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Enrolment No.: 2018IMSCS017

In [ ]:

1. Preprocessing on the dataset

In [1]:

```
# necessary imports
import pandas as pd
import numpy as np

import warnings
warnings.filterwarnings('ignore')

import seaborn as sns
sns.set()
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.preprocessing import MinMaxScaler
# Display all the columns of the dataframe
pd.pandas.set_option('display.max_columns', None)
```

In [2]:

```
df = pd.read_csv('data/golf-dataset.csv')
df.head()
```

Out[2]:

	Outlook	Temp	Humidity	Windy	Decision
0	Rainy	Hot	High	False	No
1	Rainy	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Sunny	Mild	High	False	Yes
4	Sunny	Cool	Normal	False	Yes

In [3]:

```
df.dtypes
```

Out[3]:

```
Outlook      object
Temp         object
Humidity     object
Windy          bool
Decision     object
dtype: object
```

In [4]:

```
# Import label encoder
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()
```

```
df['Outlook']= label_encoder.fit_transform(df['Outlook'])
df['Temp']= label_encoder.fit_transform(df['Temp'])
df['Humidity']= label_encoder.fit_transform(df['Humidity'])
df['Decision']= label_encoder.fit_transform(df['Decision'])
```

In [5]:
```
df.head()
```

Out[5]:

	Outlook	Temp	Humidity	Windy	Decision
0	1	1	0	False	0
1	1	1	0	True	0
2	0	1	0	False	1
3	2	2	0	False	1
4	2	0	1	False	1

In [6]:
```
X = df.drop(columns = ['Decision'])
y = df['Decision']
```

In [7]:
```
# splitting the data into testing and training data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
```

2. Decision Tree using ID3

In [8]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

dtc = DecisionTreeClassifier(criterion='entropy')
dtc.fit(X_train, y_train)

y_pred = dtc.predict(X_test)

dtc_train_acc = accuracy_score(y_train, dtc.predict(X_train))
dtc_test_acc = accuracy_score(y_test, y_pred)

print(f"Training Accuracy of Decision Tree Model is {dtc_train_acc}")
print(f"Test Accuracy of Decision Tree Model is {dtc_test_acc}")
```

```
Training Accuracy of Decision Tree Model is 1.0
Test Accuracy of Decision Tree Model is 0.5
```

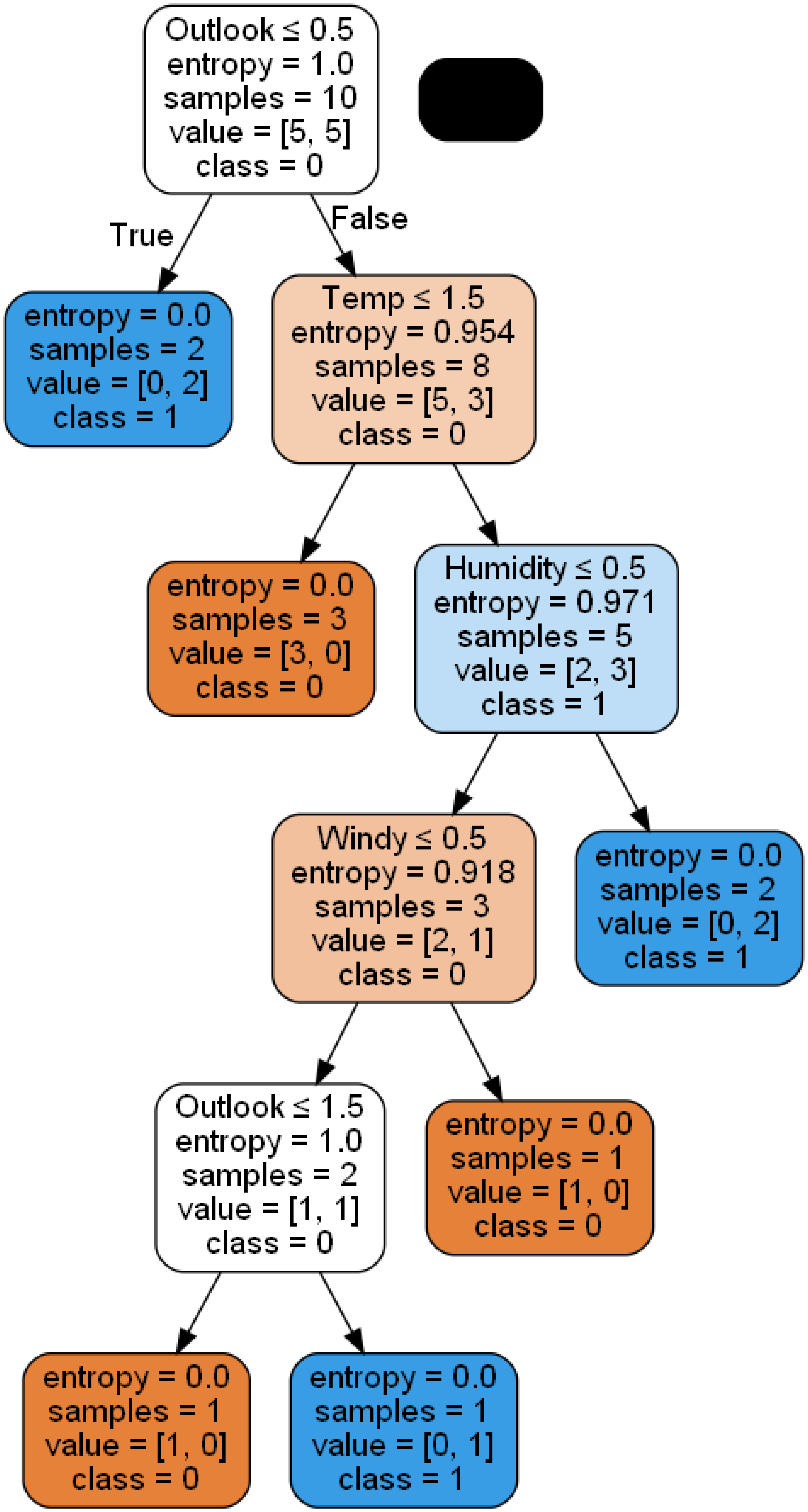
In [9]:
```
from sklearn.tree import export_graphviz
from six import StringIO
from IPython.display import Image
import pydotplus

feature_cols = ['Outlook','Temp','Humidity','Windy']

dot_data = StringIO()

export_graphviz(dtc, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names = feature_cols,class_names=['0','1
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('data.png')
Image(graph.create_png())
```

Out[9]:



3. Decision Tree using CART

In [10]:

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)
```

```
y_pred = dtc.predict(X_test)

dtc_train_acc = accuracy_score(y_train, dtc.predict(X_train))
dtc_test_acc = accuracy_score(y_test, y_pred)

print(f"Training Accuracy of Decision Tree Model is {dtc_train_acc}")
print(f"Test Accuracy of Decision Tree Model is {dtc_test_acc}")
```

```
Training Accuracy of Decision Tree Model is 1.0
Test Accuracy of Decision Tree Model is 0.5
```

In [11]:

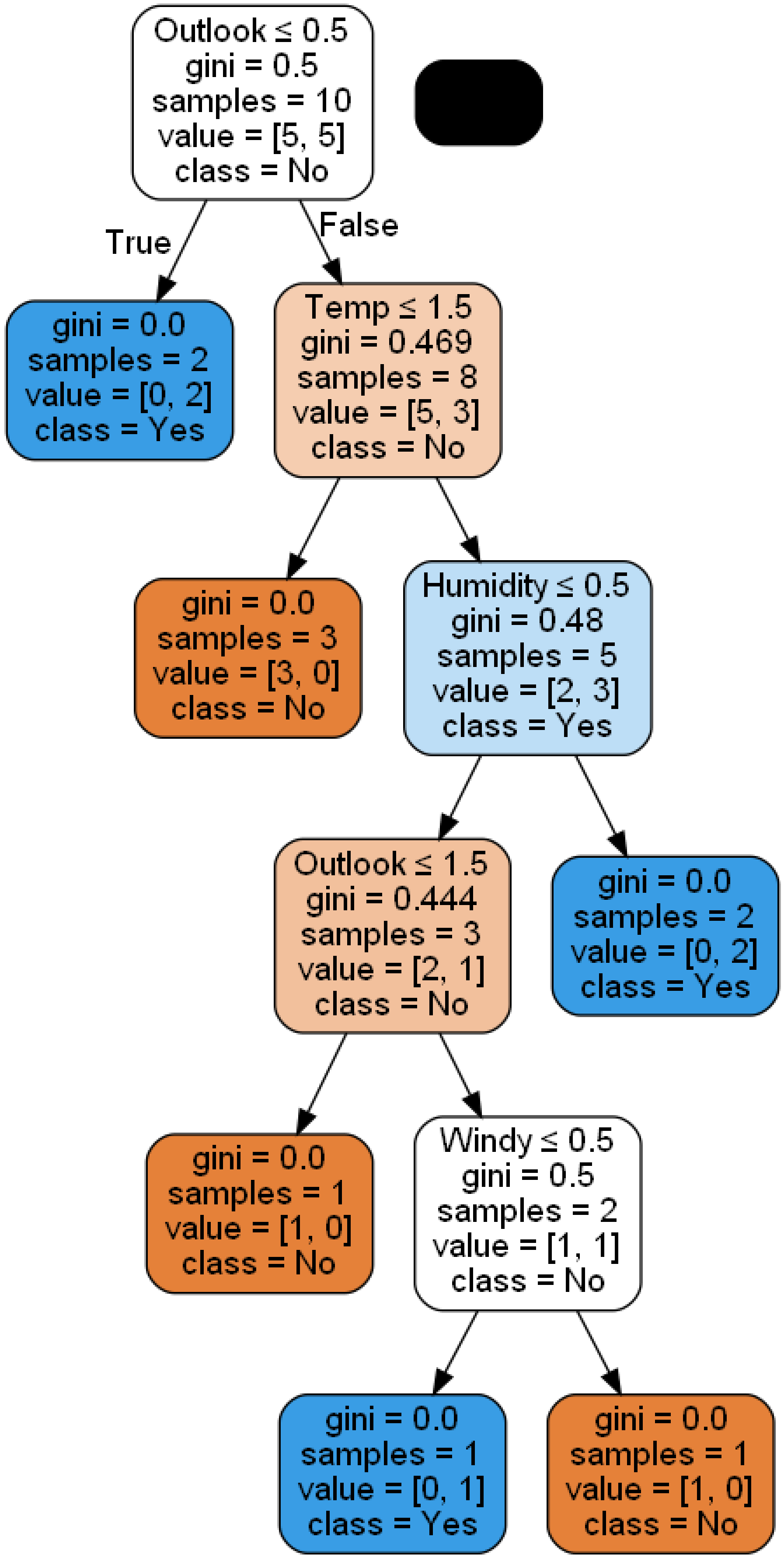
```
from sklearn.tree import export_graphviz
from six import StringIO
from IPython.display import Image
import pydotplus

feature_cols = ['Outlook','Temp','Humidity','Windy']

dot_data = StringIO()

export_graphviz(dtc, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names = feature_cols,class_names=['No','
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('data.png')
Image(graph.create_png())
```

Out[11]:



4. Decision Tree using C 4.5

In [17]:
```
from chefboost import Chefboost as chef
```

In [18]:
```
config={'algorithm ':' (C4.5)'}
```

In [19]:
```
model = chef.fit(df,config)
```

```
[INFO]:  2 CPU cores will be allocated in parallel running
WARNING: You set the algorithm to  ID3  but the Decision column of your data set has non
-object type.
That's why, the algorithm is set to Regression to handle the data set.
Regression  tree is going to be built...
-------------------------
finished in  0.8205151557922363  seconds
-------------------------
Evaluate  train set
-------------------------
MAE:  0.16666666666666669
MSE:  0.08333333333333334
RMSE:  0.2886751345948129
RAE:  0.36004114991154784
RRSE:  0.6024640760767094
Mean:  0.6428571428571429
MAE / Mean:  25.925925925925927 %
RMSE / Mean:  44.90502093697089 %
```

In [ ]:

5. Implementing Apriori Algorithm

In [40]:
```
import numpy as np # linear algebra
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

import seaborn as sns
```

In [41]:
```
df = pd.read_csv('Data/G.csv')
df.head()
```

Out[41]:

	Item(s)	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	...	Item 23	Item 24	Item 25	Item 26	I
0	4	citrus fruit	semi-finished bread	margarine	ready soups	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	I
1	3	tropical fruit	yogurt	coffee	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	I
2	1	whole milk	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	I
3	4	pip fruit	yogurt	cream cheese	meat spreads	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	I
4	4	other vegetables	whole milk	condensed milk	long life bakery product	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	I

5 rows × 33 columns

In [42]:
```
df.shape
```

Out[42]:
```
(9835, 33)
```

In [45]:
```
trans = []
for i in range(0, 5000):
  trans.append([str(df.values[i,j]) for j in range(1, 33)])
```

In [46]:
```
from apyori import apriori
rules = apriori(transactions = trans, min_support = 0.003, min_confidence = 0.2, min_lif
```

In [47]:
```
print(rules)
```

```
<generator object apriori at 0x000001D32DF759A0>
```

In [48]:
```
output = list(rules) # returns a non-tabular output
# putting output into a pandas dataframe
def inspect(output):
    lhs         = [tuple(result[2][0][0])[0] for result in output]
    rhs         = [tuple(result[2][0][1])[0] for result in output]
    support    = [result[1] for result in output]
    confidence = [result[2][0][2] for result in output]
    lift       = [result[2][0][3] for result in output]
    return list(zip(lhs, rhs, support, confidence, lift))
result = pd.DataFrame(inspect(output), columns = ['Left_Hand_Side', 'Right_Hand_Side', '
```

In [49]:
```
result.head()
```

Out[49]:

	Left_Hand_Side	Right_Hand_Side	Support	Confidence	Lift
0	baking powder	domestic eggs	0.0040	0.208333	3.147029
1	baking powder	sugar	0.0048	0.250000	6.830601
2	baking powder	whipped/sour cream	0.0064	0.333333	4.385965
3	berries	whipped/sour cream	0.0088	0.287582	3.783970
4	liquor	bottled beer	0.0042	0.396226	4.716981

