Graded Project

Machine Learning - Unsupervised Learning

Import the required libraries and load the data

1.Import all necessary libraries

In [1]:

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

from sklearn.preprocessing import StandardScaler,LabelEncoder,MinMaxScaler
from scipy import stats
from sklearn.cluster import KMeans
from scipy.stats import zscore
from scipy.spatial import distance
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
from sklearn.cluster import AgglomerativeClustering
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.preprocessing import Normalizer
from sklearn.metrics import silhouette_score
```

2.Load the Data and Check the Shape and Info of the data

Load the CSV file and display the Samples of Record

In [2]:

```python
df = pd.read_csv('renttherunway.csv')
df.head()
```

Out[2]:

	Unnamed: 0	fit	user_id	bust size	item_id	weight	rating	rented for	review_text	body type	revi
0	0	fit	420272	34d	2260466	137lbs	10.0	vacation	An adorable romper! Belt and zipper were a lit...	hourglass	
1	1	fit	273551	34b	153475	132lbs	10.0	other	I rented this dress for a photo shoot. The the...	straight & narrow	
2	2	fit	360448	NaN	1063761	NaN	10.0	party	This hugged in all the right places! It was a ...	NaN	tin
3	3	fit	909926	34c	126335	135lbs	8.0	formal affair	I rented this for my company's black tie award...	pear	Dr pe
4	4	fit	151944	34b	616682	145lbs	10.0	wedding	I have always been petite in my upper body and...	athletic	W

In [3]:

```
df.tail()
```

Out[3]:

	Unnamed: 0	fit	user_id	bust size	item_id	weight	rating	rented for	review_text	b t
192539	192539	fit	66386	34dd	2252812	140lbs	10.0	work	Fit like a glove!	hourg
192540	192540	fit	118398	32c	682043	100lbs	10.0	work	The pattern contrast on this dress is really s...	p
192541	192541	fit	47002	36a	683251	135lbs	6.0	everyday	Like the other DVF wraps, the fit on this is f...	straig na
192542	192542	fit	961120	36c	126335	165lbs	10.0	wedding	This dress was PERFECTION. it looked incredib...	l
192543	192543	fit	123612	36b	127865	155lbs	10.0	wedding	This dress was wonderful! I had originally pla...	ath

Checking the shape and info

In [4]:

```
df.shape
```

Out[4]:

```
(192544, 16)
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 192544 entries, 0 to 192543
Data columns (total 16 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Unnamed: 0      192544 non-null  int64
 1   fit             192544 non-null  object
 2   user_id         192544 non-null  int64
 3   bust size       174133 non-null  object
 4   item_id         192544 non-null  int64
 5   weight          162562 non-null  object
 6   rating          192462 non-null  float64
 7   rented for      192534 non-null  object
 8   review_text     192482 non-null  object
 9   body type       177907 non-null  object
 10  review_summary  192199 non-null  object
 11  category        192544 non-null  object
 12  height          191867 non-null  object
 13  size            192544 non-null  int64
 14  age             191584 non-null  float64
 15  review_date     192544 non-null  object
dtypes: float64(2), int64(4), object(10)
memory usage: 23.5+ MB
```

In [6]:

```
df.size
```

Out[6]:

```
3080704
```

In [7]:

```
df.ndim
```

Out[7]:

```
2
```

Inference

- The dataset has 192544 rows and 16 columns
- There is missing values in some columns, so we have to treat with appropriate method

Data cleansing and Exploratory data analysis

3. Check if there are any duplicate records in the dataset? If any, drop them.

In [8]:

```
df.duplicated().sum()
```

Out[8]:

```
0
```

- There is no duplicated record in this dataset

4. Drop the columns which you think redundant for the analysis.

In [9]:

```
df.columns
```

Out[9]:

```
Index(['Unnamed: 0', 'fit', 'user_id', 'bust size', 'item_id', 'weight',
       'rating', 'rented for', 'review_text', 'body type', 'review_summar
y',
       'category', 'height', 'size', 'age', 'review_date'],
      dtype='object')
```

Inferences

- We dropped 6 redundant columns namely for this analysis: 'Unnamed:0', 'user_id', 'item_id', 'review_text', 'review_summary', 'review_date' Currently there are 10 columns after dropped the redundant columns.

There are some redundant columns for the analysis

In [10]:

```
df=df.drop(columns=['Unnamed: 0','user_id','item_id','review_text','review_summary','revi
```

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 192544 entries, 0 to 192543
Data columns (total 10 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   fit         192544 non-null  object 
 1   bust size   174133 non-null  object 
 2   weight      162562 non-null  object 
 3   rating      192462 non-null  float64
 4   rented for  192534 non-null  object 
 5   body type   177907 non-null  object 
 6   category    192544 non-null  object 
 7   height      191867 non-null  object 
 8   size        192544 non-null  int64  
 9   age         191584 non-null  float64
dtypes: float64(2), int64(1), object(7)
memory usage: 14.7+ MB
```

Inferences:

- We dropped 6 redundant columns namely for this analysis: 'Unnamed:0', 'user_id', 'item_id', 'review_text', 'review_summary', 'review_date'
- Currently there are 10 columns after dropped the redundant columns.

5. Check the column 'weight', Is there any presence of string data? If yes, remove the string data and convert to float.

In [12]:

```
df['weight'].dtype
```

Out[12]:

```
dtype('O')
```

In [13]:

```
df['weight']=df['weight'].str.replace('lbs', '')
```

In [14]:

```
df['weight']=df['weight'].astype(float)
```

In [15]:

```
df['weight'].dtype
```

Out[15]:

```
dtype('float64')
```

- If yes, remove the string data and converted to float.

In [16]:

```
df.head(2)
```

Out[16]:

	fit	bust size	weight	rating	rented for	body type	category	height	size	age
0	fit	34d	137.0	10.0	vacation	hourglass	romper	5' 8"	14	28.0
1	fit	34b	132.0	10.0	other	straight & narrow	gown	5' 6"	12	36.0

- There is a string data in the weight column, as per our requirement. The lbs unit present in the dataset is removed and converted into float datatype

6. Check the unique categories for the column 'rented for' and group 'party:cocktail' category with 'party'.

In [17]:

```
df['rented for'].unique()
```

Out[17]:

```
array(['vacation', 'other', 'party', 'formal affair', 'wedding', 'date',
       'everyday', 'work', nan, 'party: cocktail'], dtype=object)
```

In [18]:

```
df['rented for']=df['rented for'].replace(['party: cocktail'],'party')
```

In [19]:

```
df['rented for'].unique()
```

Out[19]:

```
array(['vacation', 'other', 'party', 'formal affair', 'wedding', 'date',
       'everyday', 'work', nan], dtype=object)
```

7. The column 'height' is in feet with a quotation mark, Convert to inches with float datatype.

In [20]:

```
df['height'].dtype
```

Out[20]:

```
dtype('O')
```

In [21]:

```
df.head(2)
```

Out[21]:

	fit	bust size	weight	rating	rented for	body type	category	height	size	age
0	fit	34d	137.0	10.0	vacation	hourglass	romper	5' 8"	14	28.0
1	fit	34b	132.0	10.0	other	straight & narrow	gown	5' 6"	12	36.0

In [22]:

```
df.height = [np.nan if 'nan' in x else ((float(str(x).split("'")[0]) * 12) + (float(str(x
                                          for x in df.height.astype(str)]

#df.height = df.height.fillna(df.height.median())

df.height = df.height.astype(float)

df.height
```

Out[22]:

```
0         68.0
1         66.0
2         64.0
3         65.0
4         69.0
          ...
192539    69.0
192540    61.0
192541    68.0
192542    66.0
192543    66.0
Name: height, Length: 192544, dtype: float64
```

- The height column is converted into float using above steps.

8. Check for missing values in each column of the dataset? If it exists, impute them with appropriate methods

In [23]:

```
df.isnull().sum()
```

Out[23]:

```
fit                0
bust size      18411
weight         29982
rating            82
rented for        10
body type      14637
category           0
height           677
size               0
age              960
dtype: int64
```

In [24]:

```
## Now filling "NAN" with the most frequent value- the mode.
for col in ['bust size', 'body type', 'rented for']:
    df[col].fillna(df[col].mode()[0], inplace=True)

##
for col in ['weight', 'height', 'age', 'rating']:
    df[col].fillna(df[col].median(), inplace=True)
```

In [25]:

```
df.isnull().sum()
```

Out[25]:

```
fit           0
bust size     0
weight        0
rating        0
rented for    0
body type     0
category      0
height        0
size          0
age           0
dtype: int64
```

- There is missing values in the categorical columns of 'fit','bust size', 'body type', 'rented for' and numerical columns of 'weight', 'height', 'age', 'rating'. That are filled with above appropriate method.

