In [80]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [81]:

```
df=pd.read_csv("mcdonalds.csv")
df.head(10)
```

Out[81]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	healthy	disgusting	Like	Age	VisitFrequency
0	No	Yes	No	Yes	No	Yes	Yes	No	Yes	No	No	-3	61	Every three months
1	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	+2	51	Every three months
2	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	+1	62	Every three months
3	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	+4	69	Once a week
4	No	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes	No	+2	49	Once a month
5	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No	No	No	+2	55	Every three months
6	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No	+2	56	Every three months
7	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	No	I love it!+5	23	Once a week
8	No	No	No	Yes	Yes	No	No	No	Yes	No	Yes	I hate it!-5	58	Once a year
9	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	No	+1	32	Every three months

In [82]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1453 entries, 0 to 1452
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   yummy           1453 non-null   object
 1   convenient      1453 non-null   object
 2   spicy           1453 non-null   object
 3   fattening       1453 non-null   object
 4   greasy          1453 non-null   object
 5   fast            1453 non-null   object
 6   cheap           1453 non-null   object
 7   tasty           1453 non-null   object
 8   expensive       1453 non-null   object
 9   healthy         1453 non-null   object
 10  disgusting      1453 non-null   object
 11  Like            1453 non-null   object
 12  Age             1453 non-null   int64
 13  VisitFrequency  1453 non-null   object
 14  Gender          1453 non-null   object
```

```
dtypes: int64(1), object(14)
memory usage: 170.4+ KB
```

In [83]:

```
df.shape
```

Out[83]:

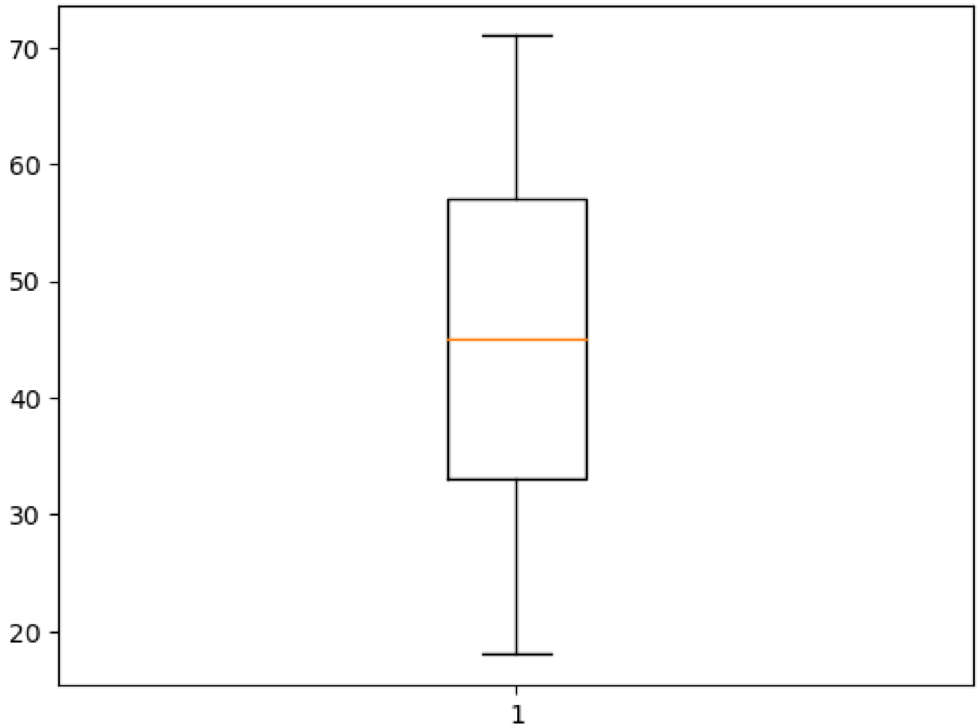
```
(1453, 15)
```

In [84]:

```
#let's check for the outlier's in age column
plt.boxplot(df['Age'])


