(https://skills.network/?utm_medium=Exinfluencer&utm_source=Exinfluencer&utm_content=000026UJ&utm_term=10006555&utm_id=NA-SkillsNetwork-Channel-SkillsNetworkCoursesIBMDeveloperSkillsNetworkML0101ENSkillsNetwork20718538-2022-01-01)

Supervised Machine Learning: Regression - Final Assignment

Instructions:

In this Assignment, you will demonstrate the data regression skills you have learned by completing this course. You are expected to leverage a wide variety of tools, but also this report should focus on present findings, insights, and next steps. You may include some visuals from your code output, but this report is intended as a summary of your findings, not as a code review.

The grading will center around 5 main points:

1. Does the report include a section describing the data?
2. Does the report include a paragraph detailing the main objective(s) of this analysis?
3. Does the report include a section with variations of linear regression models and specifies which one is the model that best suits the main objective(s) of this analysis.
4. Does the report include a clear and well-presented section with key findings related to the main objective(s) of the analysis?
5. Does the report highlight possible flaws in the model and a plan of action to revisit this analysis with additional data or different predictive modeling techniques?

Import the required libraries

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import warnings
import numpy as np
import os
warnings.filterwarnings('ignore')
%matplotlib inline
```

Importing the Dataset

In [2]:

```
beans=pd.read_csv("drybeans.csv")
```

1. About the Data

In [3]:

```
beans.describe()
```

Out[3]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Exten
count	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	13611.000000	13611.00000
mean	53048.284549	855.283459	320.141867	202.270714	1.583242	0.750895	53768.200206	253.064220	0.74973
std	29324.095717	214.289696	85.694186	44.970091	0.246678	0.092002	29774.915817	59.177120	0.04908
min	20420.000000	524.736000	183.601165	122.512653	1.024868	0.218951	20684.000000	161.243764	0.55531
25%	36328.000000	703.523500	253.303633	175.848170	1.432307	0.715928	36714.500000	215.068003	0.71863
50%	44652.000000	794.941000	296.883367	192.431733	1.551124	0.764441	45178.000000	238.438026	0.75985
75%	61332.000000	977.213000	376.495012	217.031741	1.707109	0.810466	62294.000000	279.446467	0.78685
max	254616.000000	1985.370000	738.860154	460.198497	2.430306	0.911423	263261.000000	569.374358	0.86619

AREA: The area and number of pixels within the bean's boundaries.

PERIMETER:Length of bean border.

MAJORAXISLENGTH: The length of the longest line that can be drawn on the bean.

ASPECTRATIO:Ratio between length and width.

MNIORAXISLENGTH:The length of longest line that can be drawn perpendicular to the main axis of the bean.

ASPECTRATIO:Ratio between length and width.

ECCENTRICITY:Eccentricity of the ellipse.

CONVEXAREA:Number of pixels in the smallest convex polygon containing the bean.

EQUIVDIAMETER:The diameter of a circle having the same area as the bean's area.

EXTENT:The ratio of the pixels in the bounding box to the bean area.

SOLIDITY:Convexity of the bean.

ROUNDNESS:Measures the roundness of the bean

COMPACTNESS:Compactness of the bean

SHAPEFACTORS:SHAPEFACTOR1,SHAPEFACTOR2,SHAPEFACTOR3, SHAPEFACTOR4

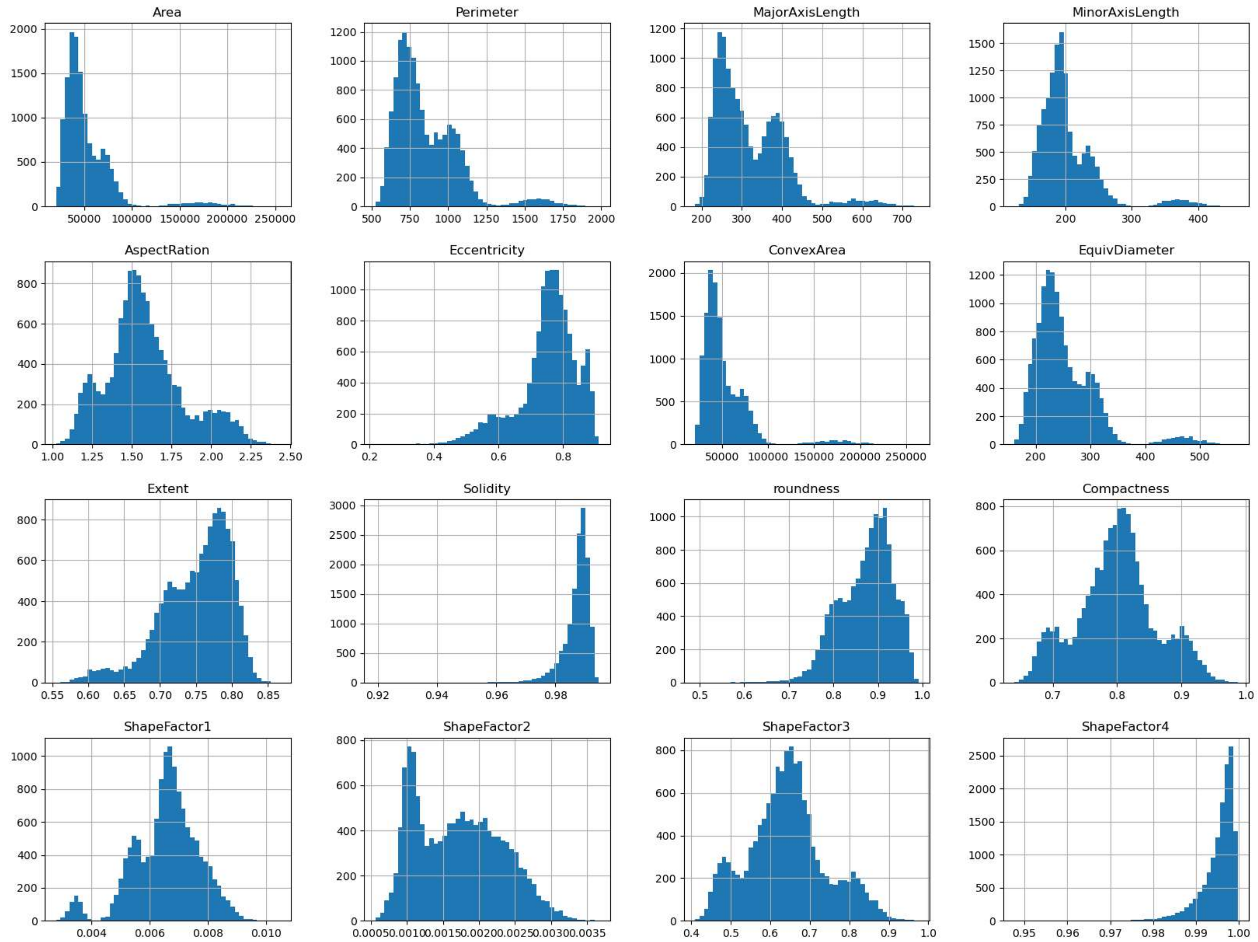
CLASS:Seker, Barbunya, Bombay, Cali, Dermosan, Horoz and Sira

In [4]:

```
beans.hist(bins=50,figsize=(20,15))
```

Out[4]:

```
array([[<AxesSubplot:title={'center':'Area'}>,
        <AxesSubplot:title={'center':'Perimeter'}>,
        <AxesSubplot:title={'center':'MajorAxisLength'}>,
        <AxesSubplot:title={'center':'MinorAxisLength'}>],
       [<AxesSubplot:title={'center':'AspectRation'}>,
        <AxesSubplot:title={'center':'Eccentricity'}>,
        <AxesSubplot:title={'center':'ConvexArea'}>,
        <AxesSubplot:title={'center':'EquivDiameter'}>],
       [<AxesSubplot:title={'center':'Extent'}>,
        <AxesSubplot:title={'center':'Solidity'}>,
        <AxesSubplot:title={'center':'roundness'}>,
        <AxesSubplot:title={'center':'Compactness'}>],
       [<AxesSubplot:title={'center':'ShapeFactor1'}>,
        <AxesSubplot:title={'center':'ShapeFactor2'}>,
        <AxesSubplot:title={'center':'ShapeFactor3'}>,
        <AxesSubplot:title={'center':'ShapeFactor4'}>]], dtype=object)
```



In [5]:

```
beans.shape
```

Out[5]:

```
(13611, 17)
```

In [6]:

```
beans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13611 entries, 0 to 13610
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Area             13611 non-null  int64  
 1   Perimeter        13611 non-null  float64
 2   MajorAxisLength  13611 non-null  float64
 3   MinorAxisLength  13611 non-null  float64
 4   AspectRation     13611 non-null  float64
 5   Eccentricity     13611 non-null  float64
 6   ConvexArea       13611 non-null  int64  
 7   EquivDiameter    13611 non-null  float64
 8   Extent           13611 non-null  float64
 9   Solidity         13611 non-null  float64
 10  roundness        13611 non-null  float64
 11  Compactness      13611 non-null  float64
 12  ShapeFactor1     13611 non-null  float64
 13  ShapeFactor2     13611 non-null  float64
 14  ShapeFactor3     13611 non-null  float64
 15  ShapeFactor4     13611 non-null  float64
 16  Class            13611 non-null  object 
dtypes: float64(14), int64(2), object(1)
memory usage: 1.8+ MB
```

The dataset I have chosen is about 13611 dry beans of 7 kinds. In the dataset we have retrieved 16 features from the dry beans. Since the number of entries for all columns in our dataset is equal, we do not have to fill any NULL value points.
We have 14 float types, 2 int types and 1 class type with 4 classes.

In [7]:

```
beans.head()
```

Out[7]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Extent	Solidity	roundness
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28715	190.141097	0.763923	0.988856	0.958027
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29172	191.272751	0.783968	0.984986	0.887034
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29690	193.410904	0.778113	0.989559	0.947849
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30724	195.467062	0.782681	0.976696	0.903936
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30417	195.896503	0.773098	0.990893	0.984877

Percentage of classes

In [8]:

```
class_perc = beans.Class.value_counts(normalize=True).to_frame()
class_perc["Class"] = class_perc["Class"] * 100
class_perc
```

Out[8]:

	Class
DERMASON	26.052458
SIRA	19.366689
SEKER	14.892366
HOROZ	14.165014
CALI	11.975608
BARBUNYA	9.712732
BOMBAY	3.835133

Label encoding the class category from string to numeric value

In [9]:

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
beans['Class']=le.fit_transform(beans.Class)
beans.head()
```

Out[9]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Extent	Solidity	roundness
0	28395	610.291	208.178117	173.888747	1.197191	0.549812	28715	190.141097	0.763923	0.988856	0.958027
1	28734	638.018	200.524796	182.734419	1.097356	0.411785	29172	191.272751	0.783968	0.984986	0.887034
2	29380	624.110	212.826130	175.931143	1.209713	0.562727	29690	193.410904	0.778113	0.989559	0.947849
3	30008	645.884	210.557999	182.516516	1.153638	0.498616	30724	195.467062	0.782681	0.976696	0.903936
4	30140	620.134	201.847882	190.279279	1.060798	0.333680	30417	195.896503	0.773098	0.990893	0.984877

the classes are sorted alphabetically so barbunya is 0, bombay is 1, cali is 2, derma son is 3, horoz is 4, seker is 5, sira is 6

Examining the relations using correlation matrix

In [10]:

```
cmat = beans.corr()
for x in range(cmat.shape[0]):
    cmat.iloc[x,x] = 0.0
cmat
```