9. Check the statistical summary for the numerical and categorical columns and write your findings.

In [26]:

```
df.describe()
```

Out[26]:

	weight	rating	height	size	age
count	192544.000000	192544.000000	192544.000000	192544.000000	192544.000000
mean	137.019284	9.092758	65.309529	12.245175	33.861689
std	20.141448	1.429862	2.658857	8.494877	8.039050
min	50.000000	2.000000	54.000000	0.000000	0.000000
25%	125.000000	8.000000	63.000000	8.000000	29.000000
50%	135.000000	10.000000	65.000000	12.000000	32.000000
75%	145.000000	10.000000	67.000000	16.000000	37.000000
max	300.000000	10.000000	78.000000	58.000000	117.000000

In [27]:

```
## Checking Statistical Summary for Object data type
df.describe(include='O')
```

Out[27]:

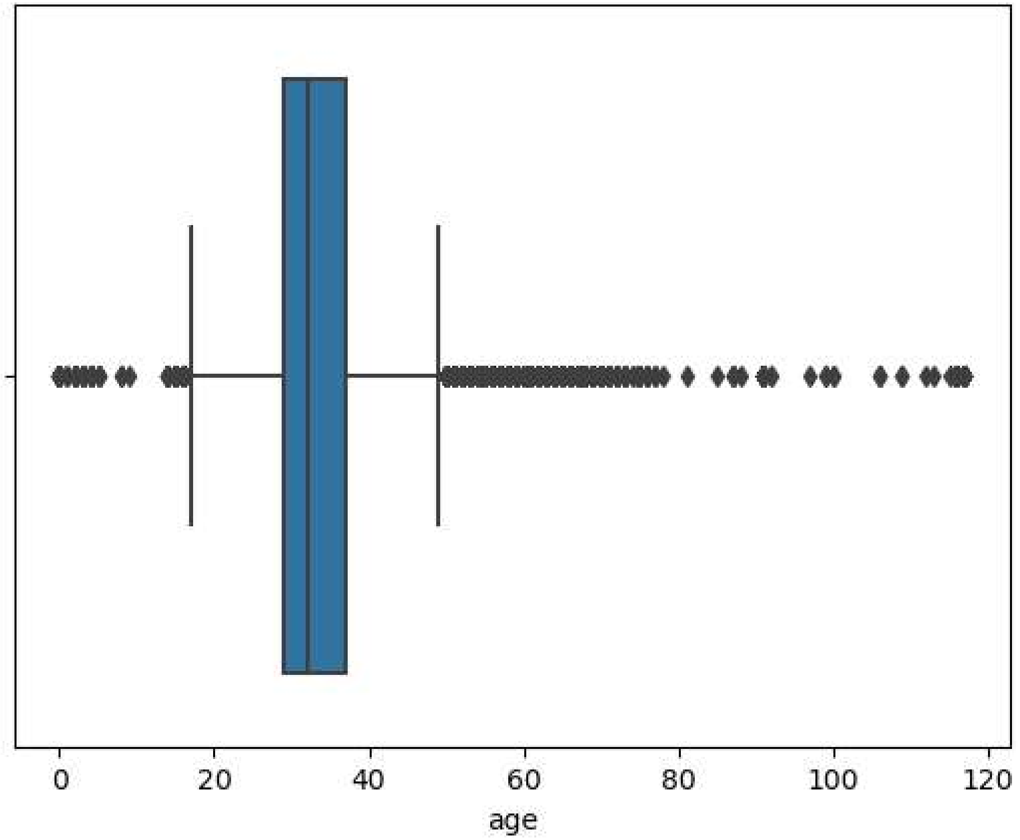
	fit	bust size	rented for	body type	category
count	192544	192544	192544	192544	192544
unique	3	106	8	7	68
top	fit	34b	wedding	hourglass	dress
freq	142058	45696	57794	69986	92884

- while analysing the weight, age column with min, max, mean there can clearly see that ouliers are present in that.

10. Are there outliers present in the column age? If yes, treat them with the appropriate method.

In [28]:

```
sns.boxplot(df['age'])
plt.show()
```



- Yes there is outlier in the column 'age', i try with Log Transformation method

In [29]:

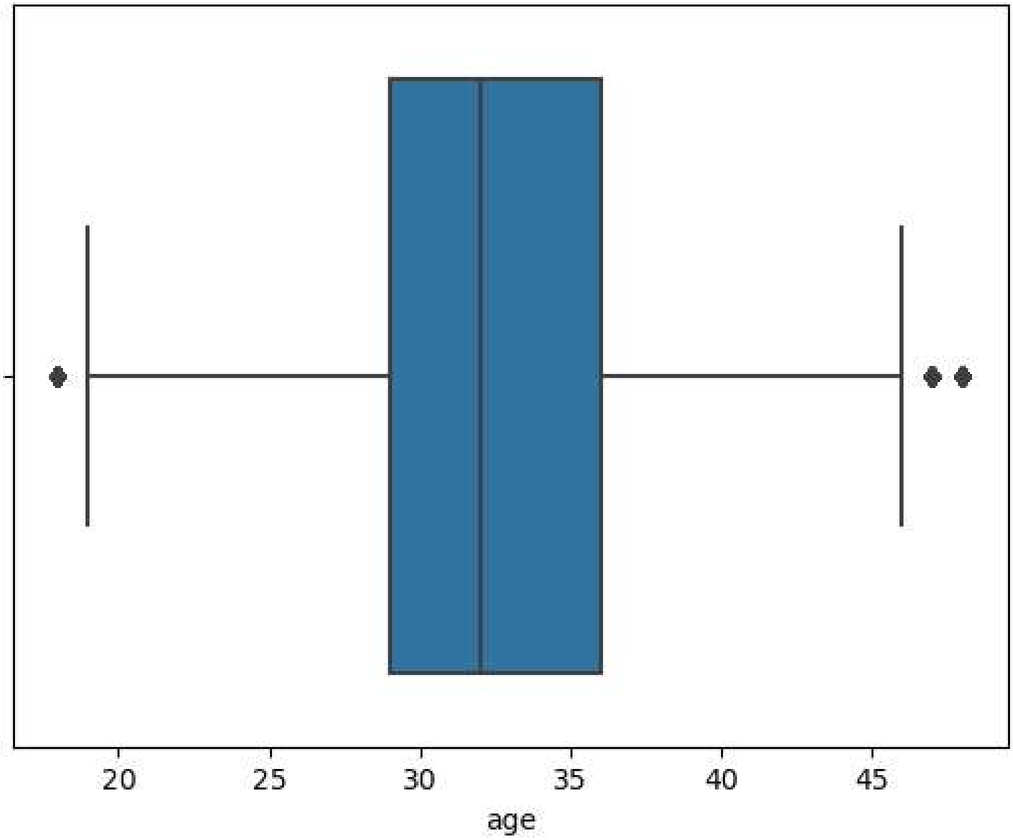
```
Q1= df['age'].quantile(0.25)
Q3= df['age'].quantile(0.75)
IQR = Q3-Q1

lower_whisker = Q1-(1.5*IQR)
upper_whisker = Q3+(1.5*IQR)
```

In [30]:

```
df_out = df.loc[(df['age'] < upper_whisker) & (df['age'] > lower_whisker)]
```

In [31]:

```
sns.boxplot(df_out['age'])
plt.show()
```

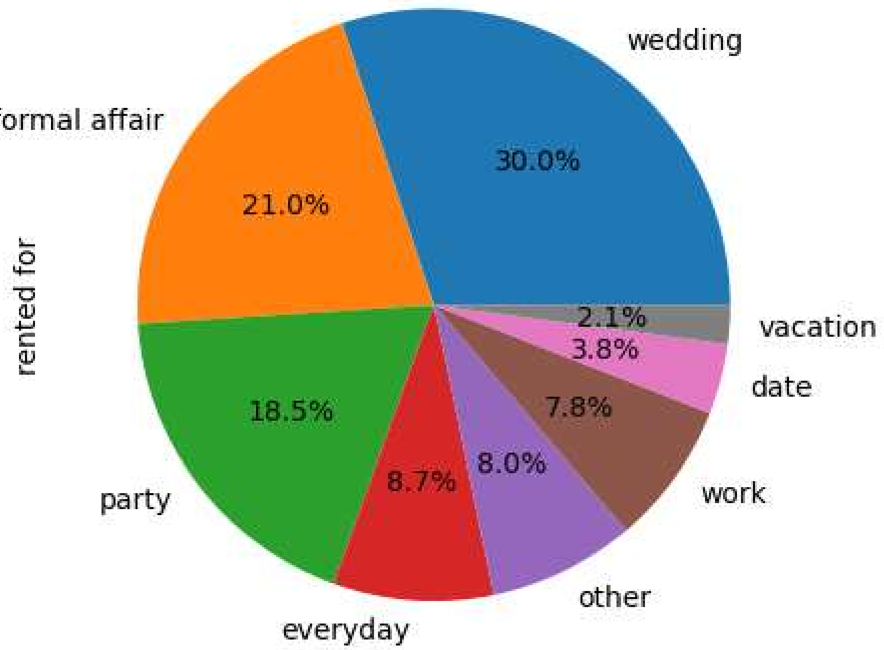


- After using IQR method, the outliers are minimised.