In [50]:
```
result.nlargest(n = 10, columns = 'Lift')
```

Out[50]:

	Left_Hand_Side	Right_Hand_Side	Support	Confidence	Lift
9	flour	sugar	0.0054	0.296703	8.106647
15	processed cheese	white bread	0.0048	0.315789	7.483163
1	baking powder	sugar	0.0048	0.250000	6.830601
13	ham	white bread	0.0054	0.204545	4.847049
4	liquor	bottled beer	0.0042	0.396226	4.716981
2	baking powder	whipped/sour cream	0.0064	0.333333	4.385965
8	flour	margarine	0.0046	0.252747	3.999165
14	roll products	margarine	0.0030	0.250000	3.955696
11	mustard	frankfurter	0.0032	0.242424	3.935458
3	berries	whipped/sour cream	0.0088	0.287582	3.783970

In [ ]:

6. Implementing Naive Bayes

In [42]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

1. Golf Data

Read Data

In [43]:
```python
df = pd.read_csv('data/golf-dataset.csv')
df.head()
```

Out[43]:

	Outlook	Temp	Humidity	Windy	Decision
0	Rainy	Hot	High	False	No
1	Rainy	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Sunny	Mild	High	False	Yes
4	Sunny	Cool	Normal	False	Yes

In [44]:
```python
df.dtypes
```

Out[44]:
```
Outlook      object
Temp         object
Humidity     object
Windy          bool
Decision     object
dtype: object
```

Data Preprocessing

In [45]:
```python
# Import label encoder
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

df['Outlook']= label_encoder.fit_transform(df['Outlook'])
df['Temp']= label_encoder.fit_transform(df['Temp'])
df['Humidity']= label_encoder.fit_transform(df['Humidity'])
df['Decision']= label_encoder.fit_transform(df['Decision'])
```

In [46]:
```python
df.head()
```

Out[46]:

	Outlook	Temp	Humidity	Windy	Decision
0	1	1	0	False	0
1	1	1	0	True	0
2	0	1	0	False	1
3	2	2	0	False	1
4	2	0	1	False	1

In [47]:
```python
X = df.drop(columns = ['Decision'])
y = df['Decision']
```

In [48]:
```python
# splitting the data into testing and training data.

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
```

Apply Naive Bayes

In [49]:
```python
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

Out[49]:
```
▾ GaussianNB
GaussianNB()
```

In [50]:
```python
y_pred = classifier.predict(X_test)
```

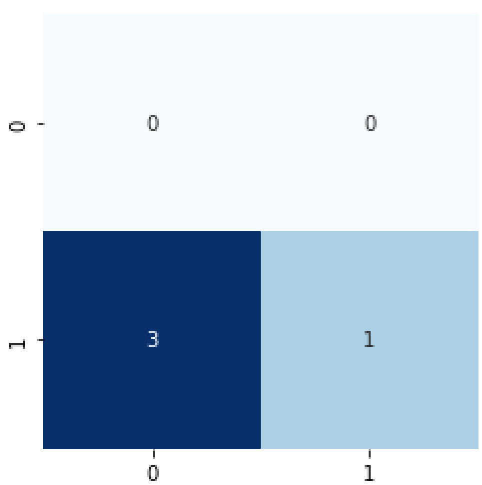
In [51]:
```python
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [52]:
```python
print("Accuracy: ", ac)
```

```
Accuracy:  0.25
```

In [53]:
```python
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[53]:
```
<AxesSubplot:>
```



In [ ]:
```python

```

2. Customer Data (Kaggle)

Read Data

In [54]:
```python
df = pd.read_csv('data/kaggle/customer_data.csv')
df.head()
```

Out[54]:

	label	id	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fea_10	fea_11
0	1	54982665	5	1245.5	3	77000.0	2	15	5	109	5	151300	244.948974

1	0	59004779	4	1277.0	1	113000.0	2	8	-1	100	3	341759	207.173840
2	0	58990862	7	1298.0	1	110000.0	2	11	-1	101	5	72001	1.000000
3	1	58995168	7	1335.5	1	151000.0	2	11	5	110	3	60084	1.000000
4	0	54987320	7	NaN	2	59000.0	2	11	5	108	4	450081	197.403141

In [55]:
```
df.dtypes
```

Out[55]:
```
label        int64
id           int64
fea_1        int64
fea_2      float64
fea_3        int64
fea_4      float64
fea_5        int64
fea_6        int64
fea_7        int64
fea_8        int64
fea_9        int64
fea_10       int64
fea_11     float64
dtype: object
```

Data Preprocessing

In [56]:
```
df.isna().sum()
```

Out[56]:
```
label        0
id           0
fea_1        0
fea_2      149
fea_3        0
fea_4        0
fea_5        0
fea_6        0
fea_7        0
fea_8        0
fea_9        0
fea_10       0
fea_11       0
dtype: int64
```

In [57]:
```
df.dropna(inplace=True)
```

In [58]:
```
df.tail()
```

Out[58]:

	label	id	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fea_10	fea_11
1119	0	54985816	7	1320.5	3	108000.0	2	11	5	110	4	510068	248.997992
1120	0	58988196	5	1289.0	1	173000.0	2	15	5	112	3	350702	200.000000
1122	0	58995381	7	1220.0	3	76000.0	2	11	2	90	5	71002	1.000000
1123	0	58998054	4	1250.0	3	137000.0	2	8	5	90	5	72000	1.000000
1124	0	54989781	4	1415.0	3	93000.0	2	8	5	113	4	151300	273.861279

In [59]:
```
df.dtypes
```

Out[59]:
```
label        int64
id           int64
```

```
fea_1        int64
fea_2      float64
fea_3        int64
fea_4      float64
fea_5        int64
fea_6        int64
fea_7        int64
fea_8        int64
fea_9        int64
fea_10       int64
fea_11     float64
dtype: object
```

In [60]:
```
# Import MinMaxScaler
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
minMaxScaler = preprocessing.MinMaxScaler()

df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [61]:
```
X = df.drop(columns = ['label'])
y = df['label']
```

In [62]:
```
# splitting the data into testing and training data.

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
```

Apply Naive Bayes

In [63]:
```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

Out[63]:
```
▾ GaussianNB
GaussianNB()
```

In [64]:
```
y_pred = classifier.predict(X_test)
```

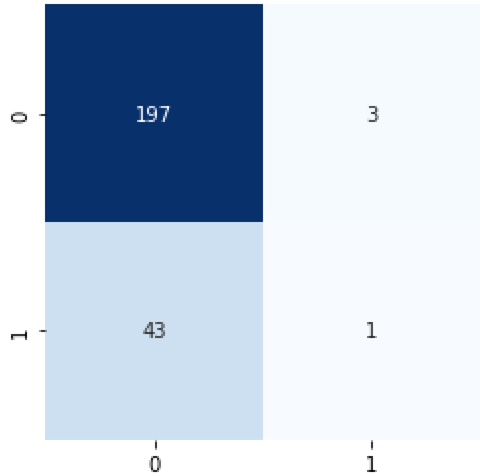
In [65]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [66]:
```
print("Accuracy: ", ac)
```

```
Accuracy:  0.8114754098360656
```

In [67]:
```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[67]:
```
<AxesSubplot:>
```




```
In [ ]:
```

7. Implementing KNN

```python
In [97]: import numpy as np
         import matplotlib.pyplot as plt
         import pandas
```

1. Golf Data

Read Data

```python
In [98]: df = pd.read_csv('data/golf-dataset.csv')
         df.head()
```

Out[98]:

	Outlook	Temp	Humidity	Windy	Decision
0	Rainy	Hot	High	False	No
1	Rainy	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Sunny	Mild	High	False	Yes
4	Sunny	Cool	Normal	False	Yes

```python
In [99]: df.dtypes
```

```
Out[99]: Outlook      object
         Temp         object
         Humidity     object
         Windy          bool
         Decision     object
         dtype: object
```

Data Preprocessing

```python
In [100…: # Import label encoder
          from sklearn import preprocessing

          # label_encoder object knows how to understand word labels.
          label_encoder = preprocessing.LabelEncoder()
```

```
df['Outlook']= label_encoder.fit_transform(df['Outlook'])
df['Temp']= label_encoder.fit_transform(df['Temp'])
df['Humidity']= label_encoder.fit_transform(df['Humidity'])
df['Decision']= label_encoder.fit_transform(df['Decision'])
```

In [101…

```
df.head()
```

Out[101]:

	Outlook	Temp	Humidity	Windy	Decision
0	1	1	0	False	0
1	1	1	0	True	0
2	0	1	0	False	1
3	2	2	0	False	1
4	2	0	1	False	1

In [102…

```
X = df.drop(columns = ['Decision'])
y = df['Decision']
```

In [103…

```
# splitting the data into testing and training data.

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
```

Apply KNN

In [104…

```
from sklearn.neighbors import KNeighborsClassifier
knn_classifier = KNeighborsClassifier(n_neighbors=2)
knn_classifier.fit(X_train, y_train)
```

Out[104]:

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=2)
```

In [105…

```
y_pred = knn_classifier.predict(X_test)
```

In [106…

```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [107…

```
print("Accuracy: ", ac)
```

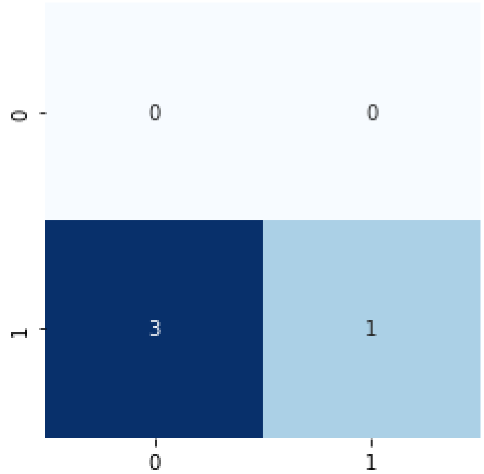
```
Accuracy:  0.25
```

In [108…

```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[108]:

```
<AxesSubplot:>
```



In [ ]:

2. Customer Data (Kaggle)

Read Data

In [109…

```
df = pd.read_csv('data/kaggle/customer_data.csv')
df.head()
```

Out[109]:

	label	id	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fea_10	fea_11
0	1	54982665	5	1245.5	3	77000.0	2	15	5	109	5	151300	244.948974
1	0	59004779	4	1277.0	1	113000.0	2	8	-1	100	3	341759	207.173840
2	0	58990862	7	1298.0	1	110000.0	2	11	-1	101	5	72001	1.000000
3	1	58995168	7	1335.5	1	151000.0	2	11	5	110	3	60084	1.000000
4	0	54987320	7	NaN	2	59000.0	2	11	5	108	4	450081	197.403141

In [110…

```
df.dtypes
```

Out[110]:

```
label        int64
id           int64
fea_1        int64
fea_2      float64
fea_3        int64
fea_4      float64
fea_5        int64
fea_6        int64
fea_7        int64
fea_8        int64
fea_9        int64
fea_10       int64
fea_11     float64
dtype: object
```

Data Preprocessing

In [111…

```
df.isna().sum()
```

Out[111]:

```
label        0
id           0
fea_1        0
```

```
fea_2      149
fea_3        0
fea_4        0
fea_5        0
fea_6        0
fea_7        0
fea_8        0
fea_9        0
fea_10       0
fea_11       0
dtype: int64
```

In [112…
```
df.dropna(inplace=True)
```

In [113…
```
df.tail()
```

Out[113]:

	label	id	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fea_10	fea_11
1119	0	54985816	7	1320.5	3	108000.0	2	11	5	110	4	510068	248.997992
1120	0	58988196	5	1289.0	1	173000.0	2	15	5	112	3	350702	200.000000
1122	0	58995381	7	1220.0	3	76000.0	2	11	2	90	5	71002	1.000000
1123	0	58998054	4	1250.0	3	137000.0	2	8	5	90	5	72000	1.000000
1124	0	54989781	4	1415.0	3	93000.0	2	8	5	113	4	151300	273.861279

In [114…
```
df.dtypes
```

Out[114]:
```
label        int64
id           int64
fea_1        int64
fea_2      float64
fea_3        int64
fea_4      float64
fea_5        int64
fea_6        int64
fea_7        int64
fea_8        int64
fea_9        int64
fea_10       int64
fea_11     float64
dtype: object
```

In [115…
```
# Import MinMaxScaler
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
minMaxScaler = preprocessing.MinMaxScaler()

df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [116…
```
X = df.drop(columns = ['label'])
y = df['label']
```

In [117…
```
# splitting the data into testing and training data.

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
```

Apply KNN

In [118…
```
from sklearn.neighbors import KNeighborsClassifier
knn_classifier = KNeighborsClassifier(n_neighbors=10)
knn_classifier.fit(X_train, y_train)
```

Out[118]:
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=10)
```

In [119…
```
y_pred = knn_classifier.predict(X_test)
```

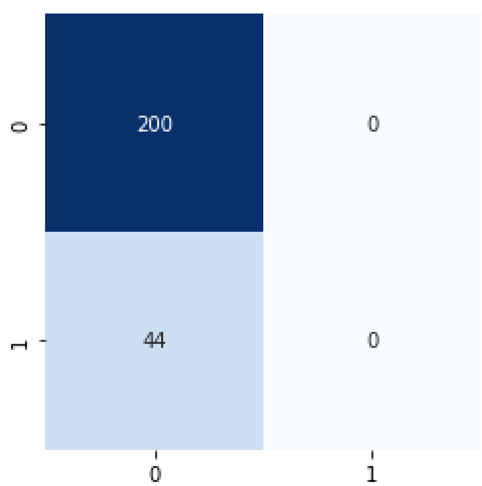
In [120…
```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [121…
```
print("Accuracy: ", ac)
```

```
Accuracy:  0.819672131147541
```

In [122…
```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[122]:
```
<AxesSubplot:>
```



In [ ]:
```

```

8. Implementing SVM

In [18]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

1. Golf Data

Read Data

In [19]:
```
df = pd.read_csv('data/golf-dataset.csv')
df.head()
```

Out[19]:

	Outlook	Temp	Humidity	Windy	Decision
0	Rainy	Hot	High	False	No
1	Rainy	Hot	High	True	No

2	Overcast	Hot	High	False	Yes
3	Sunny	Mild	High	False	Yes
4	Sunny	Cool	Normal	False	Yes

In [20]:
```
df.dtypes
```

Out[20]:
```
Outlook      object
Temp         object
Humidity     object
Windy          bool
Decision     object
dtype: object
```

Data Preprocessing

In [21]:
```
# Import label encoder
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

df['Outlook']= label_encoder.fit_transform(df['Outlook'])
df['Temp']= label_encoder.fit_transform(df['Temp'])
df['Humidity']= label_encoder.fit_transform(df['Humidity'])
df['Decision']= label_encoder.fit_transform(df['Decision'])
```

In [22]:
```
df.head()
```

Out[22]:

	Outlook	Temp	Humidity	Windy	Decision
0	1	1	0	False	0
1	1	1	0	True	0
2	0	1	0	False	1
3	2	2	0	False	1
4	2	0	1	False	1

In [23]:
```
X = df.drop(columns = ['Decision'])
y = df['Decision']
```

In [24]:
```
# splitting the data into testing and training data.