Out[10]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Extent	
Area	0.000000	0.966722	0.931834	0.951602	0.241735	0.267481	0.999939	0.984968	0.054345	-0
Perimeter	0.966722	0.000000	0.977338	0.913179	0.385276	0.391066	0.967689	0.991380	-0.021160	-0
MajorAxisLength	0.931834	0.977338	0.000000	0.826052	0.550335	0.541972	0.932607	0.961733	-0.078062	-0
MinorAxisLength	0.951602	0.913179	0.826052	0.000000	-0.009161	0.019574	0.951339	0.948539	0.145957	-0
AspectRation	0.241735	0.385276	0.550335	-0.009161	0.000000	0.924293	0.243301	0.303647	-0.370184	-0
Eccentricity	0.267481	0.391066	0.541972	0.019574	0.924293	0.000000	0.269255	0.318667	-0.319362	-0
ConvexArea	0.999939	0.967689	0.932607	0.951339	0.243301	0.269255	0.000000	0.985226	0.052564	-0
EquivDiameter	0.984968	0.991380	0.961733	0.948539	0.303647	0.318667	0.985226	0.000000	0.028383	-0
Extent	0.054345	-0.021160	-0.078062	0.145957	-0.370184	-0.319362	0.052564	0.028383	0.000000	0
Solidity	-0.196585	-0.303970	-0.284302	-0.155831	-0.267754	-0.297592	-0.206191	-0.231648	0.191389	0
roundness	-0.357530	-0.547647	-0.596358	-0.210344	-0.766979	-0.722272	-0.362083	-0.435945	0.344411	0
Compactness	-0.268067	-0.406857	-0.568377	-0.015066	-0.987687	-0.970313	-0.269922	-0.327650	0.354212	0
ShapeFactor1	-0.847958	-0.864623	-0.773609	-0.947204	0.024593	0.019920	-0.847950	-0.892741	-0.141616	0
ShapeFactor2	-0.639291	-0.767592	-0.859238	-0.471347	-0.837841	-0.860141	-0.640862	-0.713069	0.237956	0
ShapeFactor3	-0.272145	-0.408435	-0.568185	-0.019326	-0.978592	-0.981058	-0.274024	-0.330389	0.347624	0
ShapeFactor4	-0.355721	-0.429310	-0.482527	-0.263749	-0.449264	-0.449354	-0.362049	-0.392512	0.148502	0
Class	-0.475252	-0.507638	-0.455175	-0.458492	-0.116332	-0.200356	-0.477459	-0.481099	-0.031184	0

Paiwise correlation between features A and B

In [11]:

```
cmax  = cmat.abs().max().to_frame()
id_max = cmat.abs().idxmax().to_frame()
pair_corr = pd.merge(id_max,cmax, on = cmax.index)
pair_corr=pair_corr.sort_values('0_y', ascending=False)
pair_corr = pair_corr.rename(columns = {'key_0':'A', '0_x':'B', '0_y':'Relation ratio'})
pair_corr = pair_corr.reset_index().drop('index', axis=1)
pair_corr
```

Out[11]:

	A	B	Relation ratio
0	Area	ConvexArea	0.999939
1	ConvexArea	Area	0.999939
2	Compactness	ShapeFactor3	0.998686
3	ShapeFactor3	Compactness	0.998686
4	EquivDiameter	Perimeter	0.991380
5	Perimeter	EquivDiameter	0.991380
6	AspectRation	Compactness	0.987687
7	Eccentricity	ShapeFactor3	0.981058
8	MajorAxisLength	Perimeter	0.977338
9	MinorAxisLength	Area	0.951602
10	ShapeFactor1	MinorAxisLength	0.947204
11	ShapeFactor2	ShapeFactor3	0.872971
12	roundness	ShapeFactor2	0.782824
13	ShapeFactor4	Solidity	0.702163
14	Solidity	ShapeFactor4	0.702163
15	Class	Perimeter	0.507638
16	Extent	AspectRation	0.370184

2. Objectives

In this project, I will use various unsupervised learning algorithms on it like clustering, HAC, DBSCAN,etc to gain more information on our dataset and clean and retrieve more data from it.