11. Check the distribution of the different categories in the column 'rented for' using appropriate plot.

In [32]:

```
df['rented for'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.show()
```



- Majorly the dress is rented for the wedding, party, formal affiar purposes.

Data Preparation for model building

12. Encode the categorical variables in the dataset.

In [33]:

```
df_cat = df.select_dtypes(include='object')

## Label encoding
le = LabelEncoder()
for col in df_cat:
    df[col] = le.fit_transform(df[col])

df.head()
```

Out[33]:

	fit	bust size	weight	rating	rented for	body type	category	height	size	age
0	0	39	137.0	10.0	5	3	44	68.0	14	28.0
1	0	37	132.0	10.0	3	6	20	66.0	12	36.0
2	0	37	135.0	10.0	4	3	45	64.0	4	116.0
3	0	38	135.0	8.0	2	4	16	65.0	8	34.0
4	0	37	145.0	10.0	6	1	20	69.0	12	27.0

13. Standardize the data, so that the values are within a particular range

In [34]:

```
## Standardization
df1 = df.copy()
scaled_features = StandardScaler().fit_transform(df1.values)
scaled_features_df = pd.DataFrame(scaled_features, index=df1.index, columns=df1.columns)
```

In [35]:

```
scaled_features_df.head()
```

Out[35]:

	fit	bust size	weight	rating	rented for	body type	category	height	
0	-0.556291	-0.004640	-0.000957	0.634498	0.514420	0.020953	1.569310	1.011893	0.20
1	-0.556291	-0.187210	-0.249202	0.634498	-0.456753	1.927582	-0.307247	0.259688	-0.02
2	-0.556291	-0.187210	-0.100255	0.634498	0.028833	0.020953	1.647500	-0.492517	-0.97
3	-0.556291	-0.095925	-0.100255	-0.764242	-0.942340	0.656496	-0.620006	-0.116415	-0.49
4	-0.556291	-0.187210	0.396235	0.634498	1.000007	-1.250132	-0.307247	1.387995	-0.02

Principal Component Analysis and Clustering

14. Apply PCA on the above dataset and determine the number of PCA components to be used so that 90-95% of the variance in data is explained by the same.

In [36]:

```
## Calculating covariance matrix
cov_matrix = np.cov(scaled_features_df.T)
print('Covariance matrix','\n',cov_matrix)
```

```
Covariance matrix
 [[ 1.00000519e+00  9.05525666e-03  1.36712983e-02 -2.45044635e-01
   8.35378787e-03 -7.61016810e-03  3.35892077e-04  1.44717645e-04
   6.54006939e-02  1.59721574e-03]
 [ 9.05525666e-03  1.00000519e+00  5.68663389e-01 -2.09457651e-02
  -2.07814670e-03 -2.15702411e-01 -1.09647683e-02  1.47036167e-01
   6.27115858e-01  1.65476458e-01]
 [ 1.36712983e-02  5.68663389e-01  1.00000519e+00 -2.08485232e-02
   9.70156108e-03 -2.34400313e-01 -1.44172746e-02  3.49055850e-01
   7.23391050e-01  6.29822084e-02]
 [-2.45044635e-01 -2.09457651e-02 -2.08485232e-02  1.00000519e+00
   1.27900970e-02  4.72965534e-03 -2.37071846e-02  1.74835660e-03
  -3.67286881e-02 -3.51310734e-02]
 [ 8.35378787e-03 -2.07814670e-03  9.70156108e-03  1.27900970e-02
   1.00000519e+00 -9.08626233e-03 -5.76351186e-02 -1.70706029e-02
   4.87422452e-03 -3.82507449e-02]
 [-7.61016810e-03 -2.15702411e-01 -2.34400313e-01  4.72965534e-03
  -9.08626233e-03  1.00000519e+00 -1.85295641e-03 -1.33577071e-01
  -2.14155816e-01 -4.17804903e-02]
 [ 3.35892077e-04 -1.09647683e-02 -1.44172746e-02 -2.37071846e-02
  -5.76351186e-02 -1.85295641e-03  1.00000519e+00 -4.34401436e-03
  -5.62602705e-03  2.45069570e-02]
 [ 1.44717645e-04  1.47036167e-01  3.49055850e-01  1.74835660e-03
  -1.70706029e-02 -1.33577071e-01 -4.34401436e-03  1.00000519e+00
   2.28425433e-01 -7.28094995e-03]
 [ 6.54006939e-02  6.27115858e-01  7.23391050e-01 -3.67286881e-02
   4.87422452e-03 -2.14155816e-01 -5.62602705e-03  2.28425433e-01
   1.00000519e+00  1.55120227e-01]
 [ 1.59721574e-03  1.65476458e-01  6.29822084e-02 -3.51310734e-02
  -3.82507449e-02 -4.17804903e-02  2.45069570e-02 -7.28094995e-03
   1.55120227e-01  1.00000519e+00]]
```

In [37]:

```
## Calculating eigen values and eigen vectors
eig_vals, eig_vecs = np.linalg.eig(cov_matrix)
print('Eigen vectors:','\n',eig_vecs)
print('\n')
print('Eigen values:','\n',eig_vals)
```

```
Eigen vectors:
 [[ 3.79182406e-02  5.21339725e-02 -3.73184198e-02  6.88434588e-01
   6.93932057e-01 -1.76424493e-01  5.38601361e-02  6.33233638e-02
  -3.03727146e-02  2.97369220e-03]
 [ 4.96913898e-01  1.06638737e-01 -7.89323759e-01 -1.84310214e-02
  -4.70940698e-02  7.62941588e-02 -1.83968543e-01  2.48180115e-01
   1.56953838e-02 -1.20872949e-01]
 [ 5.43366077e-01  6.70187842e-01  4.54017747e-01 -5.09818200e-02
  -3.46047997e-02 -7.31970933e-02  8.00361572e-02  5.47991186e-02
  -1.11402528e-02 -1.75448454e-01]
 [-3.64031019e-02  7.04524838e-03 -6.01937589e-04 -7.00031122e-01
   7.03930568e-01  4.58063321e-02 -4.05279947e-02  8.70339882e-02
   2.32987301e-02 -3.47061487e-02]
 [-1.94047852e-04 -2.65517065e-03 -1.48403766e-02 -4.65662187e-02
  -2.69087466e-02 -5.95847893e-01 -3.74763049e-01 -2.22693417e-01
   6.69042233e-01 -6.47167696e-02]
 [-2.54214421e-01  1.92370737e-02 -2.76410781e-02  4.84620878e-02
   6.13850242e-04  6.32829507e-02 -1.41897827e-01 -1.49609530e-01
  -1.59830054e-01 -9.27266736e-01]
 [-8.28640768e-03  6.21298550e-03 -6.76633329e-03  9.29863376e-02
   4.60785449e-02  5.49109526e-01  3.98043909e-01  2.00040328e-02
   7.13111284e-01 -1.42088601e-01]
 [ 2.71344343e-01 -1.10132087e-01 -2.12596292e-01 -9.63048660e-02
   5.43547512e-02 -1.76807075e-01  5.16393599e-01 -7.36531005e-01
  -1.25466543e-01 -2.59626083e-02]
 [ 5.46084895e-01 -7.20632984e-01  3.42083443e-01  1.95930931e-02
   2.12737937e-02  1.61608807e-02 -8.53606225e-02  1.50972381e-01
   6.03532338e-03 -1.85054451e-01]
 [ 1.36149797e-01  6.96574442e-02  7.87054472e-02  1.01259249e-01
   1.15195527e-01  5.13337057e-01 -6.01860683e-01 -5.34951224e-01
  -2.63643648e-02  1.85132311e-01]]


Eigen values:
 [2.54938767 0.25577858 0.41695454 1.24894331 0.75210664 1.08478886
 1.01807319 0.83998391 0.9453528  0.88868245]
```