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
```

Apply Support Vector Classifier

In [25]:
```
from sklearn.svm import SVC
svclassifier = SVC(kernel='linear')
svclassifier.fit(X_train, y_train)
```

Out[25]:
```
▾ SVC
SVC(kernel='linear')
```

In [26]:
```python
y_pred = svclassifier.predict(X_test)
```

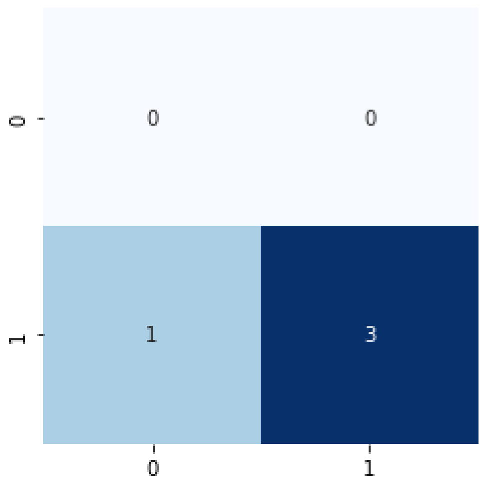
In [27]:
```python
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [28]:
```python
print("Accuracy: ", ac)
```

```
Accuracy:  0.75
```

In [29]:
```python
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[29]:
```
<AxesSubplot:>
```



In [ ]:

2. Customer Data (Kaggle)

Read Data

In [30]:
```python
df = pd.read_csv('data/kaggle/customer_data.csv')
df.head()
```

Out[30]:

	label	id	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fea_10	fea_11
0	1	54982665	5	1245.5	3	77000.0	2	15	5	109	5	151300	244.948974
1	0	59004779	4	1277.0	1	113000.0	2	8	-1	100	3	341759	207.173840
2	0	58990862	7	1298.0	1	110000.0	2	11	-1	101	5	72001	1.000000
3	1	58995168	7	1335.5	1	151000.0	2	11	5	110	3	60084	1.000000
4	0	54987320	7	NaN	2	59000.0	2	11	5	108	4	450081	197.403141

In [31]:
```python
df.dtypes
```

Out[31]:
```
label        int64
id           int64
fea_1        int64
fea_2      float64
fea_3        int64
fea_4      float64
fea_5        int64
fea_6        int64
```

```
fea_7        int64
fea_8        int64
fea_9        int64
fea_10       int64
fea_11     float64
dtype: object
```

Data Preprocessing

In [32]:
```
df.isna().sum()
```

Out[32]:
```
label        0
id           0
fea_1        0
fea_2      149
fea_3        0
fea_4        0
fea_5        0
fea_6        0
fea_7        0
fea_8        0
fea_9        0
fea_10       0
fea_11       0
dtype: int64
```

In [33]:
```
df.dropna(inplace=True)
```

In [34]:
```
df.tail()
```

Out[34]:

	label	id	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fea_10	fea_11
1119	0	54985816	7	1320.5	3	108000.0	2	11	5	110	4	510068	248.997992
1120	0	58988196	5	1289.0	1	173000.0	2	15	5	112	3	350702	200.000000
1122	0	58995381	7	1220.0	3	76000.0	2	11	2	90	5	71002	1.000000
1123	0	58998054	4	1250.0	3	137000.0	2	8	5	90	5	72000	1.000000
1124	0	54989781	4	1415.0	3	93000.0	2	8	5	113	4	151300	273.861279

In [35]:
```
df.dtypes
```

Out[35]:
```
label        int64
id           int64
fea_1        int64
fea_2      float64
fea_3        int64
fea_4      float64
fea_5        int64
fea_6        int64
fea_7        int64
fea_8        int64
fea_9        int64
fea_10       int64
fea_11     float64
dtype: object
```

In [36]:
```
# Import MinMaxScaler
from sklearn import preprocessing

minMaxScaler = preprocessing.MinMaxScaler()
```

```
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [37]:
```
X = df.drop(columns = ['label'])
y = df['label']
```

In [38]:
```
# splitting the data into testing and training data.

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state
```

Apply Support Vector Classifier

In [68]:
```
from sklearn.svm import SVC
svclassifier = SVC(kernel='linear')
svclassifier.fit(X_train, y_train)
```

Out[68]:
```
SVC
SVC(kernel='linear')
```

In [69]:
```
y_pred = svclassifier.predict(X_test)
```

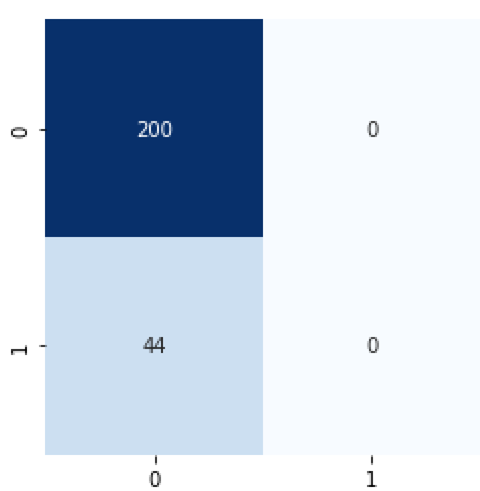
In [70]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
```

In [71]:
```
print("Accuracy: ", ac)
```

```
Accuracy:  0.819672131147541
```

In [72]:
```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[72]: <AxesSubplot:>



In [ ]:

9. Implementing K-Means Clustering Algorithm

In [196…
```
import numpy as np
import matplotlib.pyplot as plt
```

```
import pandas as pd
```

1. Social_Network_Ads Data

Read Data

In [197…
```
df = pd.read_csv('data/Social_Network_Ads.csv')
df.head()
```

Out[197]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

In [198…
```
df.dtypes
```

Out[198]:
```
User ID             int64
Gender             object
Age                 int64
EstimatedSalary     int64
Purchased           int64
dtype: object
```

Data Preprocessing

In [199…
```
df.isna().sum()
```

Out[199]:
```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [200…
```
df = df.drop(columns = ["User ID"])
```

In [201…
```
# Import label encoder
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
df['Gender']= label_encoder.fit_transform(df['Gender'])
```

In [202…
```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [203…
```
df.head()
```

Out[203]:

	Gender	Age	EstimatedSalary	Purchased
0	1.0	0.023810	0.029630	0.0
1	1.0	0.404762	0.037037	0.0
2	0.0	0.190476	0.207407	0.0

3	0.0	0.214286	0.311111	0.0
4	1.0	0.023810	0.451852	0.0

In [204…

```
y = df['Purchased'].to_numpy()
x = df.iloc[:, [0, 1, 2]].values
```

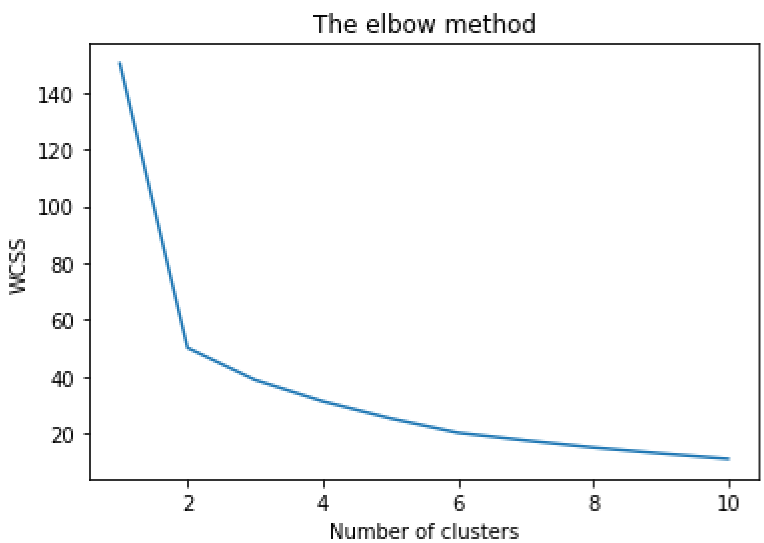
Apply K Means

In [205…

```
from sklearn.cluster import KMeans
wcss = []

for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, ran
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()
```



In [206…

```
kmeans = KMeans(n_clusters = 2, init = 'k-means++', max_iter = 300, n_init = 10, random_
y_kmeans = kmeans.fit_predict(x)
```

In [207…

```
len(y_kmeans)
```

Out[207]:

```
400
```

In [208…

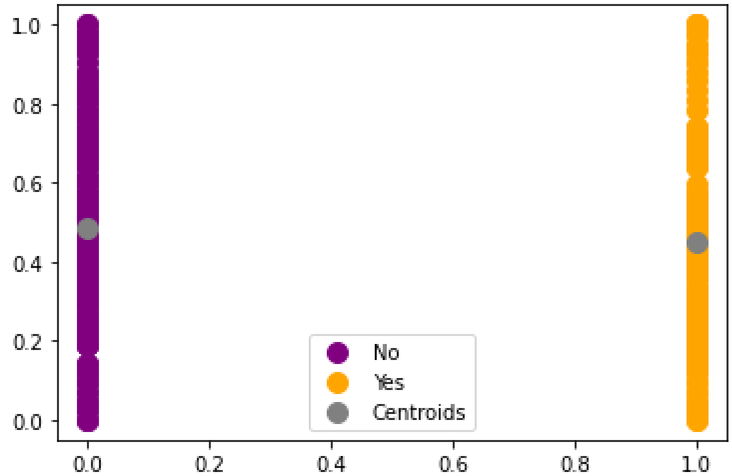
```
#Visualising the clusters
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], s = 100, c = 'purple', label = 'No
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], s = 100, c = 'orange', label = 'Ye

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'g

plt.legend()
```

Out[208]:

```
<matplotlib.legend.Legend at 0x254df308670>
```

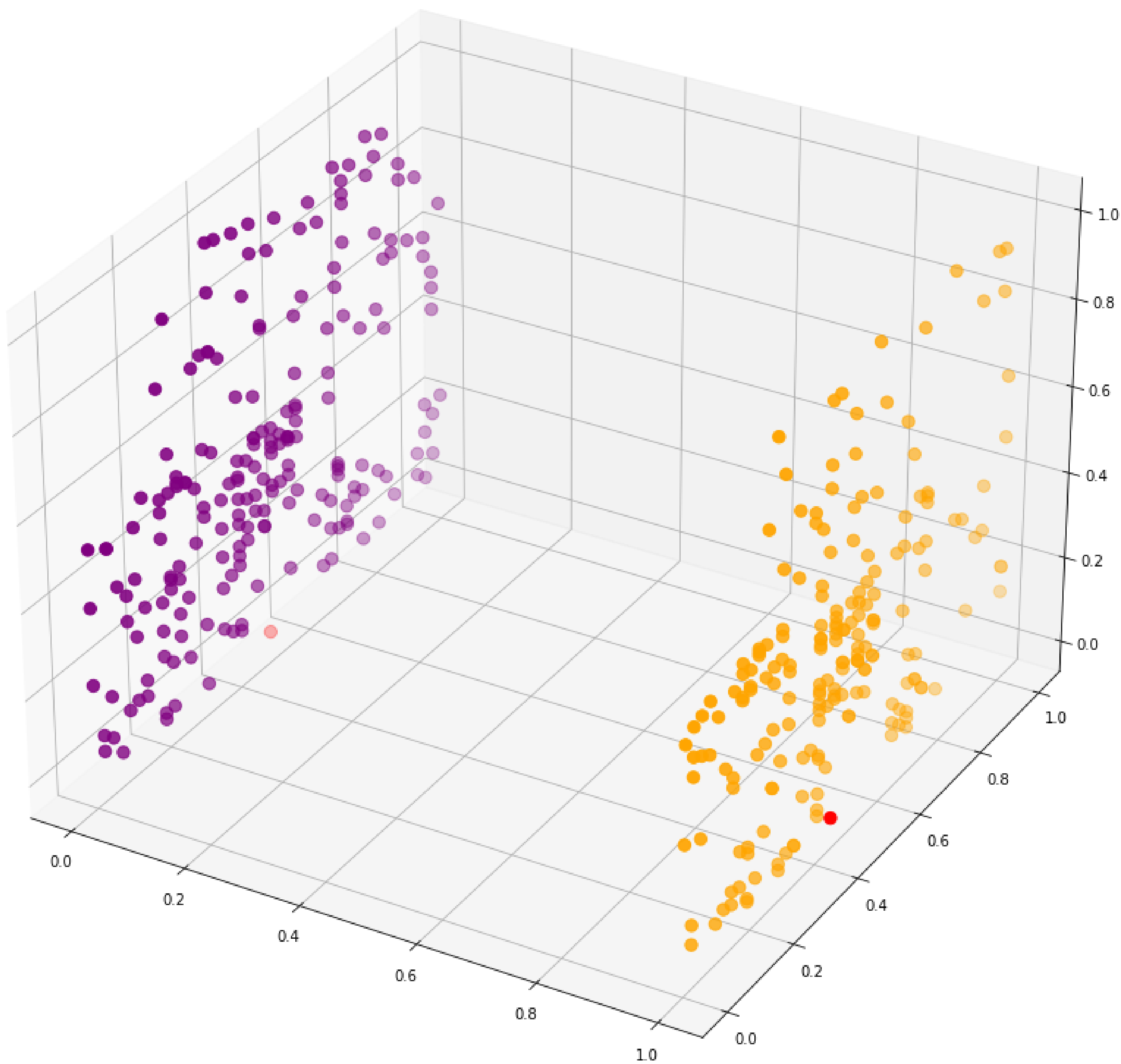


In [209…

```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], x[y_kmeans == 0, 2], s = 70, c = 'p
ax.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], x[y_kmeans == 1, 2], s = 70, c = 'o
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 70, c = 're

plt.show()
```