#hence there is no outliers
```

Out[84]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x218d8b05430>,
  <matplotlib.lines.Line2D at 0x218d8b05700>],
 'caps': [<matplotlib.lines.Line2D at 0x218d8b058b0>,
  <matplotlib.lines.Line2D at 0x218d8b05b80>],
 'boxes': [<matplotlib.lines.Line2D at 0x218d8b05160>],
 'medians': [<matplotlib.lines.Line2D at 0x218d8b05e50>],
 'fliers': [<matplotlib.lines.Line2D at 0x218d8b15160>],
 'means': []}
```



In [85]:

```
df.describe()
```

Out[85]:

	Age
count	1453.000000
mean	44.604955
std	14.221178
min	18.000000
25%	33.000000
50%	45.000000

	Age
75%	57.000000
max	71.000000

In [86]:

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

Out[86]:

```
0
```

In [87]:

```
# Determining unique values of each columns

for col in df.columns:
    print('{} : {}'.format(col,df[col].unique()))
```

```
yummy : ['No' 'Yes']
convenient : ['Yes' 'No']
spicy : ['No' 'Yes']
fattening : ['Yes' 'No']
greasy : ['No' 'Yes']
fast : ['Yes' 'No']
cheap : ['Yes' 'No']
tasty : ['No' 'Yes']
expensive : ['Yes' 'No']
healthy : ['No' 'Yes']
disgusting : ['No' 'Yes']
Like : ['-3' '+2' '+1' '+4' 'I love it!+5' 'I hate it!-5' '-2' '+3' '0' '-4' '-1']
Age : [61 51 62 69 49 55 56 23 58 32 53 28 65 54 67 34 31 47 37 41 36 50 39 35
 20 24 44 40 48 38 57 60 66 42 26 52 29 25 22 45 18 68 43 21 27 33 63 46
 59 19 64 70 30 71]
VisitFrequency : ['Every three months' 'Once a week' 'Once a month' 'Once a year'
 'More than once a week' 'Never']
Gender : ['Female' 'Male']
```

In [88]:

```
# By Observation from above data following rows have contradictary information. The value is given as 'Yes' for both 'yummy' and 'disgusting'.
# not yummy doesnt give you the meaning that the food is disgusting, so we exclude the No-No combination from contradictions.


contradict_1=df[(df['yummy']=='Yes') & (df['disgusting']=='Yes')]
contradict_1
```

Out[88]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	healthy	disgusting	Like	Age	VisitFrequer
3	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	+4	69	Once a we
11	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	+3	28	Once a mo
19	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	I love it!+5	37	More th once a we
20	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	+2	41	Once a y
22	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	-2	23	Once a we
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1311	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	+4	20	Once a we
1344	Yes	Yes	No	Yes	No	Yes	Yes	No	Yes	No	Yes	-3	55	Once a y
1381	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	No	Yes	+3	26	Once a we
1434	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	+4	41	Once a we
1439	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	+1	61	Once a mo

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	healthy	disgusting	Like	Age	VisitFrequer

65 rows × 15 columns

In [89]:

```
# same way,The value is 'Yes' for both 'tasty' and 'disgusting'
# Not tasty need not mean that the food is disgusting, so we exclude the No-No combinatio
n from contradictions.


contradict_2=df[(df['tasty']=='Yes') & (df['disgusting']=='Yes')]
contradict_2
```

Out[89]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	healthy	disgusting	Like	Age	VisitFrequer
3	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	+4	69	Once a we
11	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	+3	28	Once a mo
19	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	I love it!+5	37	More th once a we
20	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	+2	41	Once a y
22	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	-2	23	Once a we
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1364	No	Yes	No	Yes	No	Yes	Yes	Yes	No	No	Yes	+1	46	Every th mon
1415	No	Yes	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	-3	57	Every th mon
1434	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	+4	41	Once a we
1439	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes	+1	61	Once a mo
1445	No	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	+1	18	Once a mo

97 rows × 15 columns

In [90]:

```
# Removing rows which contains the above mentioned contradictory information

union_df=pd.concat([contradict_1,contradict_2],ignore_index=False)
union_df=union_df.drop_duplicates()
indices_to_drop = union_df.index.tolist()
data=df.drop(indices_to_drop)
```