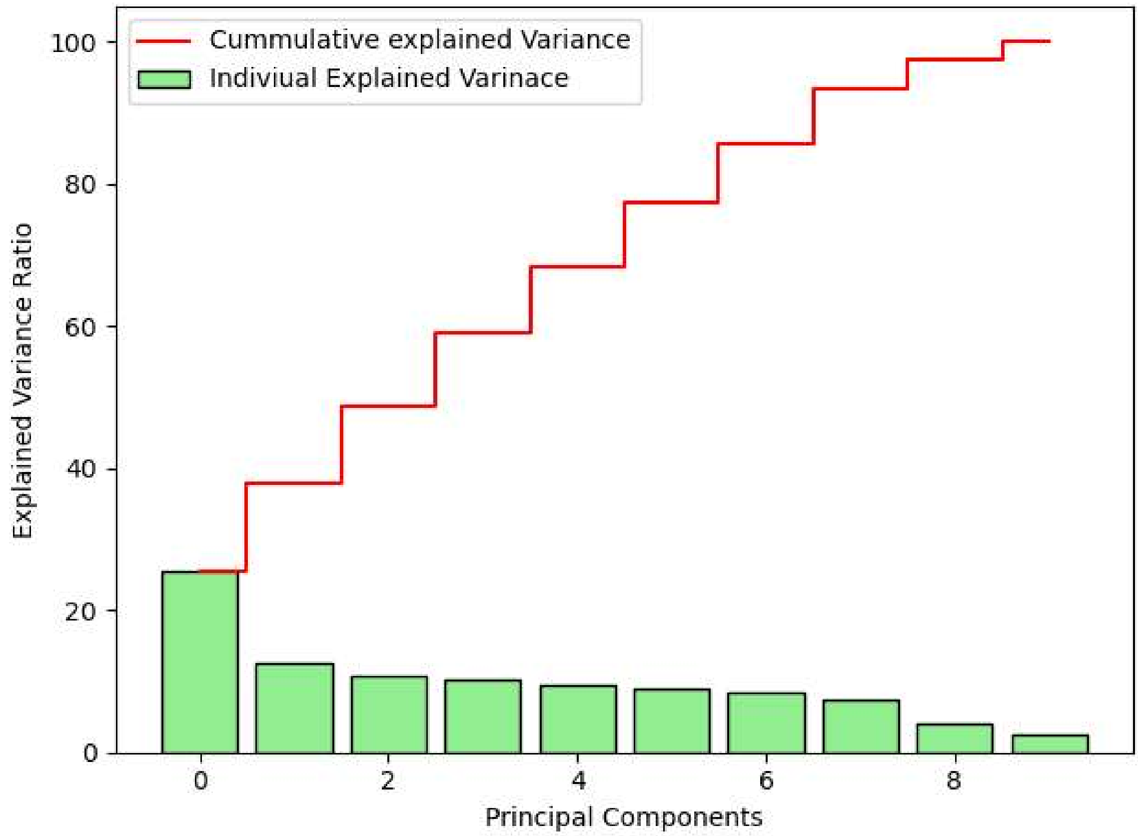
In [38]:

```
## Calculating the Variance explained and the cummulative variance explained
total = sum(eig_vals)
var_exp = [ (i/total)*100  for i in sorted(eig_vals,reverse=True)]
cum_var_exp = np.cumsum(var_exp)
print('Variance Explained: ',var_exp, '\n')
print('Cummulative Variance Explained: ',cum_var_exp)
```

```
Variance Explained:  [25.493744303499692, 12.489368205336868, 10.847832273
773115, 10.180678986925304, 9.4534788747705, 8.886778360335535, 8.39979547
7769073, 7.521027307046054, 4.169523708096748, 2.557772502447119]

Cummulative Variance Explained:  [ 25.4937443   37.98311251  48.83094478
59.01162377  68.46510264
  77.351881    85.75167648  93.27270379  97.4422275  100.        ]
```

In [39]:

```
## Scree plot
plt.bar(range(10),var_exp, align='center',color='lightgreen',edgecolor='black',label='Ind
plt.step(range(10), cum_var_exp, where='mid',color='red',label='Cummulative explained Var
plt.legend(loc = 'best')
plt.ylabel('Explained Variance Ratio')
plt.xlabel('Principal Components')
plt.tight_layout()
plt.show()
```



- We can see that approximately 93% of variance is explained by the first 8 variables.
- so, we can choose the optimal number of principal components as 8.

In [40]:

```
## Fitting the PCA model
pca=PCA(n_components = 8)
pca.fit(scaled_features_df)
```

Out[40]:

```
PCA(n_components=8)
```

In [41]:

```
data_pca = pca.transform(scaled_features_df)
data_pca = pd.DataFrame(data_pca,columns=['PC1','PC2','PC3','PC4','PC5','PC6','PC7','PC8'
data_pca.head()
```

Out[41]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
0	0.222657	-0.871255	0.133583	-1.317746	1.385041	0.498137	0.391549	-0.094749
1	-0.669093	-0.723509	0.446753	0.289349	-0.841026	1.623649	0.570854	-0.121513
2	0.516748	0.397317	6.325453	5.708219	1.007211	-1.845138	5.258172	-1.277636
3	-0.559129	0.180109	0.347079	0.003970	-1.167688	0.306926	0.030717	0.933800
4	0.642889	-1.200274	-1.443786	-0.923737	0.522263	-0.878866	0.616614	0.009609

15. Apply K-means clustering and segment the data. (You may use original data or PCA transformed data)

a. Find the optimal K Value using elbow plot for K Means clustering

In [42]:

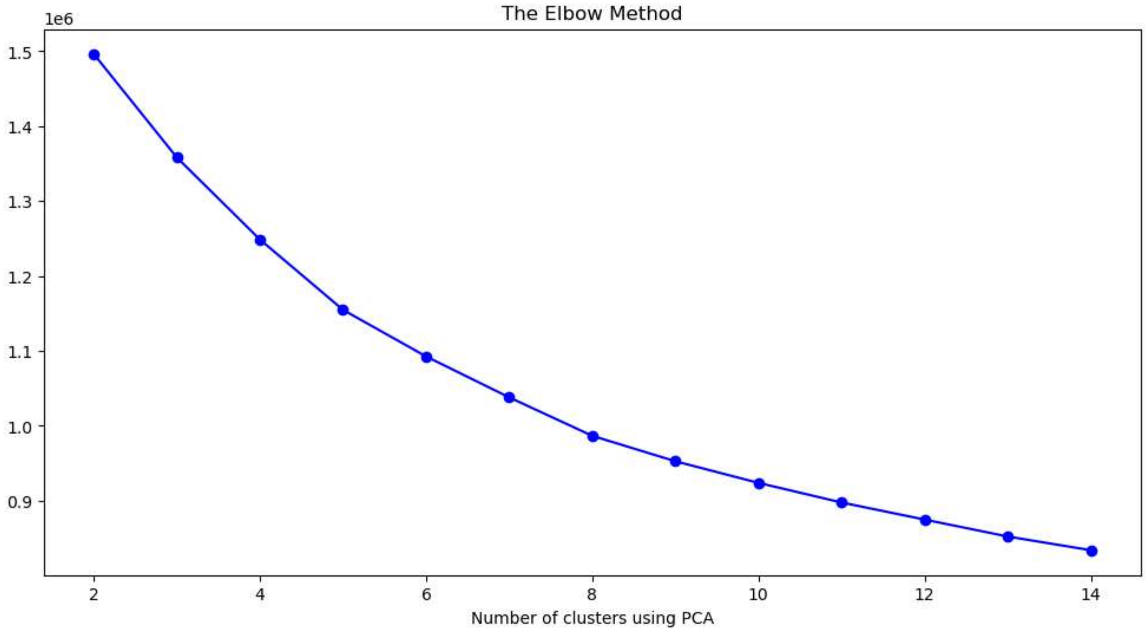
```
cluster_range = range(2,15)
cluster_errors = []

for num_clusters in cluster_range:

    clusters = KMeans(num_clusters, random_state=100)
    clusters.fit(data_pca)

    labels = clusters.labels_
    centroids = clusters.cluster_centers_

    cluster_errors.append(clusters.inertia_)

clusters_df = pd.DataFrame({'num_clusters':cluster_range,
                            'cluster_errors':cluster_errors})

clusters_df
```

Out[42]:

	num_clusters	cluster_errors
0	2	1.496415e+06
1	3	1.358288e+06
2	4	1.248766e+06
3	5	1.154887e+06
4	6	1.092696e+06
5	7	1.038090e+06
6	8	9.867346e+05
7	9	9.527621e+05
8	10	9.239364e+05
9	11	8.977387e+05
10	12	8.749403e+05
11	13	8.523610e+05
12	14	8.340490e+05

In [43]:

```
## Elbow method
plt.figure(figsize=[12,6])
plt.title('The Elbow Method')
plt.xlabel('Number of clusters using PCA')
plt.plot(clusters_df['num_clusters'],clusters_df['cluster_errors'],marker='o',color='b')
plt.show()
```



- From the Elbow plot, we can see that at K=2 the interia starts to drop significantly. So we will do it using 3 clusters.