In [210…

```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y, y_kmeans)
ac = accuracy_score(y,y_kmeans)
```

In [211…

```
print("Accuracy: ", ac)
```

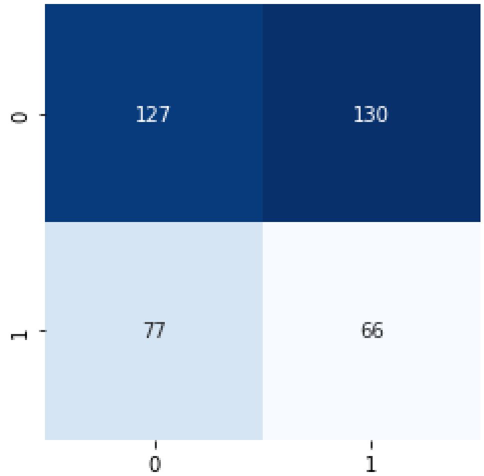
```
Accuracy:  0.4825
```

In [212…

```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[212]:

```
<AxesSubplot:>
```



In [ ]:

2. Mall Customers Data

Read Data

In [213…
```
df = pd.read_csv('data/Mall_Customers.csv')
df.head()
```

Out[213]:

	CustomerID	Genre	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 [214…
```
df.dtypes
```

Out[214]:
```
CustomerID                 int64
Genre                     object
Age                        int64
Annual Income (k$)         int64
Spending Score (1-100)     int64
dtype: object
```

Data Preprocessing

In [215…
```
df.isna().sum()
```

Out[215]:
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [216…
```
df = df.drop(columns = ["CustomerID"])
```

In [217…
```
# Import label encoder
from sklearn import preprocessing
```

```
label_encoder = preprocessing.LabelEncoder()
df['Genre']= label_encoder.fit_transform(df['Genre'])
```

In [218…

```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [219…

```
df.head()
```

Out[219]:

	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1.0	0.019231	0.000000	0.387755
1	1.0	0.057692	0.000000	0.816327
2	0.0	0.038462	0.008197	0.051020
3	0.0	0.096154	0.008197	0.775510
4	0.0	0.250000	0.016393	0.397959

In [220…

```
x = df.values
```

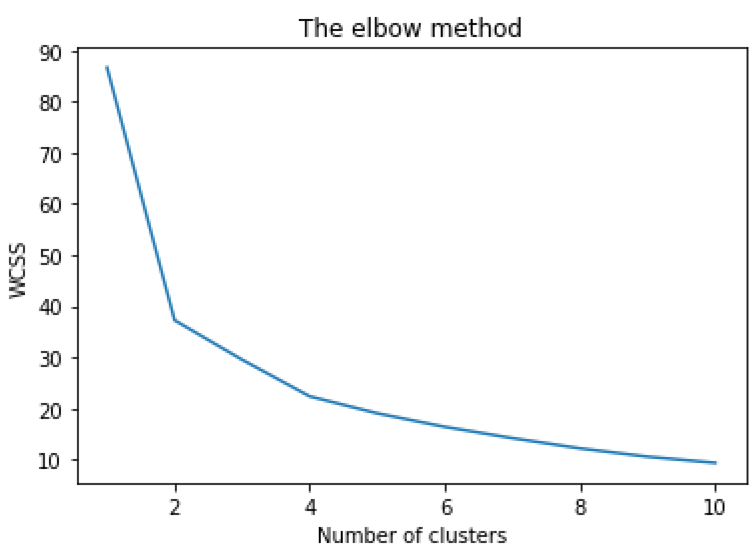
Apply K Means

In [221…

```
from sklearn.cluster import KMeans
wcss = []

for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, ran
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()
```



In [222…

```
# so taking number of clusters as 2
kmeans = KMeans(n_clusters = 2, init = 'k-means++', max_iter = 300, n_init = 10, random_
y_kmeans = kmeans.fit_predict(x)
```

In [223…

```
len(y_kmeans)
```

Out[223]: 200

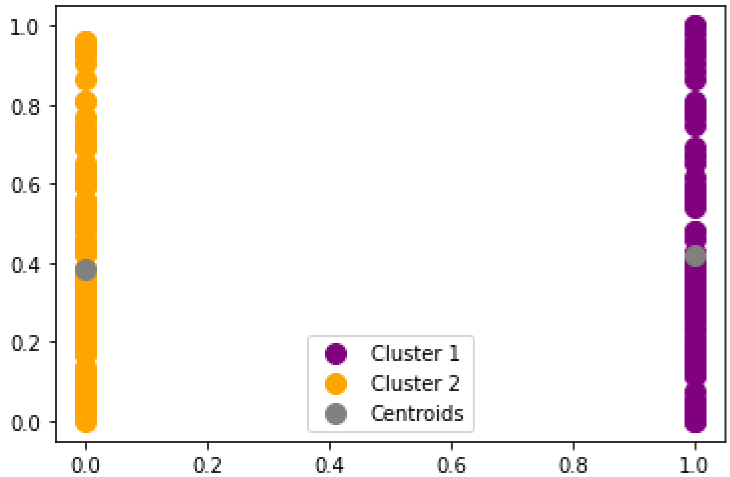
In [224…

```
#Visualising the clusters
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], s = 100, c = 'purple', label = 'Cl
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], s = 100, c = 'orange', label = 'Cl

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'g

plt.legend()
```

Out[224]: <matplotlib.legend.Legend at 0x254dd511f30>

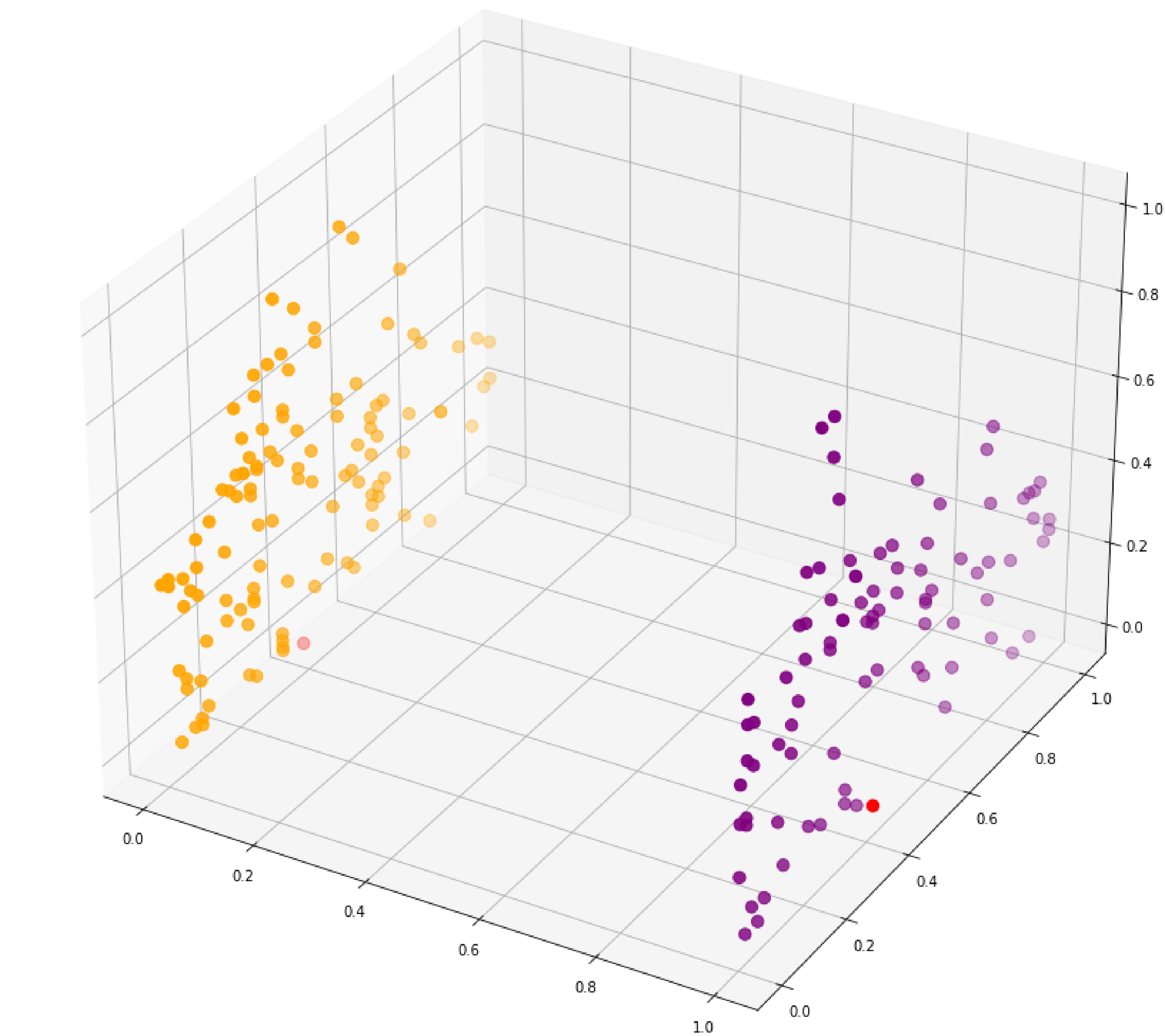


In [225…

```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], x[y_kmeans == 0, 2], s = 70, c = 'p
ax.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], x[y_kmeans == 1, 2], s = 70, c = 'o
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 70, c = 're

plt.show()
```



In [ ]:

10. Implementing k-mediods Clustering Algorithm

In [2]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

1. Social_Network_Ads Data

Read Data

In [4]:

```
df = pd.read_csv('data/Social_Network_Ads.csv')
df.head()
```

Out[4]:

	User ID	Gender	Age	EstimatedSalary	Purchased

0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

In [5]:
```
df.dtypes
```

Out[5]:
```
User ID             int64
Gender             object
Age                 int64
EstimatedSalary     int64
Purchased           int64
dtype: object
```

Data Preprocessing

In [6]:
```
df.isna().sum()
```

Out[6]:
```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [7]:
```
df = df.drop(columns = ["User ID"])
```

In [8]:
```
# Import label encoder
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
df['Gender']= label_encoder.fit_transform(df['Gender'])
```

In [9]:
```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [10]:
```
df.head()
```

Out[10]:

	Gender	Age	EstimatedSalary	Purchased
0	1.0	0.023810	0.029630	0.0
1	1.0	0.404762	0.037037	0.0
2	0.0	0.190476	0.207407	0.0
3	0.0	0.214286	0.311111	0.0
4	1.0	0.023810	0.451852	0.0

In [11]:
```
y = df['Purchased'].to_numpy()
x = df.iloc[:, [0, 1, 2]].values
```

Apply K-Medoid

In [3]:
```
from sklearn_extra.cluster import KMedoids
```

In [12]:
```
kmed = KMedoids(n_clusters=2)
y_kmed = kmed.fit_predict(x)
```

In [13]:
```
len(y_kmed)
```

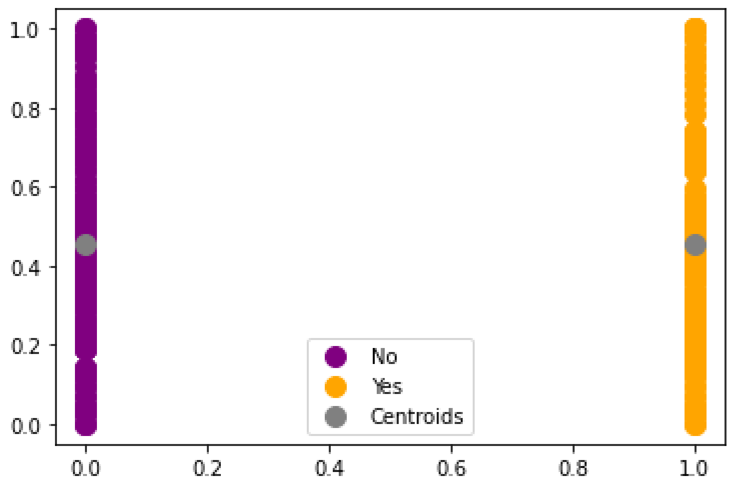
Out[13]:
```
400
```

In [14]:
```
#Visualising the clusters
plt.scatter(x[y_kmed == 0, 0], x[y_kmed == 0, 1], s = 100, c = 'purple', label = 'No')
plt.scatter(x[y_kmed == 1, 0], x[y_kmed == 1, 1], s = 100, c = 'orange', label = 'Yes')

#Plotting the centroids of the clusters
plt.scatter(kmed.cluster_centers_[:, 0], kmed.cluster_centers_[:,1], s = 100, c = 'grey'

plt.legend()
```