3. Unsupervised learning algorithms

1)KMEANS

In [ ]:

```
from sklearn.cluster import KMeans
```

In [ ]:

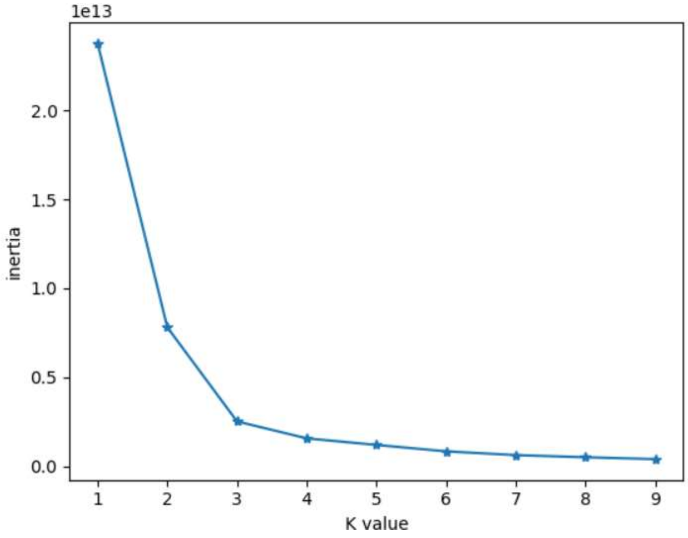
```
inertia=[]
for k in range(1,10):
    kmeans=KMeans(n_clusters=k)
    kmeans.fit(beans)
    inertia.append(kmeans.inertia_)
```

In [ ]:

```
plt.plot([1,2,3,4,5,6,7,8,9],inertia,marker='*')
plt.xlabel('K value')
plt.ylabel('inertia')
plt.show()
```

In [13]:
```
inertia=[]
for k in range(1,10):
    kmeans=KMeans(n_clusters=k)
    kmeans.fit(beans)
    inertia.append(kmeans.inertia_)
```

In [14]:
```
plt.plot([1,2,3,4,5,6,7,8,9],inertia,marker='*')
plt.xlabel('K value')
plt.ylabel('inertia')
plt.show()
```



In [ ]:
```
kmeans=KMeans(n_clusters=8)
kmeans=kmeans.fit(beans)
```

In [ ]:
```
kmeans.inertia_
```

In [ ]:
```
beans['k-means'] = kmeans
beans.sample(10)
```

In [15]:
```
kmeans=KMeans(n_clusters=8)
kmeans=kmeans.fit(beans)
```

In [16]:
```
kmeans.inertia_
```

Out[16]: 493430013172.5086

In [17]:
```
beans['k-means'] = kmeans
beans.sample(10)
```

Out[17]:

	Area	Perimeter	MajorAxisLength	MinorAxisLength	AspectRation	Eccentricity	ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactr
9360	47499	812.113	301.322458	201.443089	1.495819	0.743685	47906	245.921949	0.809293	0.991504	0.905027	0.81
4280	69371	996.596	380.282407	234.176438	1.623914	0.787906	70667	297.196737	0.808143	0.981660	0.877707	0.78
10430	26160	593.629	217.327516	153.581972	1.415059	0.707529	26449	182.504648	0.725860	0.989073	0.932862	0.83
6031	49521	893.459	372.443214	170.581095	2.183379	0.888949	50160	251.101763	0.606518	0.987261	0.779561	0.67
6988	59181	956.187	393.716349	193.478322	2.034938	0.870925	60026	274.502440	0.796847	0.985923	0.813404	0.69
13368	39509	734.501	272.741125	184.680144	1.476830	0.735867	39961	224.286471	0.769796	0.988689	0.920282	0.82
4670	74636	1040.832	404.574401	235.764273	1.716012	0.812654	75184	308.268563	0.789298	0.992711	0.865759	0.76
3234	83982	1174.925	412.055694	260.285953	1.583088	0.775232	85570	327.000311	0.741956	0.981442	0.764497	0.79
2560	67533	997.712	358.146303	241.279504	1.484363	0.739014	68874	293.233160	0.747377	0.980530	0.852541	0.81
3707	183243	1653.910	621.082856	380.455328	1.632472	0.790418	187180	483.024051	0.783572	0.978967	0.841809	0.77