In [44]:

```
## Fit the KMeans clustering model using the obtained optimal K
kmeans = KMeans(n_clusters=3, random_state=100)
kmeans.fit(data_pca)
```

Out[44]:

```
KMeans(n_clusters=3, random_state=100)
```

b. Build a Kmeans clustering model using the obtained optimal K value from the elbow plot.

In [45]:

```
## obtained labels from kmeans clustering
kmeans.labels_
```

Out[45]:

```
array([0, 0, 1, ..., 0, 1, 1])
```

In [46]:

```
## Creating a new dataframe only for labels.
df_labels = pd.DataFrame(kmeans.labels_, columns=list(['Labels']))
df_labels.head(5)
```

Out[46]:

	Labels
0	0
1	0
2	1
3	0
4	1

In [47]:

```
## Joining the label dataframe to the data_pca dataframe
kmeans_df = data_pca.join(df_labels)
kmeans_df.head()
```

Out[47]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	Labels
0	0.222657	-0.871255	0.133583	-1.317746	1.385041	0.498137	0.391549	-0.094749	[illegible]
1	-0.669093	-0.723509	0.446753	0.289349	-0.841026	1.623649	0.570854	-0.121513	[illegible]
2	0.516748	0.397317	6.325453	5.708219	1.007211	-1.845138	5.258172	-1.277636	[illegible]
3	-0.559129	0.180109	0.347079	0.003970	-1.167688	0.306926	0.030717	0.933800	[illegible]
4	0.642889	-1.200274	-1.443786	-0.923737	0.522263	-0.878866	0.616614	0.009609	[illegible]

In [48]:

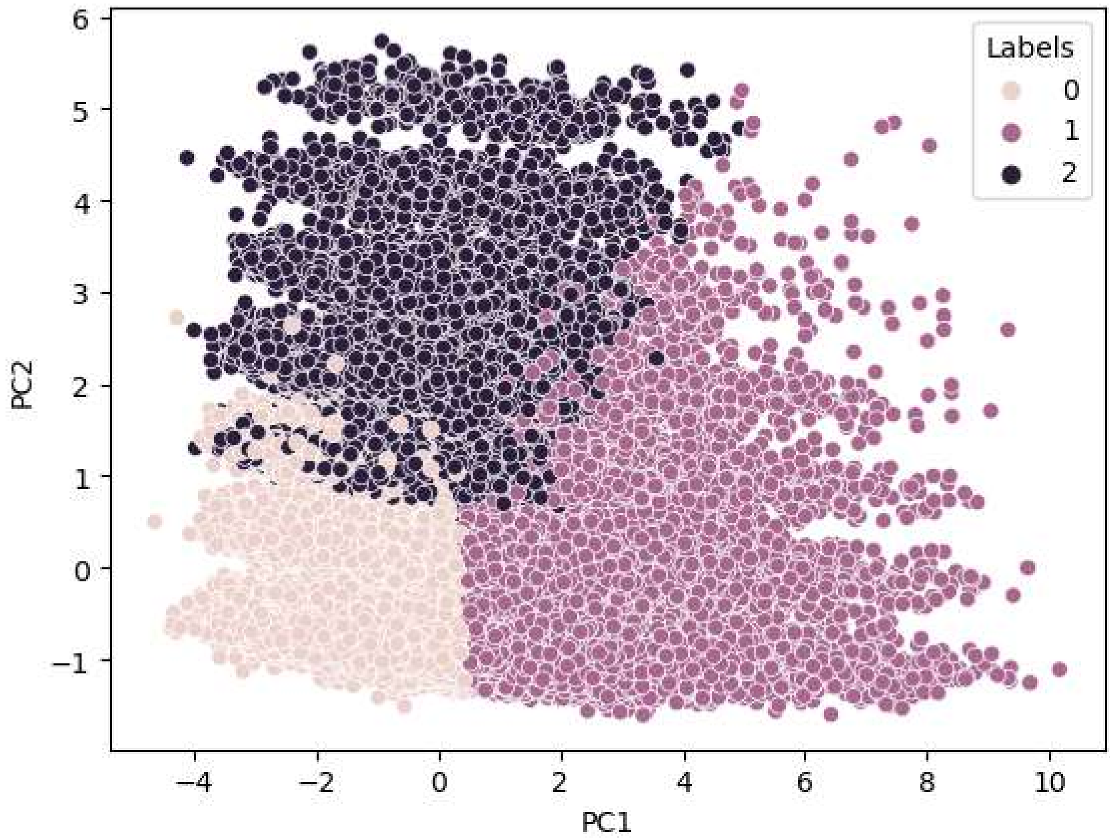
```
kmeans_df['Labels'].value_counts()
```

Out[48]:

```
0    100525
1     58016
2     34003
Name: Labels, dtype: int64
```

In [49]:

```
## Visualizing the clusters formed
sns.scatterplot(kmeans_df['PC1'],kmeans_df['PC2'],hue='Labels',data=kmeans_df)
plt.show()
```



c. Compute silhouette score for evaluating the quality of the K Means clustering technique.

In [50]:

```
kmeans_score = []

for i in range(2,10):
    kmeans = KMeans(n_clusters=i, random_state=100)
    kmeans = kmeans.fit(data_pca)
    labels = kmeans.predict(data_pca)
    print(i,silhouette_score(data_pca, labels))
```

```
2 0.16217386530234373
3 0.16312117846871463
4 0.15884547952574135
5 0.13520690621587397
6 0.13696982511439634
7 0.14246859290666297
8 0.13056828681220456
9 0.11846608904444753
```

- From above, we can observe that for 8 clusters the silhoutte score is highest, we can choose optimal clusters as 3.

16. Apply Agglomerative clustering and segment the data. (You may use original data or PCA transformed data)

a. Find the optimal K Value using dendrogram for Agglomerative clustering.

In [51]:

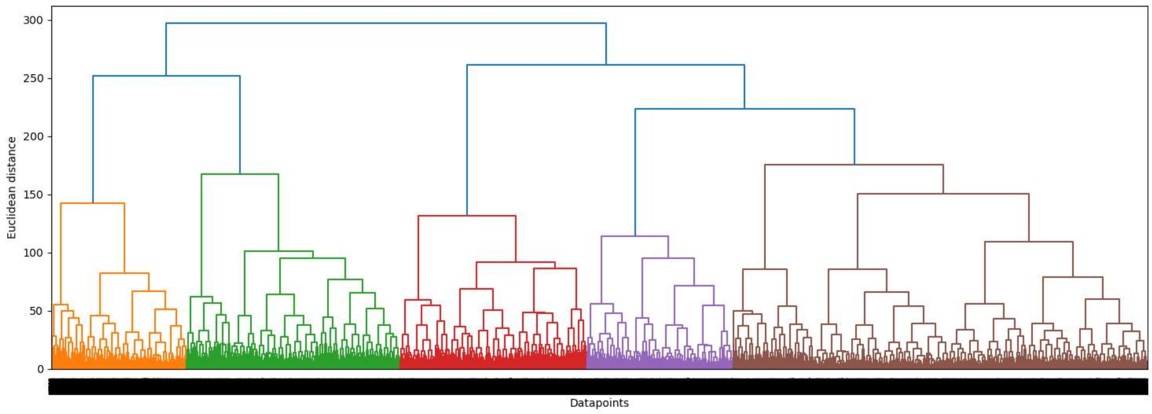
```
##- Sampling a dataset for Agglomerative clustering using PCA transformed data
sample_data_pca_agglo = data_pca.head(50000)
sample_data_pca_agglo.shape
```

Out[51]:

```
(50000, 8)
```

In [52]:

```
plt.figure(figsize=[18,6])
merg = linkage(sample_data_pca_agglo, method='ward')
dendrogram(merg, leaf_rotation=90,)
plt.xlabel('Datapoints')
plt.ylabel('Euclidean distance')
plt.show()
```



In [53]:

```
## Building hierarchical clustering model using the optimal clusters as 3
hie_cluster = AgglomerativeClustering(n_clusters=3, affinity='euclidean',
                                      linkage='ward')
hie_cluster_model = hie_cluster.fit(sample_data_pca_agglo)
```