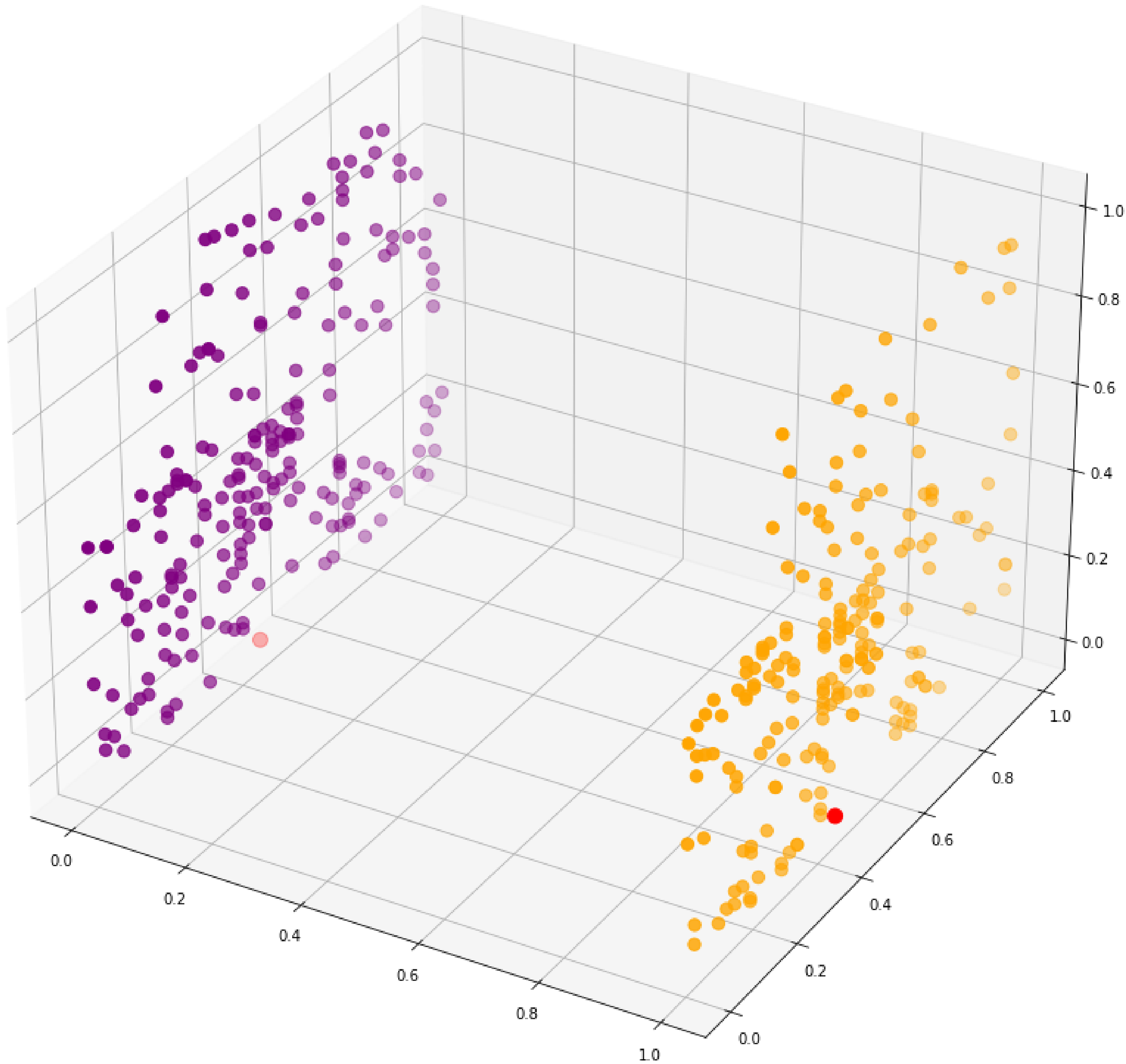
Out[14]:
```
<matplotlib.legend.Legend at 0x1c12607fe20>
```



In [16]:
```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x[y_kmed == 0, 0], x[y_kmed == 0, 1], x[y_kmed == 0, 2], s = 70, c = 'purple'
ax.scatter(x[y_kmed == 1, 0], x[y_kmed == 1, 1], x[y_kmed == 1, 2], s = 70, c = 'orange'
plt.scatter(kmed.cluster_centers_[:, 0], kmed.cluster_centers_[:,1], s = 100, c = 'red',

plt.show()
```



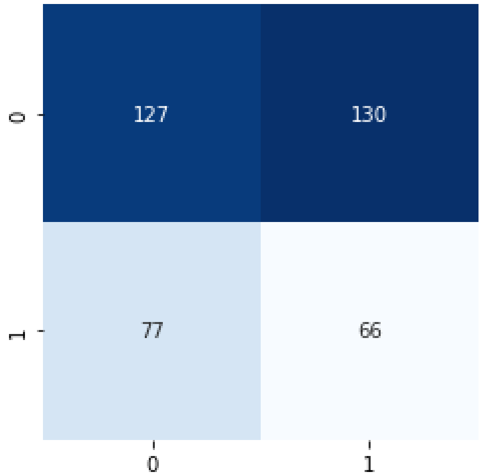
In [18]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y, y_kmed)
ac = accuracy_score(y,y_kmed)
```

In [19]:
```
print("Accuracy: ", ac)
```

```
Accuracy:  0.4825
```

In [20]:
```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[20]: <AxesSubplot:>



In [ ]:

2. Mall Customers Data

Read Data

In [21]:
```
df = pd.read_csv('data/Mall_Customers.csv')
df.head()
```

Out[21]:

	CustomerID	Genre	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 [22]:
```
df.dtypes
```

Out[22]:
```
CustomerID                  int64
Genre                      object
Age                         int64
Annual Income (k$)          int64
Spending Score (1-100)      int64
dtype: object
```

Data Preprocessing

In [23]:
```
df.isna().sum()
```

Out[23]:
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [24]:
```
df = df.drop(columns = ["CustomerID"])
```

In [25]:
```
# Import label encoder
from sklearn import preprocessing
```

```
label_encoder = preprocessing.LabelEncoder()
df['Genre']= label_encoder.fit_transform(df['Genre'])
```

In [26]:
```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [27]:
```
df.head()
```

Out[27]:

	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1.0	0.019231	0.000000	0.387755
1	1.0	0.057692	0.000000	0.816327
2	0.0	0.038462	0.008197	0.051020
3	0.0	0.096154	0.008197	0.775510
4	0.0	0.250000	0.016393	0.397959

In [28]:
```
x = df.values
```

Apply K-Medoids

In [29]:
```
kmed = KMedoids(n_clusters=2)
y_kmed = kmed.fit_predict(x)
```

In [30]:
```
len(y_kmed)
```

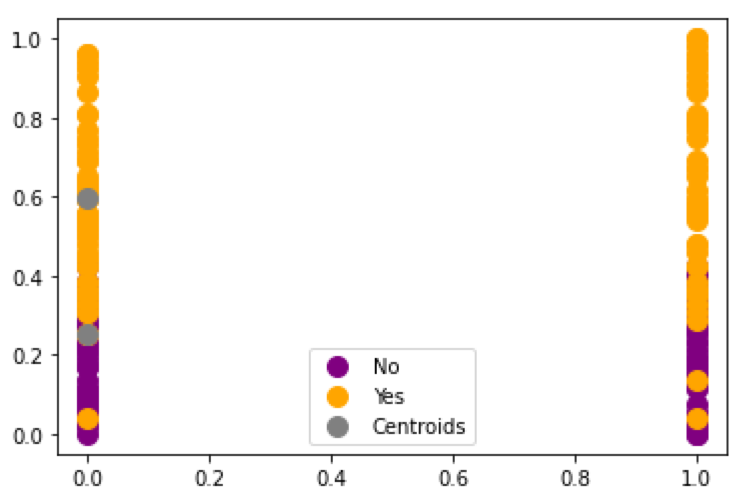
Out[30]:
```
200
```

In [31]:
```
#Visualising the clusters
plt.scatter(x[y_kmed == 0, 0], x[y_kmed == 0, 1], s = 100, c = 'purple', label = 'No')
plt.scatter(x[y_kmed == 1, 0], x[y_kmed == 1, 1], s = 100, c = 'orange', label = 'Yes')

#Plotting the centroids of the clusters
plt.scatter(kmed.cluster_centers_[:, 0], kmed.cluster_centers_[:,1], s = 100, c = 'grey'

plt.legend()
```

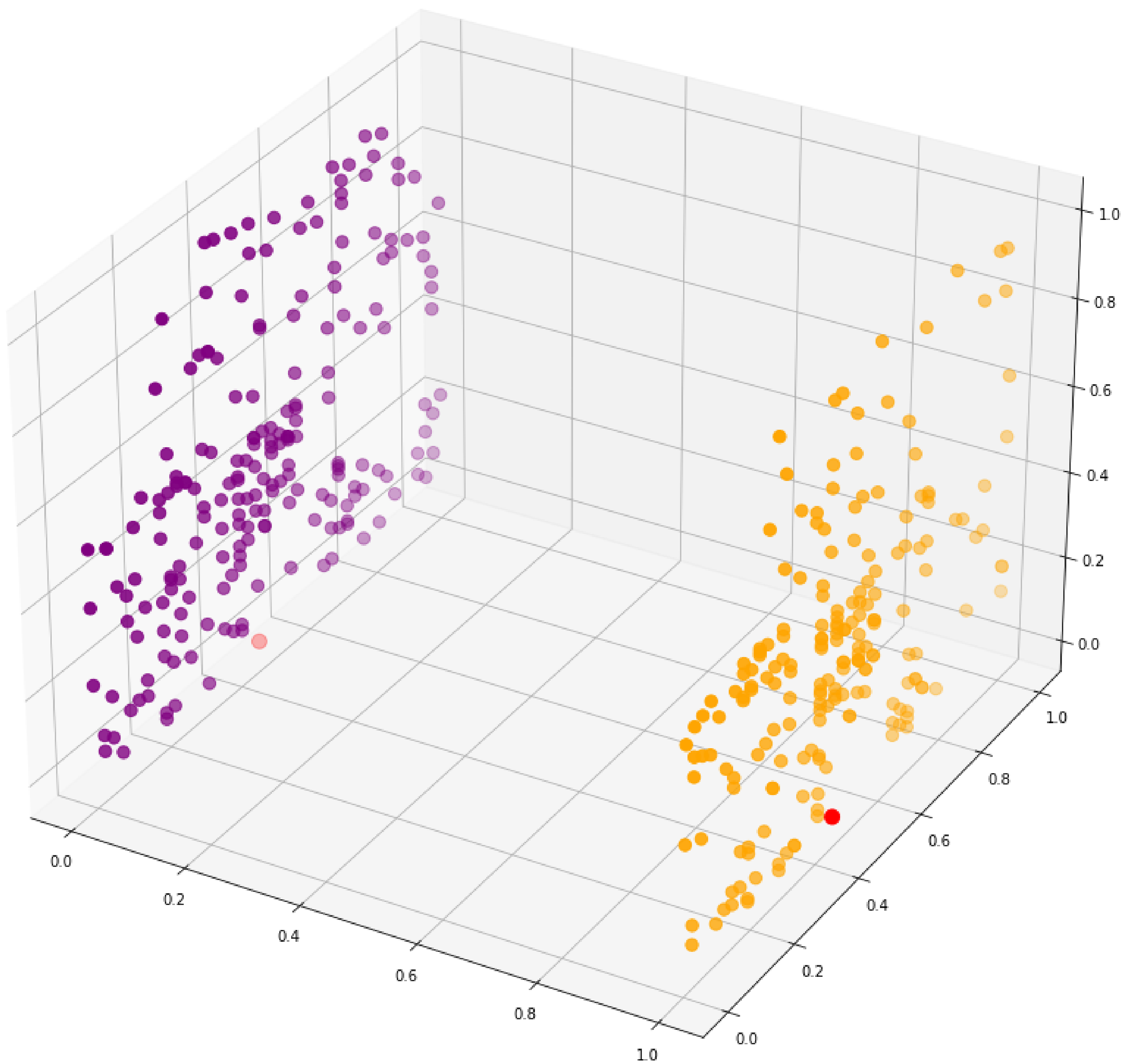
Out[31]:
```
<matplotlib.legend.Legend at 0x1c128b3f0a0>
```



In [ ]:
```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')
```

```
ax.scatter(x[y_kmed == 0, 0], x[y_kmed == 0, 1], x[y_kmed == 0, 2], s = 70, c = 'purple'
ax.scatter(x[y_kmed == 1, 0], x[y_kmed == 1, 1], x[y_kmed == 1, 2], s = 70, c = 'orange'
plt.scatter(kmed.cluster_centers_[:, 0], kmed.cluster_centers_[:,1], s = 100, c = 'red',

plt.show()
```



In [ ]:

11. Implementing Agglomerative Clustering Algorithm

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

1. Social_Network_Ads Data

Read Data

In [2]:
```
df = pd.read_csv('data/Social_Network_Ads.csv')
df.head()
```

Out[2]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

In [3]:
```
df.dtypes
```

Out[3]:
```
User ID             int64
Gender             object
Age                 int64
EstimatedSalary     int64
Purchased           int64
dtype: object
```

Data Preprocessing

In [4]:
```
df.isna().sum()
```

Out[4]:
```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [5]:
```
df = df.drop(columns = ["User ID"])
```

In [6]:
```
# Import label encoder
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
df['Gender']= label_encoder.fit_transform(df['Gender'])
```