Above shows that the values are presemt in different clusters

Above shows that the values are presemt in different clusters

In [ ]:

```
(beans[['Class','k-means']].groupby(['Class','k-means']).size().to_frame().rename(columns={0:'quantity'}))
```


In [18]:

```
(beans[['Class','k-means']].groupby(['Class','k-means']).size().to_frame().rename(columns={0:'quantity'}))
```


Out[18]:

Class	k-means	quantity
0	KMeans()	1322
1	KMeans()	522
2	KMeans()	1630
3	KMeans()	3546
4	KMeans()	1928
5	KMeans()	2027
6	KMeans()	2636

where barbunya is 0, bombay is 1, cali is 2, derma son is 3, horoz is 4, seker is 5, sira is 6.

where barbunya is 0, bombay is 1, cali is 2, derma son is 3, horoz is 4, seker is 5, sira is 6.

2)HEIRARCHICAL AGGLOMERATIVE CLUSTERING

In [ ]:

```
from sklearn.cluster import AgglomerativeClustering
agg= AgglomerativeClustering(n_clusters=7, linkage='ward', compute_full_tree=True)
agg= agg.fit(beans)
beans['out'] = agg.fit_predict(beans)
```

In [ ]:

```
from scipy.cluster import hierarchy

Z = hierarchy.linkage(agg.children_, method='ward')

fig, ax = plt.subplots(figsize=(15,5))

den = hierarchy.dendrogram(Z,p=50, truncate_mode='lastp',show_leaf_counts=True)
```


In [12]:

```
from sklearn.cluster import AgglomerativeClustering
agg= AgglomerativeClustering(n_clusters=7, linkage='ward', compute_full_tree=True)
agg= agg.fit(beans)
beans['out'] = agg.fit_predict(beans)
```

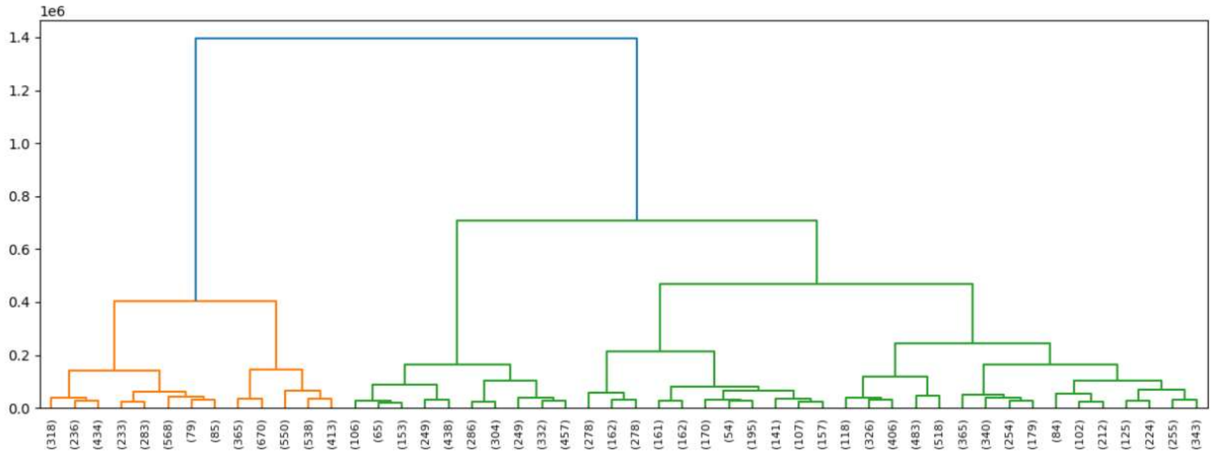
In [13]:

```
from scipy.cluster import hierarchy

Z = hierarchy.linkage(agg.children_, method='ward')

fig, ax = plt.subplots(figsize=(15,5))

den = hierarchy.dendrogram(Z,p=50, truncate_mode='lastp',show_leaf_counts=True)
```