In [54]:

```
## Creating a dataframe of the labels
df_label1 = pd.DataFrame(hie_cluster_model.labels_,columns=['Labels'])
df_label1.head(5)
```

Out[54]:

	Labels
0	2
1	1
2	1
3	1
4	1

In [55]:

```
## Joining the label dataframe to the data_pca dataframe
df_hier = sample_data_pca_agglo.join(df_label1)
df_hier.head()
```

Out[55]:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	Label:
0	0.222657	-0.871255	0.133583	-1.317746	1.385041	0.498137	0.391549	-0.094749	[illegible]
1	-0.669093	-0.723509	0.446753	0.289349	-0.841026	1.623649	0.570854	-0.121513	[illegible]
2	0.516748	0.397317	6.325453	5.708219	1.007211	-1.845138	5.258172	-1.277636	[illegible]
3	-0.559129	0.180109	0.347079	0.003970	-1.167688	0.306926	0.030717	0.933800	[illegible]
4	0.642889	-1.200274	-1.443786	-0.923737	0.522263	-0.878866	0.616614	0.009609	[illegible]

In [56]:

```
for i in range(2,10):
    hier = AgglomerativeClustering(n_clusters=i,affinity='euclidean',linkage='ward')
    hier = hier.fit(sample_data_pca_agglo)
    labels = hier.fit_predict(sample_data_pca_agglo)
    print(i,silhouette_score(sample_data_pca_agglo,labels))
```

```
2 0.1215820714574751
3 0.11174415735206854
4 0.11678934920868941
5 0.09395592493923934
6 0.08796099922058562
7 0.09778937370977198
8 0.06631611356350972
9 0.0651317860044264
```

- From above, we can observe that for 8 clusters the silhoutte score is highest, we can choose optimal clusters as 2.

Conclusion

17. Perform cluster analysis by doing bivariate analysis between cluster labels and different features and write your conclusion on the results.

- Based on the segmentation of clustering techniques i.e Kmeans and Agglomerative clustering and we also reduced the dimensionality of the dataset using PCA.
- we observed that the highest silhouette score for the optimized cluster is K = 3 using Kmeans clustering technique, so we take the 3 clusters for segmentation of data.

In [57]:

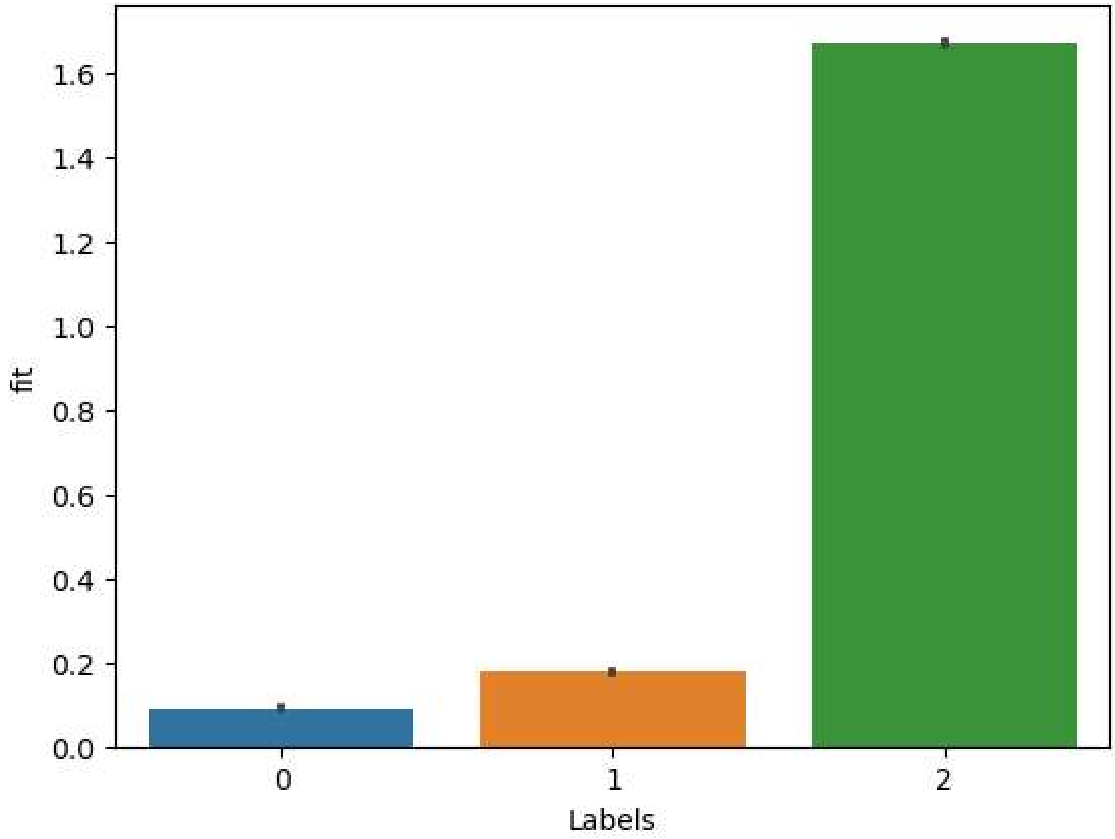
```
## Joining the label dataframe to the data_pca dataframe
kmeans_df1 = df.join(df_labels)
kmeans_df1.head()
```

Out[57]:

	fit	bust size	weight	rating	rented for	body type	category	height	size	age	Labels
0	0	39	137.0	10.0	5	3	44	68.0	14	28.0	0
1	0	37	132.0	10.0	3	6	20	66.0	12	36.0	0
2	0	37	135.0	10.0	4	3	45	64.0	4	116.0	1
3	0	38	135.0	8.0	2	4	16	65.0	8	34.0	0
4	0	37	145.0	10.0	6	1	20	69.0	12	27.0	1

In [58]:

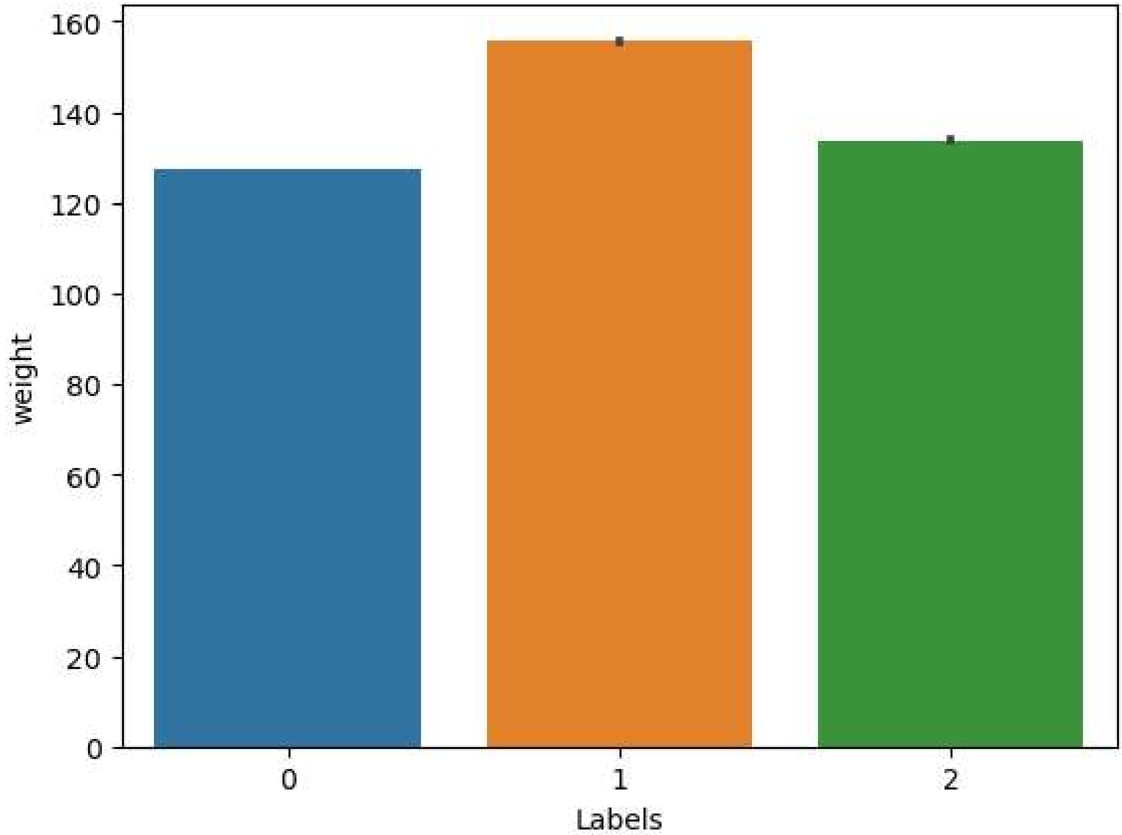
```
## Performing Clustering Analysis

sns.barplot(kmeans_df1['Labels'], kmeans_df1['fit'])
plt.show()
```