In [7]:
```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [8]:
```
df.head()
```

Out[8]:

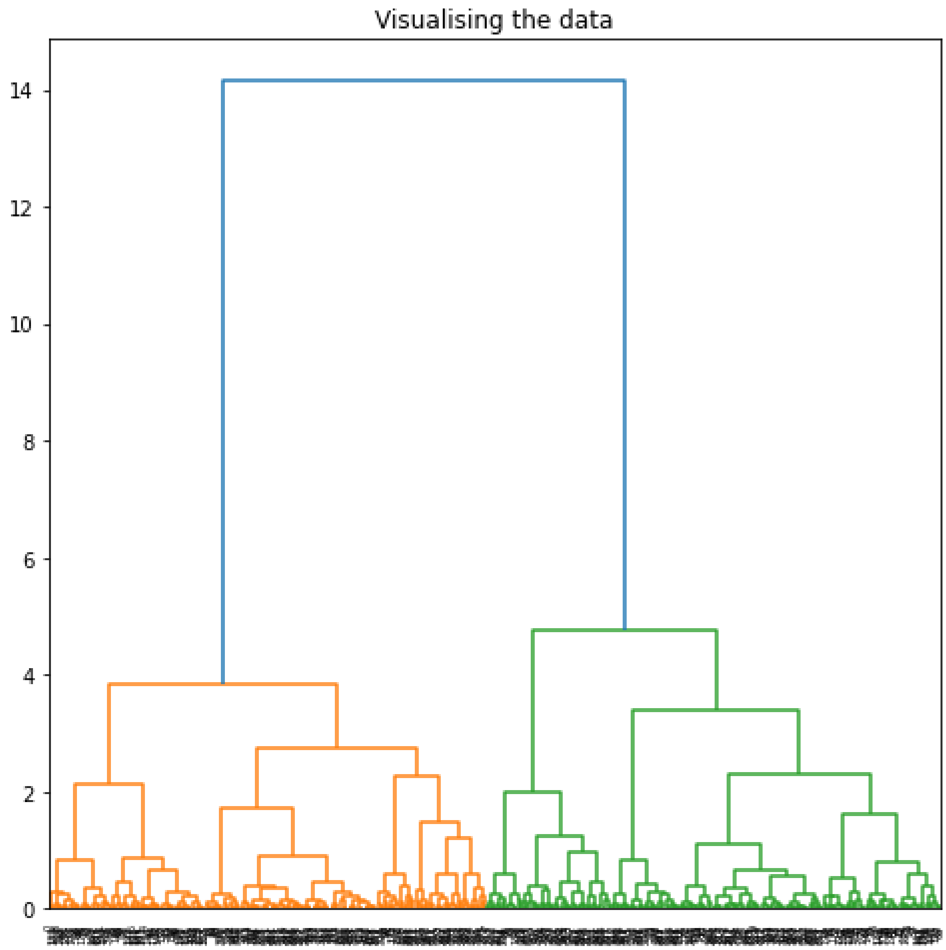
	Gender	Age	EstimatedSalary	Purchased
0	1.0	0.023810	0.029630	0.0
1	1.0	0.404762	0.037037	0.0
2	0.0	0.190476	0.207407	0.0
3	0.0	0.214286	0.311111	0.0
4	1.0	0.023810	0.451852	0.0

In [9]:
```
y = df['Purchased'].to_numpy()
x = df.iloc[:, [0, 1, 2]].values
```

Apply Agglomerative clustering

In [11]:
```
import scipy.cluster.hierarchy as shc

plt.figure(figsize =(8, 8))
plt.title('Visualising the data')
Dendrogram = shc.dendrogram((shc.linkage(x, method ='ward')))
```



In [14]:
```
from sklearn.cluster import AgglomerativeClustering


agg = AgglomerativeClustering(n_clusters = 2)

y_agg = agg.fit_predict(x)
```

In [15]:
```
len(y_agg)
```

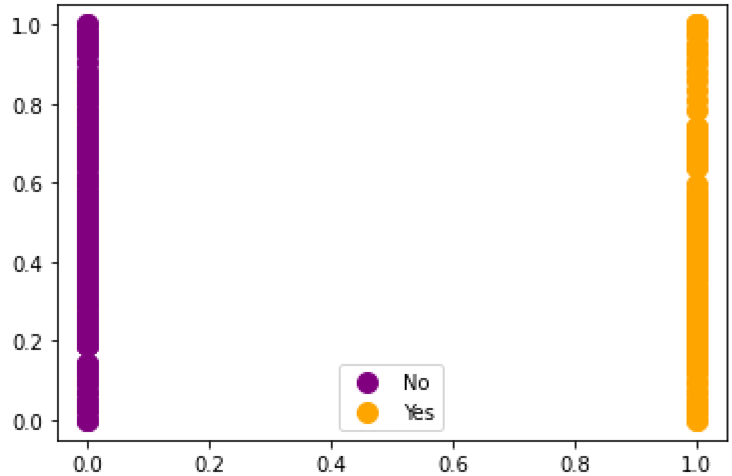
Out[15]:
```
400
```

In [17]:
```
#Visualising the clusters
plt.scatter(x[y_agg == 0, 0], x[y_agg == 0, 1], s = 100, c = 'purple', label = 'No')
plt.scatter(x[y_agg == 1, 0], x[y_agg == 1, 1], s = 100, c = 'orange', label = 'Yes')

#Plotting the centroids of the clusters
# plt.scatter(agg.cluster_centers_[:, 0], agg.cluster_centers_[:,1], s = 100, c = 'grey'

plt.legend()
```

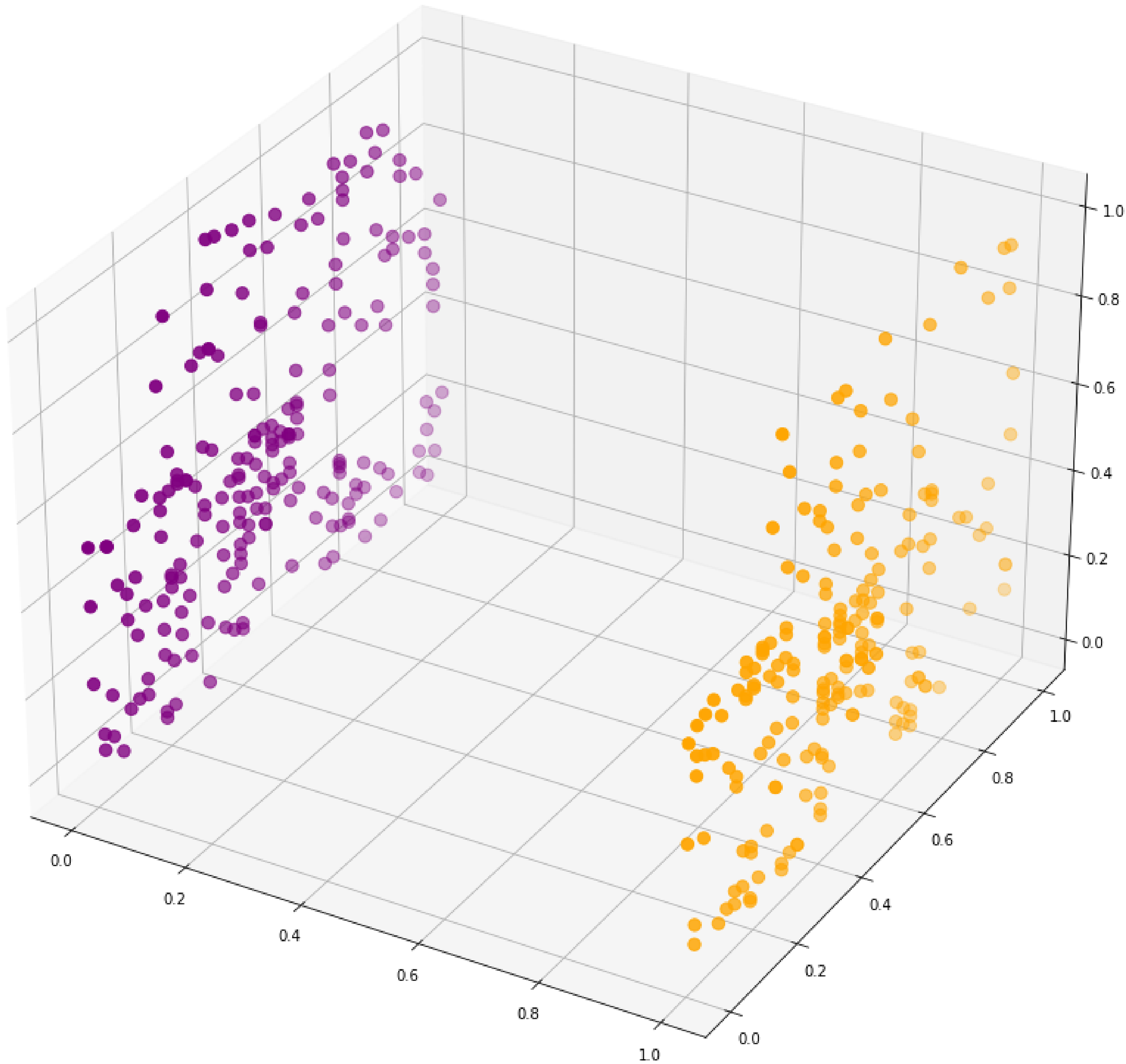
Out[17]:
```
<matplotlib.legend.Legend at 0x2651b7763b0>
```



In [18]:
```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x[y_agg == 0, 0], x[y_agg == 0, 1], x[y_agg == 0, 2], s = 70, c = 'purple', m
ax.scatter(x[y_agg == 1, 0], x[y_agg == 1, 1], x[y_agg == 1, 2], s = 70, c = 'orange', m
# plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 70, c = '

plt.show()
```



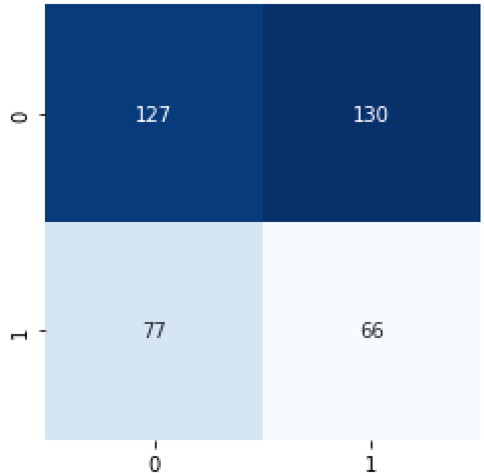
In [21]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y, y_agg)
ac = accuracy_score(y,y_agg)
```

In [22]:
```
print("Accuracy: ", ac)
```

```
Accuracy:  0.4825
```

In [23]:
```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[23]:
```
<AxesSubplot:>
```



In [ ]:

2. Mall Customers Data

Read Data

In [24]:
```
df = pd.read_csv('data/Mall_Customers.csv')
df.head()
```

Out[24]:

	CustomerID	Genre	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 [25]:
```
df.dtypes
```

Out[25]:
```
CustomerID                 int64
Genre                     object
Age                        int64
Annual Income (k$)         int64
Spending Score (1-100)     int64
dtype: object
```

Data Preprocessing

In [26]:
```
df.isna().sum()
```

Out[26]:
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [27]:
```
df = df.drop(columns = ["CustomerID"])
```

In [28]:
```
# Import label encoder
from sklearn import preprocessing
```

```
label_encoder = preprocessing.LabelEncoder()
df['Genre']= label_encoder.fit_transform(df['Genre'])
```

In [29]:
```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [30]:
```
df.head()
```

Out[30]:

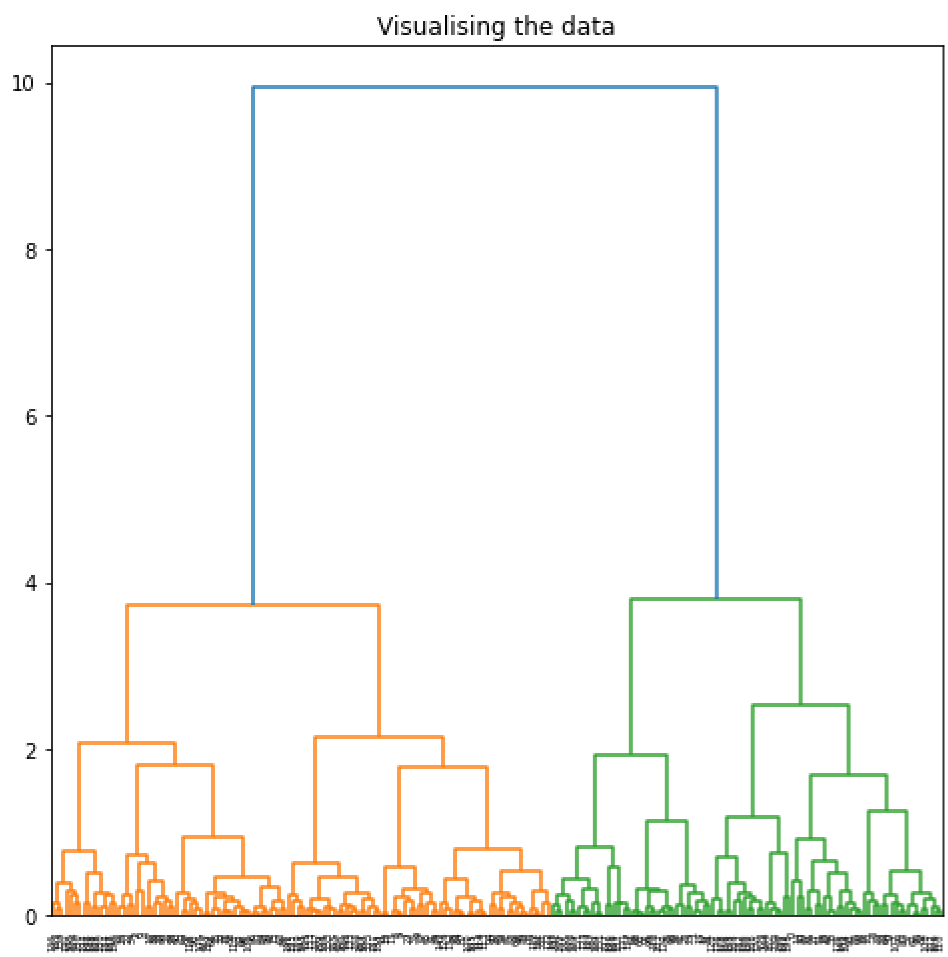
	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1.0	0.019231	0.000000	0.387755
1	1.0	0.057692	0.000000	0.816327
2	0.0	0.038462	0.008197	0.051020
3	0.0	0.096154	0.008197	0.775510
4	0.0	0.250000	0.016393	0.397959

In [31]:
```
x = df.values
```

Apply Agglomerative clustering

In [32]:
```
import scipy.cluster.hierarchy as shc

plt.figure(figsize =(8, 8))
plt.title('Visualising the data')
Dendrogram = shc.dendrogram((shc.linkage(x, method ='ward')))
```



In [33]:
```
from sklearn.cluster import AgglomerativeClustering
```

```
agg = AgglomerativeClustering(n_clusters = 2)
y_agg = agg.fit_predict(x)
```

In [34]:
```
len(y_agg)
```

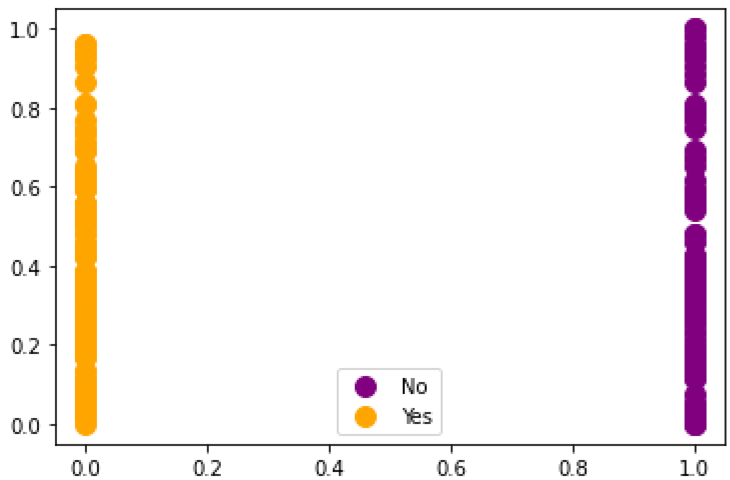
Out[34]:
```
200
```

In [35]:
```
#Visualising the clusters
plt.scatter(x[y_agg == 0, 0], x[y_agg == 0, 1], s = 100, c = 'purple', label = 'No')
plt.scatter(x[y_agg == 1, 0], x[y_agg == 1, 1], s = 100, c = 'orange', label = 'Yes')

#Plotting the centroids of the clusters
# plt.scatter(agg.cluster_centers_[:, 0], agg.cluster_centers_[:,1], s = 100, c = 'grey'

plt.legend()
```

