0	0.0
max	1.000000	1.000000	0.602041	0.0	1.0	0.0

In [97]:
```python
dat[dat['y'] == 1].describe()
```

Out[97]:

	age	income	spendscore	gender_f	gender_m	y
count	57.000000	57.000000	57.000000	57.0	57.0	57.0
mean	0.200742	0.366120	0.680451	1.0	0.0	1.0
std	0.105645	0.216916	0.190941	0.0	0.0	0.0
min	0.000000	0.008197	0.285714	1.0	0.0	1.0
25%	0.096154	0.196721	0.510204	1.0	0.0	1.0
50%	0.230769	0.385246	0.734694	1.0	0.0	1.0
75%	0.269231	0.516393	0.836735	1.0	0.0	1.0
max	0.423077	0.860656	1.000000	1.0	0.0	1.0

In [98]:
```python
dat[dat['y'] == 2].describe()
```

Out[98]:

	age	income	spendscore	gender_f	gender_m	y
count	40.000000	40.000000	40.000000	40.0	40.0	40.0
mean	0.197115	0.385246	0.721173	0.0	1.0	2.0
std	0.134139	0.238670	0.170690	0.0	0.0	0.0
min	0.000000	0.000000	0.387755	0.0	1.0	2.0
25%	0.072115	0.213115	0.584184	0.0	1.0	2.0
50%	0.192308	0.393443	0.734694	0.0	1.0	2.0
75%	0.293269	0.516393	0.892857	0.0	1.0	2.0
max	0.423077	1.000000	0.979592	0.0	1.0	2.0

In [99]:
```python
dat[dat['y'] == 3].describe()
```

Out[99]:

	age	income	spendscore	gender_f	gender_m	y
count	55.000000	55.000000	55.000000	55.0	55.0	55.0
mean	0.579021	0.359165	0.344712	1.0	0.0	3.0
std	0.189172	0.211245	0.168011	0.0	0.0	0.0
min	0.038462	0.008197	0.040816	1.0	0.0	3.0
25%	0.451923	0.213115	0.204082	1.0	0.0	3.0
50%	0.596154	0.344262	0.387755	1.0	0.0	3.0
75%	0.692308	0.483607	0.484694	1.0	0.0	3.0
max	0.961538	0.909836	0.591837	1.0	0.0	3.0

• Try if you can interpret or describe what the clusters represent based on the pattern of values in the data set and the cluster. For example, if the data was only age and income, maybe clusters one is young and richer, cluster two may be rich seniors and cluster three are poor youths. Your visualization can also help with this interpretation.

1. Females with a high spendscore, and lower age
2. Males with a low spendscore and higher age
3. Males with a high spendscore and lower age
4. Females with a lower spendscore and higher age