- The maximum fitting are used by the Cluster 2 than the cluster 1 & 0

In [59]:

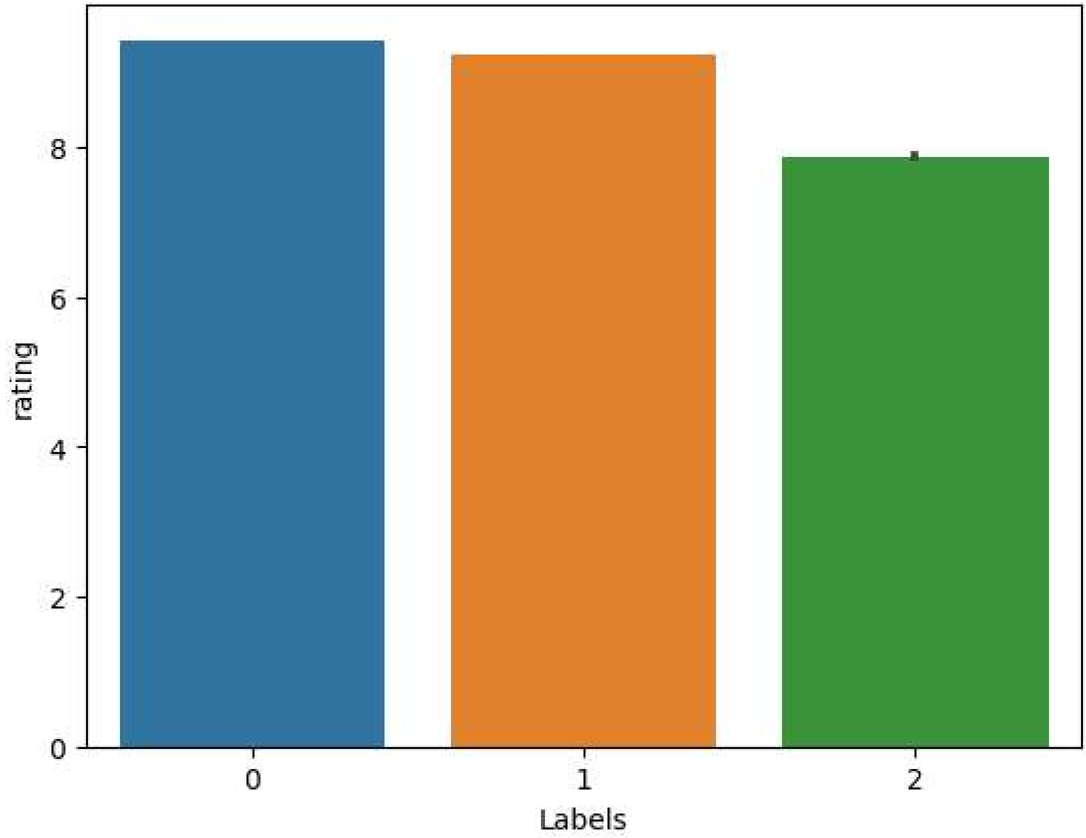
```
sns.barplot(kmeans_df1['Labels'], kmeans_df1['weight'])
plt.show()
```



- the customer weights are higher in cluster 1 than the cluster 0 & 2

In [60]:

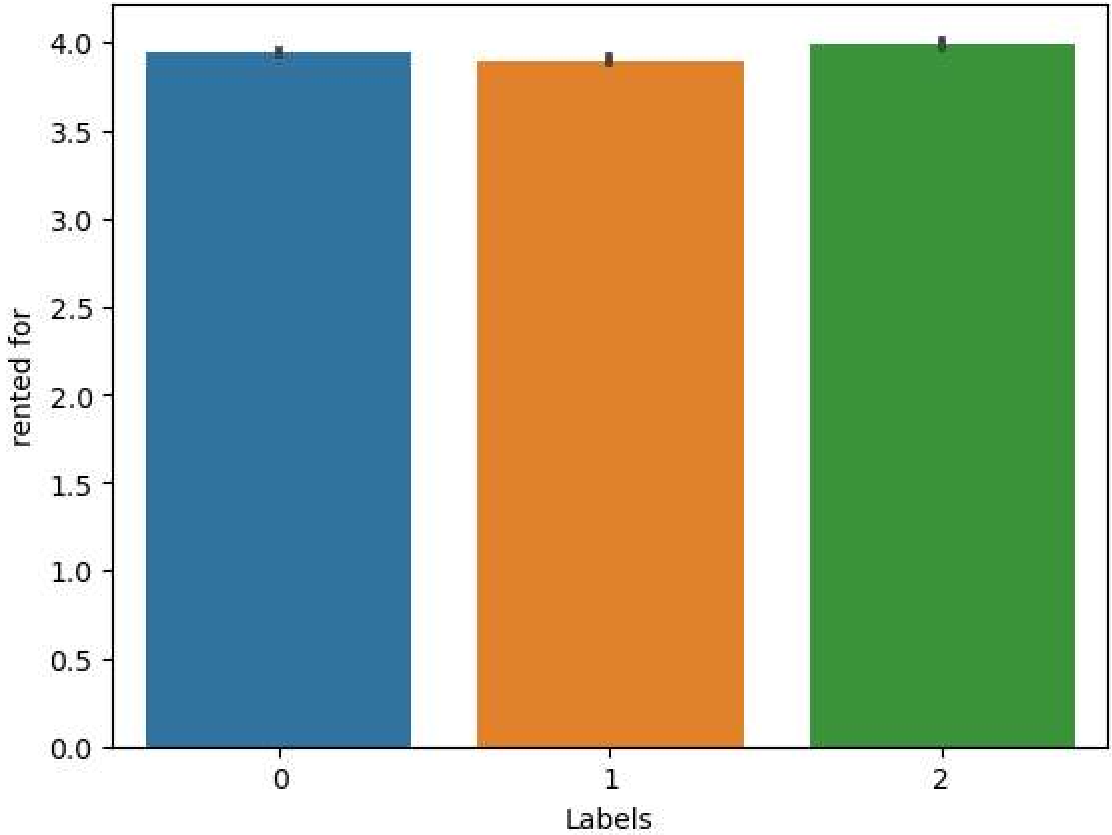
```
sns.barplot(kmeans_df1['Labels'], kmeans_df1['rating'])
plt.show()
```



- The Higher Ratings are given by the customers of cluster 0 than the cluster 1& 2.

In [61]:

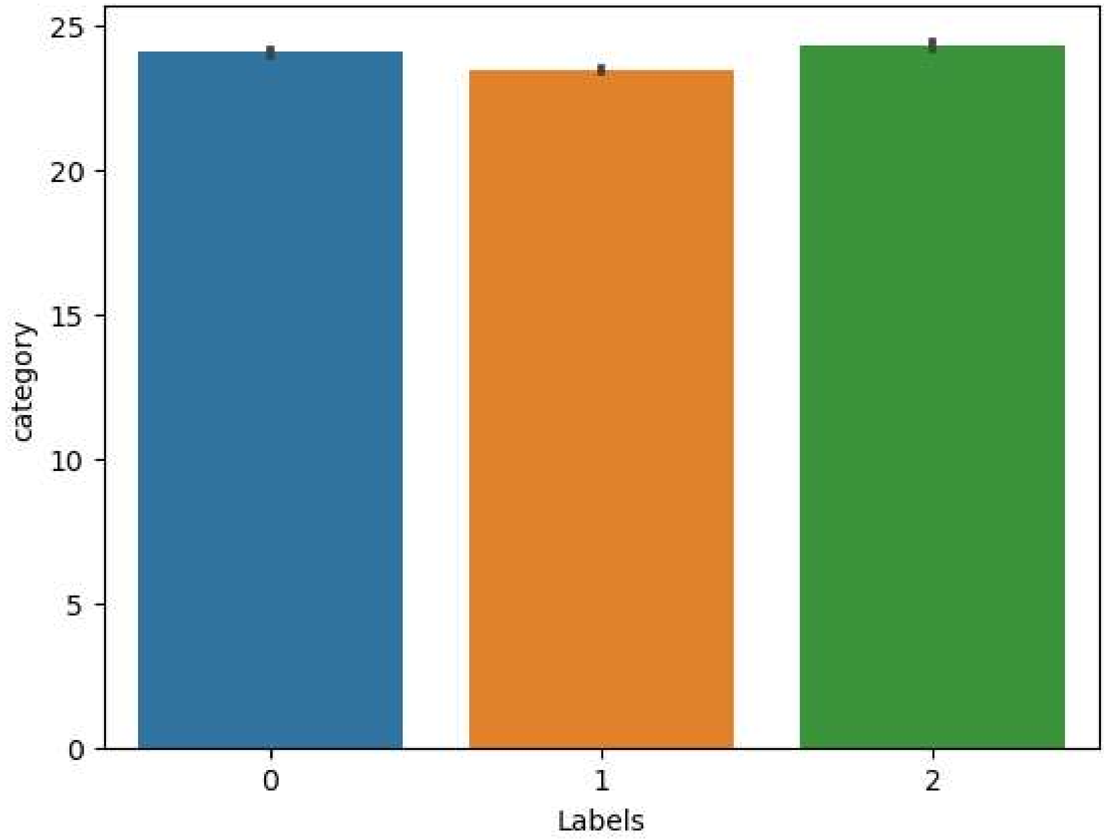
```
sns.barplot(kmeans_df1['Labels'], kmeans_df1['rented for'])
plt.show()
```