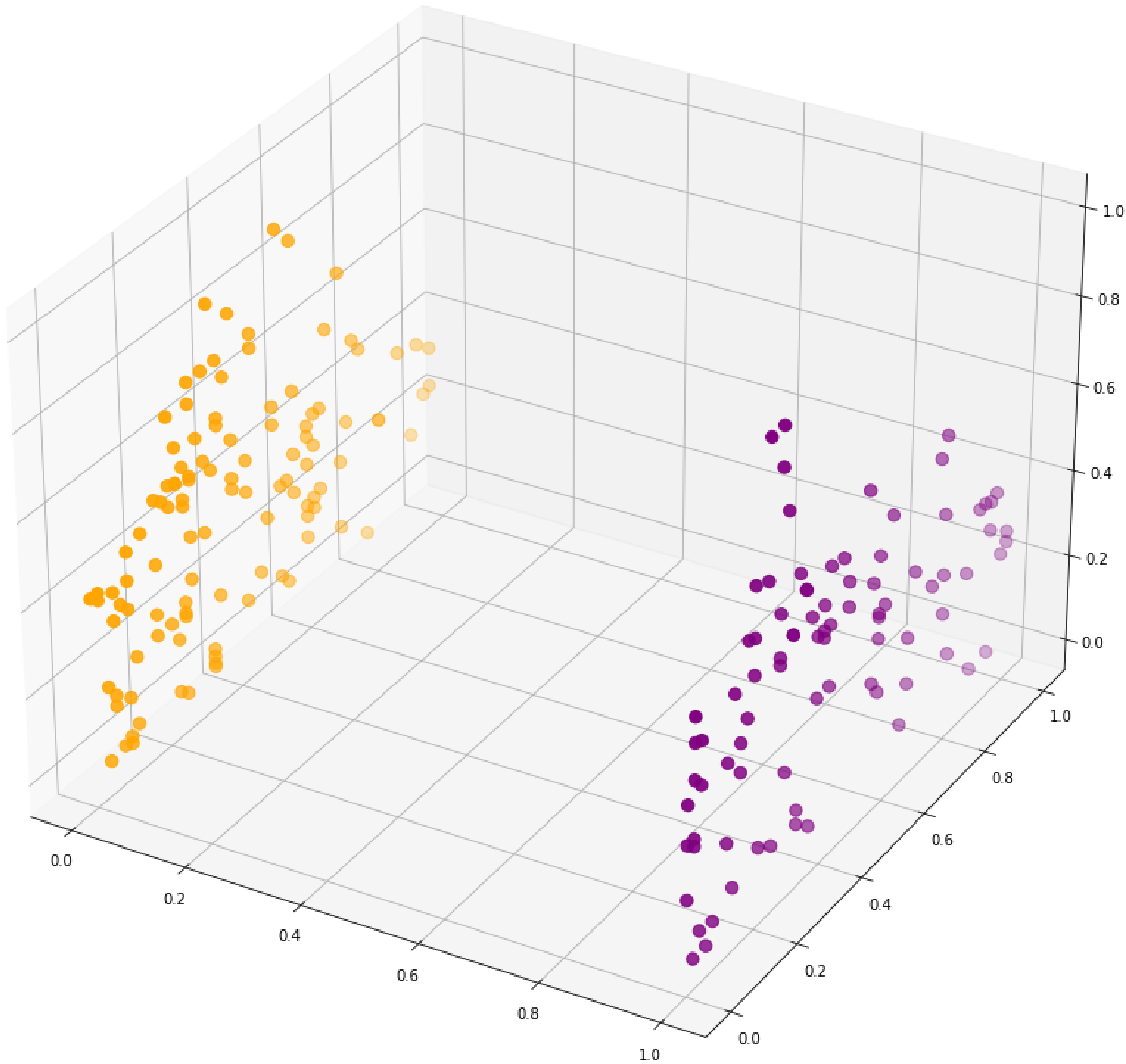
Out[35]:
```
<matplotlib.legend.Legend at 0x2651a4f5ab0>
```



In [37]:
```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x[y_agg == 0, 0], x[y_agg == 0, 1], x[y_agg == 0, 2], s = 70, c = 'purple', m
ax.scatter(x[y_agg == 1, 0], x[y_agg == 1, 1], x[y_agg == 1, 2], s = 70, c = 'orange', m

plt.show()
```



In [ ]:

12. Implementing DB-SCAN Algorithm

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

1. Social_Network_Ads Data

Read Data

In [2]:
```
df = pd.read_csv('data/Social_Network_Ads.csv')
df.head()
```

Out[2]:

	User ID	Gender	Age	EstimatedSalary	Purchased

0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

In [3]:
```
df.dtypes
```

Out[3]:
```
User ID              int64
Gender              object
Age                  int64
EstimatedSalary      int64
Purchased            int64
dtype: object
```

Data Preprocessing

In [4]:
```
df.isna().sum()
```

Out[4]:
```
User ID            0
Gender             0
Age                0
EstimatedSalary    0
Purchased          0
dtype: int64
```

In [5]:
```
df = df.drop(columns = ["User ID"])
```

In [6]:
```
# Import label encoder
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()
df['Gender']= label_encoder.fit_transform(df['Gender'])
```

In [7]:
```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

In [8]:
```
df.head()
```

Out[8]:

	Gender	Age	EstimatedSalary	Purchased
0	1.0	0.023810	0.029630	0.0
1	1.0	0.404762	0.037037	0.0
2	0.0	0.190476	0.207407	0.0
3	0.0	0.214286	0.311111	0.0
4	1.0	0.023810	0.451852	0.0

In [9]:
```
y = df['Purchased'].to_numpy()
x = df.iloc[:, [0, 1, 2]].values
```

Apply DBSCAN

In [10]:
```
from sklearn.cluster import DBSCAN
```

```
db = DBSCAN(eps = 0.5, min_samples = 10)
y_db = db.fit_predict(x)
```

In [11]:
```
len(y_db)
```

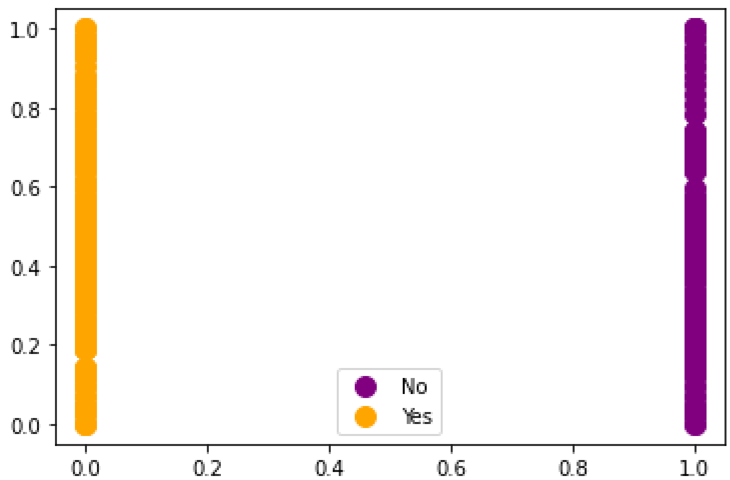
Out[11]:
```
400
```

In [13]:
```
#Visualising the clusters
plt.scatter(x[y_db == 0, 0], x[y_db == 0, 1], s = 100, c = 'purple', label = 'No')
plt.scatter(x[y_db == 1, 0], x[y_db == 1, 1], s = 100, c = 'orange', label = 'Yes')

#Plotting the centroids of the clusters
# plt.scatter(agg.cluster_centers_[:, 0], agg.cluster_centers_[:,1], s = 100, c = 'grey'

plt.legend()
```

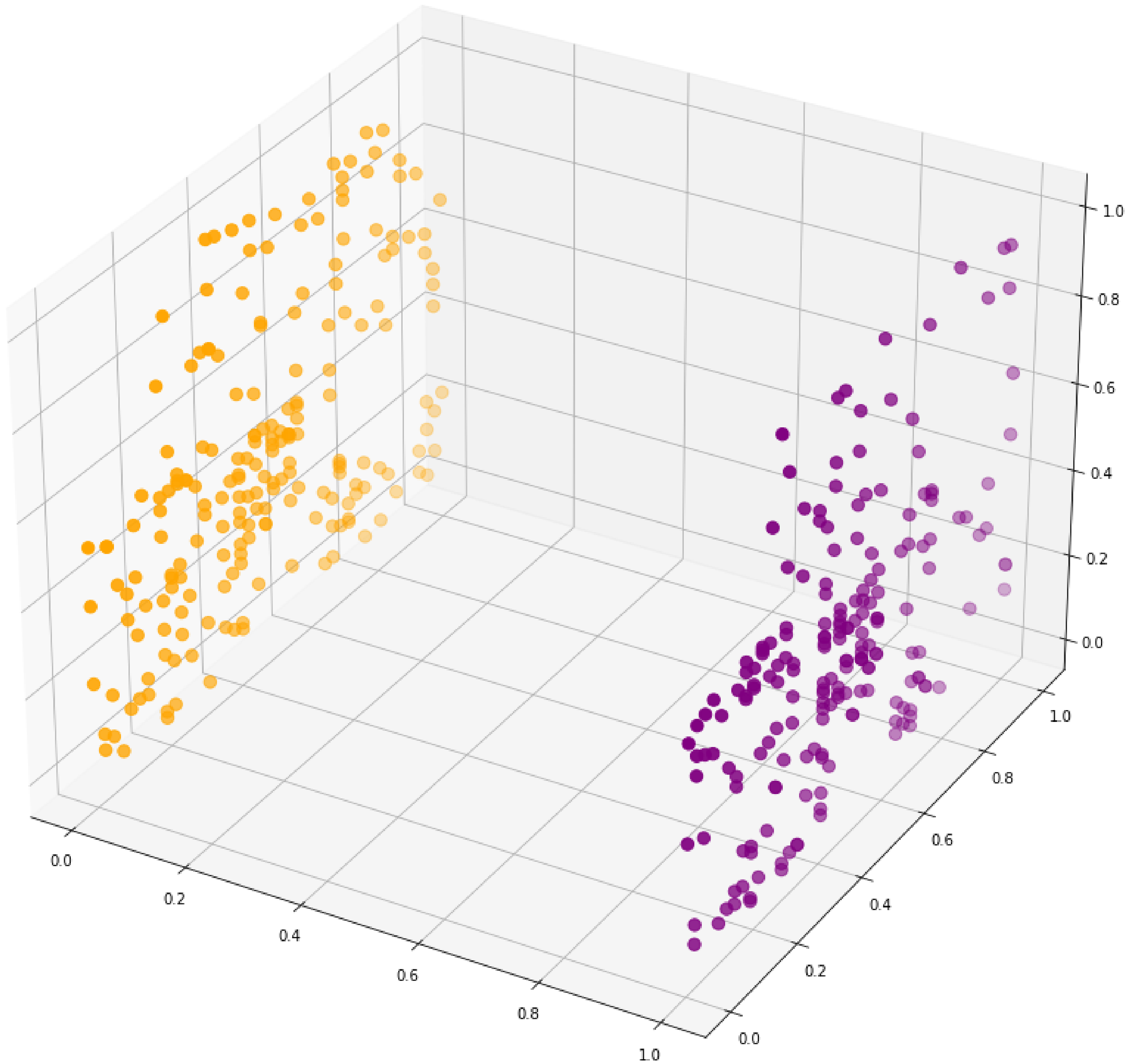
Out[13]:
```
<matplotlib.legend.Legend at 0x1bc3ed61750>
```



In [14]:
```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x[y_db == 0, 0], x[y_db == 0, 1], x[y_db == 0, 2], s = 70, c = 'purple', mark
ax.scatter(x[y_db == 1, 0], x[y_db == 1, 1], x[y_db == 1, 2], s = 70, c = 'orange', mark
# plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 70, c = '

plt.show()
```



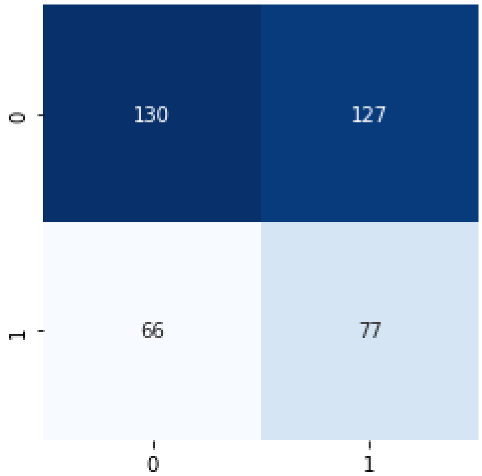
In [15]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y, y_db)
ac = accuracy_score(y,y_db)
```

In [16]:
```
print("Accuracy: ", ac)
```

```
Accuracy:  0.5175
```

In [17]:
```
import seaborn as sn
sn.heatmap(cm, square=True, annot=True, cmap='Blues', fmt='d', cbar=False)
```

Out[17]:
```
<AxesSubplot:>
```



In [ ]:

2. Mall Customers Data

Read Data

In [28]:
```
df = pd.read_csv('data/Mall_Customers.csv')
df.head()
```

Out[28]:

	CustomerID	Genre	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 [29]:
```
df.dtypes
```

Out[29]:
```
CustomerID                 int64
Genre                     object
Age                        int64
Annual Income (k$)         int64
Spending Score (1-100)     int64
dtype: object
```