In [ ]:

```
(beans[['Class','out']].groupby(['Class','out']).size().to_frame().rename(columns={0:'quantity'}))
```

Class	out	
0	0	857
	1	147
	4	313
	6	5
1	2	335
	4	2
	5	185
2	0	935
	1	32
	4	663
3	3	2644
	6	902
4	0	545
	1	1212
	3	18
	4	1
	6	152
5	0	2
	1	399
	3	364
	6	1262
6	0	6
	1	1517
	3	43

In [ ]:

```
(beans[['Class','out']].groupby(['Class','out']).size().to_frame().rename(columns={0:'quantity'}))
```

Class	out	
0	0	857
	1	147
	4	313
	6	5
1	2	335
	4	2
	5	185
2	0	935
	1	32
	4	663
3	3	2644
	6	902
4	0	545
	1	1212
	3	18
	4	1
	6	152
5	0	2
	1	399
	3	364
	6	1262
6	0	6
	1	1517
	3	43

where barbunya is 0, bombay is 1, cali is 2, derma son is 3, horoz is 4, seker is 5, sira is 6

3) DBSCAN

In [ ]:

```
from sklearn.cluster import DBSCAN
dbs = DBSCAN(eps=0.5, min_samples=11, metric='euclidean')
dbs = dbs.fit(beans)
```

In [ ]:

```
beans['dbscan'] = dbs.fit_predict(beans)
```

In [ ]:

```
(beans[['Class','dbscan']].groupby(['Class','dbscan']).size().to_frame().rename(columns={0:'quantity'}))
```

4)Mean shift algorithm

In [ ]:

```
from sklearn.cluster import MeanShift
ms  = MeanShift(bandwidth=2)
ms = ms.fit(beans)
```

In [ ]:

```
beans['MeanShift'] = ms.fit_predict(beans)
(beans[['Class','MeanShift']].groupby(['Class','MeanShift']).size().to_frame().rename(columns={0:'beans'}))
```

In [ ]:

```
(beans[['Class','out']].groupby(['Class','out']).size().to_frame().rename(columns={0:'quantity'}))
```

Class	out	
0	0	857
	1	147
	4	313
	6	5
1	2	335
	4	2
	5	185
2	0	935
	1	32
	4	663
3	3	2644
	6	902
4	0	545
	1	1212
	3	18
	4	1
	6	152
5	0	2
	1	399
	3	364
	6	1262
6	0	6
	1	1517
	3	43

4. Insights and key findings

When used to predict values, we get minimum accuracy from DBSCAN and HAC models.The reason for this could be incorrect values of epsilon and number of clusters or different cluster densities. The accuracy of our KMeans algorithm and mean shift are better but for this specific problem Kmeans algorithm is the most accurate.

5. Next Steps

Mean shift and HAC are slow processes. K means was the quickest process and has given us the most accurate results among these 4 processes so I would chose K means for this dataset. However, there are improvements that need to be made to increase the accuracy of the process and some changes in the datset for better representation.

Also, I would like to have a similar dataset I could use for prediction since the accuracy of the model I have chosen is just oven 90% and hence can be improved. I would love to hear suggestions for how I should proceed with this task. Thankyou for reading this report.

This is the end of the report made by me(Satwik Saurav) for Week 7 (final project) of Unsupervised Machine Learning course offered by IBM Skills Network on Coursera. Thank you for reading this report.