- Mostly all cluster customers are rented equally for the occasions

In [62]:

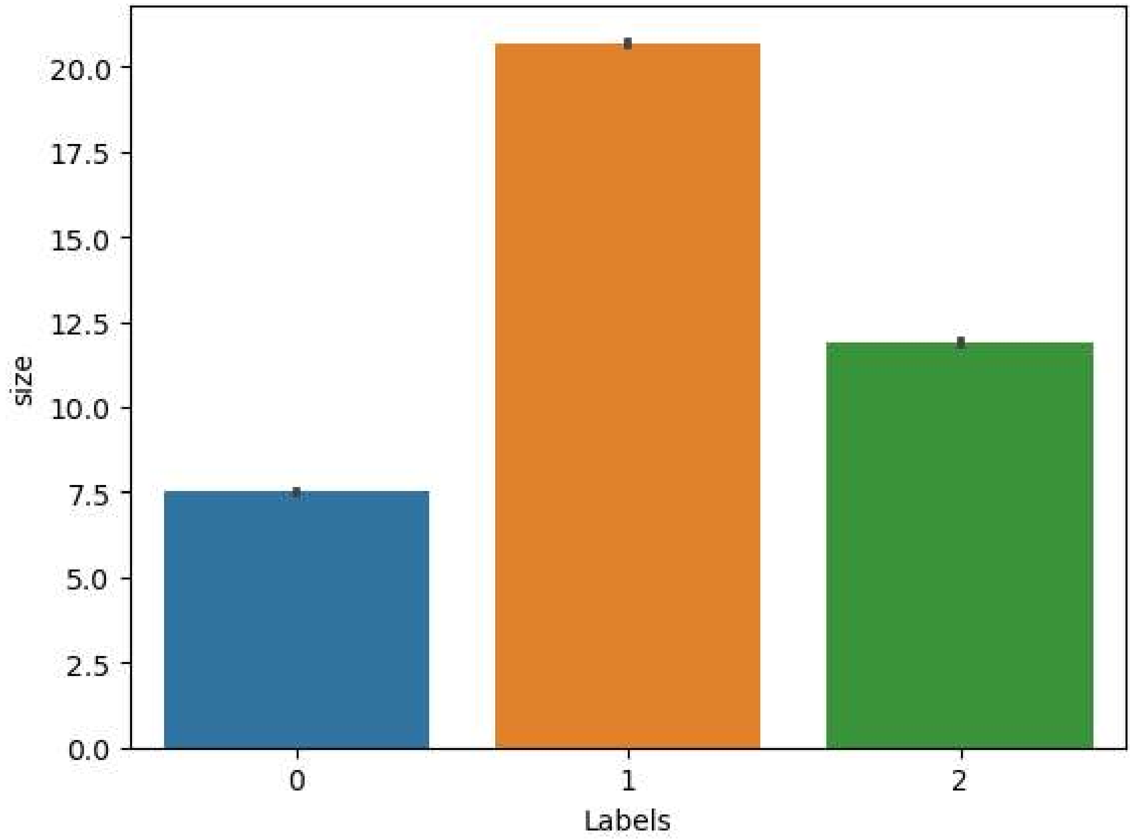
```
sns.barplot(kmeans_df1['Labels'], kmeans_df1['category'])
plt.show()
```



- Almost all type of dresses rented by the all three clusters.

In [63]:

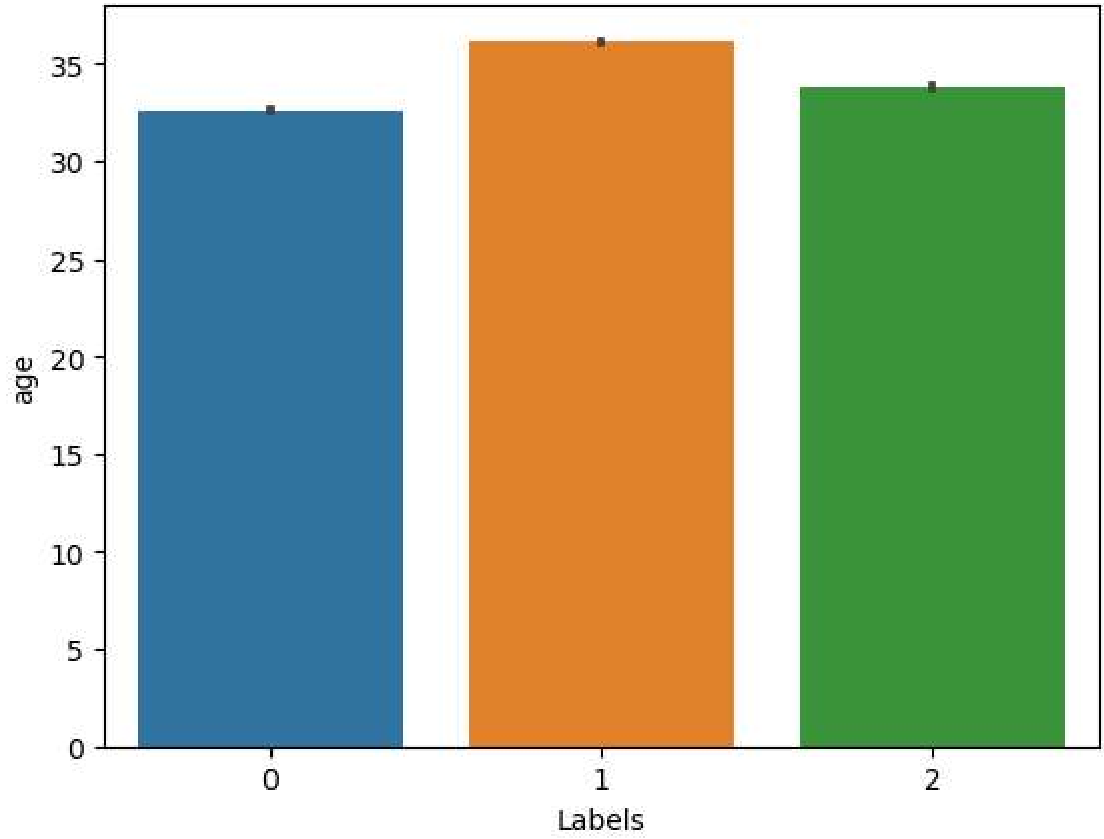
```
sns.barplot(kmeans_df1['Labels'], kmeans_df1['size'])
plt.show()
```



- The cluster 1 has the Higher age group customers followed by cluster 2 and 0

In [64]:

```
sns.barplot(kmeans_df1['Labels'], kmeans_df1['age'])
plt.show()
```



- The cluster 1 has the Higher age group customers followed by cluster 2 and 0

Conclusion

- In this case study, we try to segment the e-commerce dataset using K-means and agglomerating clustering techniques.
- The customers belongs to cluster 1 are the Most important groups, they are higher age group peoples and their weight is high when compare to other clusters, they were choosing the higher size of dressed of particular fit type of differnt categories. They giving the higher rating as feedback.
- The cluster 0 and 1 are the giving Good ratings and the cluster 2 customers took the minimal/ particular type of fit of different categories.
- Customers from cluster 2 are found with maximum fitting than cluster 0 & 1.
- Heighly, Rented-for category and Rating of customers in Cluster 0,1,2 are almost the same/ equal
- Highly weighing customers are found in Cluster 1 whereas Cluster 0 & 2 has low weight customers
- Cluster 1 has most people with higher age category than the cluster 0 & 2
- Cluster 1 has customers who demand for most varied sizes than the cluster 0 & 2.