Data Preprocessing

In [30]:
```
df.isna().sum()
```

Out[30]:
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [31]:
```
df = df.drop(columns = ["CustomerID"])
```

In [32]:
```
# Import label encoder
from sklearn import preprocessing
```

```
label_encoder = preprocessing.LabelEncoder()
df['Genre']= label_encoder.fit_transform(df['Genre'])
```

In [33]:
```
# apply minmax scalling
minMaxScaler = preprocessing.MinMaxScaler()
df[df.columns] = minMaxScaler.fit_transform(df[df.columns])
```

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

Out[34]:

	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1.0	0.019231	0.000000	0.387755
1	1.0	0.057692	0.000000	0.816327
2	0.0	0.038462	0.008197	0.051020
3	0.0	0.096154	0.008197	0.775510
4	0.0	0.250000	0.016393	0.397959

In [35]:
```
x = df.values
```

Apply DBSCAN

In [37]:
```
from sklearn.cluster import DBSCAN

db = DBSCAN(eps = 0.5, min_samples = 10)
y_db = db.fit_predict(x)
```

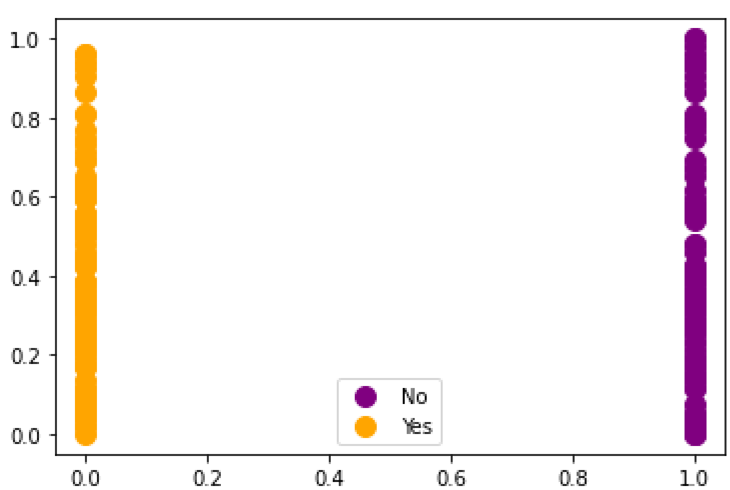
In [38]:
```
len(y_db)
```

Out[38]:
```
200
```

In [39]:
```
#Visualising the clusters
plt.scatter(x[y_db == 0, 0], x[y_db == 0, 1], s = 100, c = 'purple', label = 'No')
plt.scatter(x[y_db == 1, 0], x[y_db == 1, 1], s = 100, c = 'orange', label = 'Yes')

plt.legend()
```

Out[39]:
```
<matplotlib.legend.Legend at 0x1bc41bff220>
```

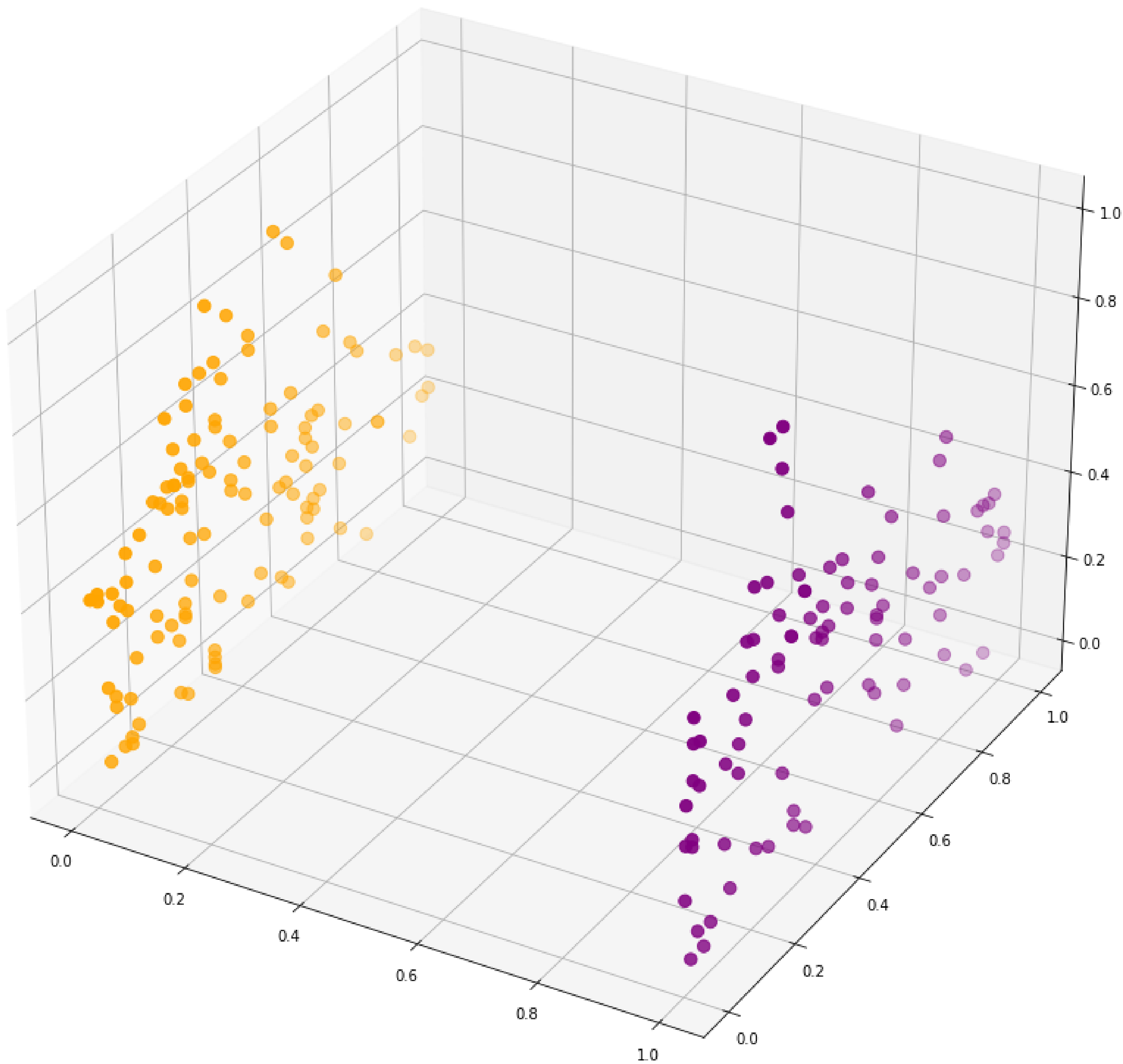


In [40]:
```
fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(x[y_db == 0, 0], x[y_db == 0, 1], x[y_db == 0, 2], s = 70, c = 'purple', mark
```

```
ax.scatter(x[y_db == 1, 0], x[y_db == 1, 1], x[y_db == 1, 2], s = 70, c = 'orange', mark

plt.show()
```



In [ ]:

```

```

13. Implementing Backpropagation Learning Algorithm for Classification

In [12]:

```
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
```

In [13]:

```
# Load dataset
data = load_iris()
```

```
# Get features and target variables
x=data.data
y=data.target

# Get dummy variable to setup binary classification
y = pd.get_dummies(y).values

y[:3]
```

Out[13]:
```
array([[1, 0, 0],
       [1, 0, 0],
       [1, 0, 0]], dtype=uint8)
```

In [14]:
```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def mean_squared_error(y_pred, y_true):
    return ((y_pred - y_true)**2).sum() / (2*y_pred.size)

def accuracy(y_pred, y_true):
    acc = y_pred.argmax(axis=1) == y_true.argmax(axis=1)
    return acc.mean()
```

In [15]:
```
# perform test train split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=20, random_state=4)

# Initialize variables
learning_rate = 0.1
iterations = 15000
N = y_train.size

# number of input features
input_size = 4

# number of hidden layers neurons
hidden_size = 2

# number of neurons at the output layer
output_size = 3

# Initialize weights
# np.random.seed(10)

# initializing weight for the hidden layer
W1 = np.random.normal(scale=0.5, size=(input_size, hidden_size))

# initializing weight for the output layer
W2 = np.random.normal(scale=0.5, size=(hidden_size , output_size))
```

In [16]:
```
for itr in range(iterations):

    # feedforward propagation
    # on hidden layer
    Z1 = np.dot(x_train, W1)
    A1 = sigmoid(Z1)

    # on output layer
    Z2 = np.dot(A1, W2)
    A2 = sigmoid(Z2)

    # Calculating error
    mse = mean_squared_error(A2, y_train)
    acc = accuracy(A2, y_train)

    # backpropagation
```

```
    E1 = A2 - y_train
    dW1 = E1 * A2 * (1 - A2)

    E2 = np.dot(dW1, W2.T)
    dW2 = E2 * A1 * (1 - A1)

    # weight updates
    W2_update = np.dot(A1.T, dW1) / N
    W1_update = np.dot(x_train.T, dW2) / N

    W2 = W2 - learning_rate * W2_update
    W1 = W1 - learning_rate * W1_update
```

In [17]:
```
# feedforward
Z1 = np.dot(x_test, W1)
A1 = sigmoid(Z1)

Z2 = np.dot(A1, W2)
A2 = sigmoid(Z2)

acc = accuracy(A2, y_test)
print("Accuracy: {}".format(acc))
```

```
Accuracy: 0.2
```

In [ ]:

14. Implementing SOM Algorithm for Clustering

In [25]:
```
# !pip install minisom
```

In [26]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# use Minisom library to implement self orgranising maps
from minisom import MiniSom
# to suppress warnings
from warnings import filterwarnings
filterwarnings('ignore')
```

In [27]:
```
# Loading Data
data = pd.read_csv('./Credit_Card_Applications.csv')
data.head()
```

Out[27]:

	CustomerID	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	Class
0	15776156	1	22.08	11.46	2	4	4	1.585	0	0	0	1	2	100	1213	0
1	15739548	0	22.67	7.00	2	8	4	0.165	0	0	0	0	2	160	1	0
2	15662854	0	29.58	1.75	1	4	4	1.250	0	0	0	1	2	280	1	0
3	15687688	0	21.67	11.50	1	5	3	0.000	1	1	11	1	2	0	1	1
4	15715750	1	20.17	8.17	2	6	4	1.960	1	1	14	0	2	60	159	1

In [28]:
```
print(data.shape)

# Seperate input and output variables
x = data.iloc[:, 1:14].values
y = data.iloc[:, -1].values
```

```
(690, 16)
```

In [30]:

```python
# define SOM
som = MiniSom(x = som_grid_rows, y = som_grid_columns, input_len=13, sigma=sigma, learni

# Initializing the weights
som.random_weights_init(x)

# Training
som.train_random(x, iterations)

# Weights
wts = som._weights
```

In [31]:

```python
som.distance_map()
```

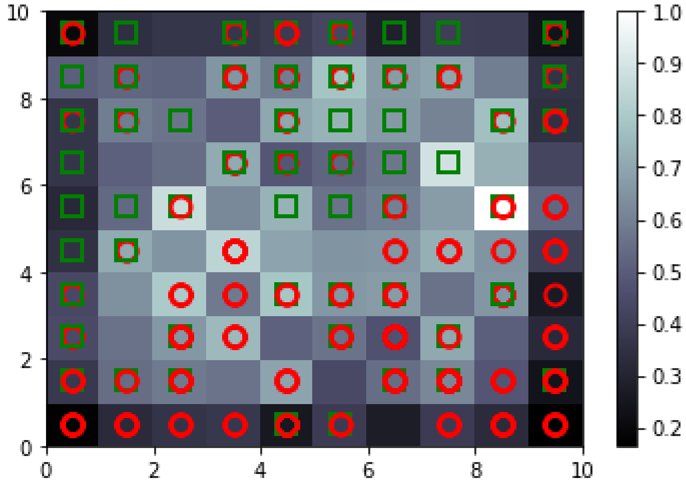
Out[31]:

```
array([[0.171542  , 0.37514082, 0.44219932, 0.43306407, 0.34974778,
        0.31535313, 0.36436955, 0.36613606, 0.50512824, 0.19775212],
       [0.32276322, 0.5442339 , 0.55647599, 0.63826895, 0.71109657,
        0.53405455, 0.50762678, 0.58896652, 0.52766897, 0.34308395],
       [0.36061388, 0.58014668, 0.6603848 , 0.79821271, 0.65008191,
        0.87175975, 0.54794228, 0.56364613, 0.5193867 , 0.36860313],
       [0.37159078, 0.55997859, 0.74901108, 0.58012615, 0.8397106 ,
        0.61899341, 0.71079819, 0.50196276, 0.65319995, 0.36943948],
       [0.25429242, 0.69303861, 0.51068077, 0.78870413, 0.69229222,
        0.73538696, 0.4820083 , 0.70274466, 0.58625674, 0.38407556],
       [0.38889509, 0.43571502, 0.56267155, 0.65796476, 0.65049078,
        0.5596785 , 0.52046934, 0.73415457, 0.77873487, 0.42857941],
       [0.27457207, 0.54695955, 0.4623616 , 0.67231051, 0.65611442,
        0.5972829 , 0.57138542, 0.66563946, 0.67083592, 0.28507369],
       [0.3872123 , 0.61596025, 0.70553937, 0.55688112, 0.72563528,
        0.67163866, 0.88904098, 0.60239826, 0.69644076, 0.39821466],
       [0.32570257, 0.48017244, 0.50553598, 0.65658645, 0.64931315,
        1.        , 0.72742855, 0.76911682, 0.58896631, 0.39378514],
       [0.16489506, 0.23847009, 0.32094721, 0.26485618, 0.40107453,
        0.52890557, 0.42381541, 0.34719349, 0.35704692, 0.23584577]])
```

In [32]:

```python
from pylab import plot, axis, show, pcolor, colorbar, bone
bone()
pcolor(som.distance_map().T)
colorbar() #gives legend

markers = ['o', 's']                     # if the observation is fraud then red circular
colors = ['r', 'g']
for i, r in enumerate(x):
    w = som.winner(r)
    plot(w[0] + 0.5,
         w[1] + 0.5,
         markers[y[i]],
         markeredgecolor = colors[y[i]],
         markerfacecolor = 'None',
         markersize = 10,
         markeredgewidth = 2)
show()
```

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