In [91]:

```
data.shape

#cleaned data
```

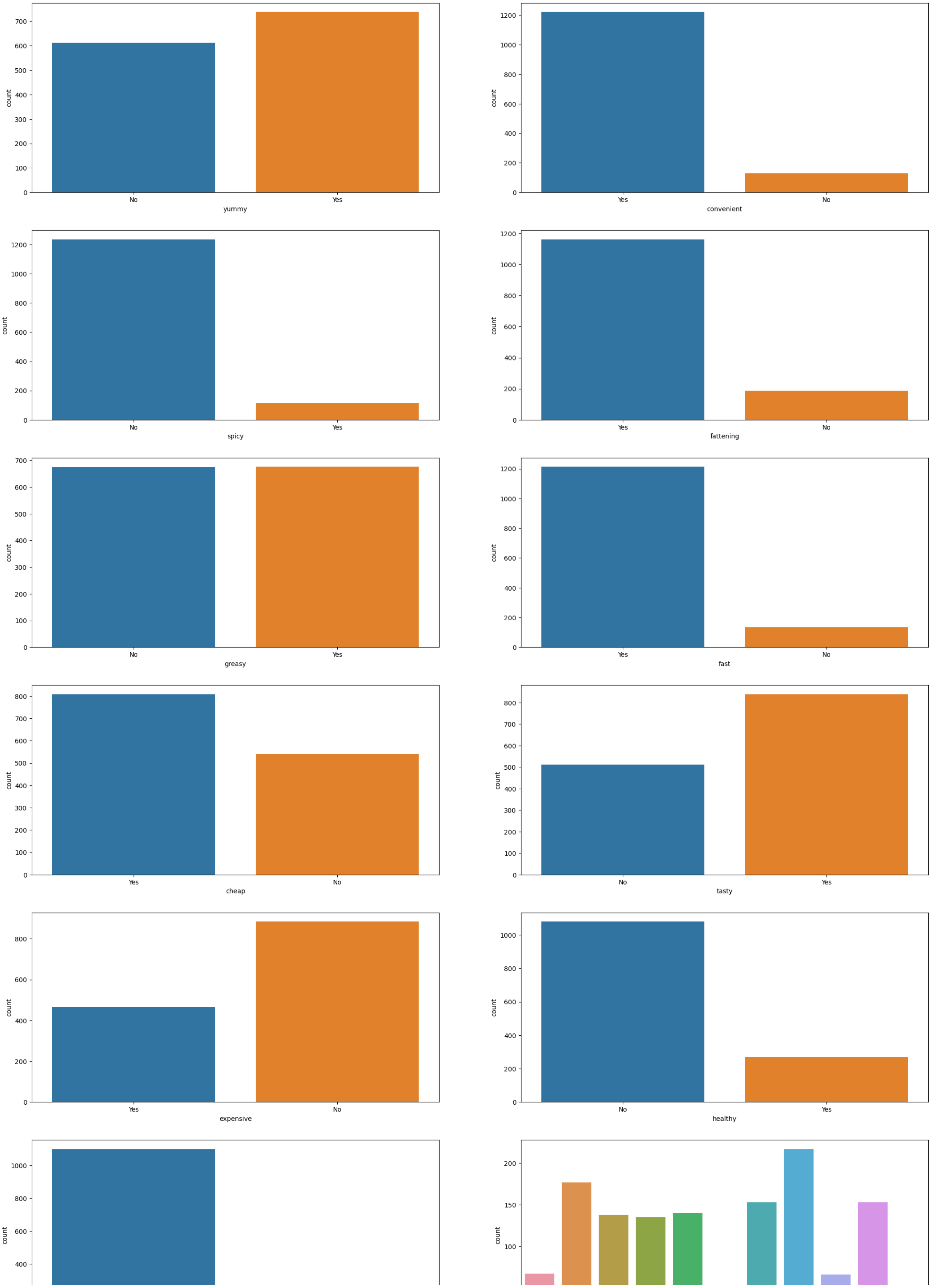
Out[91]:

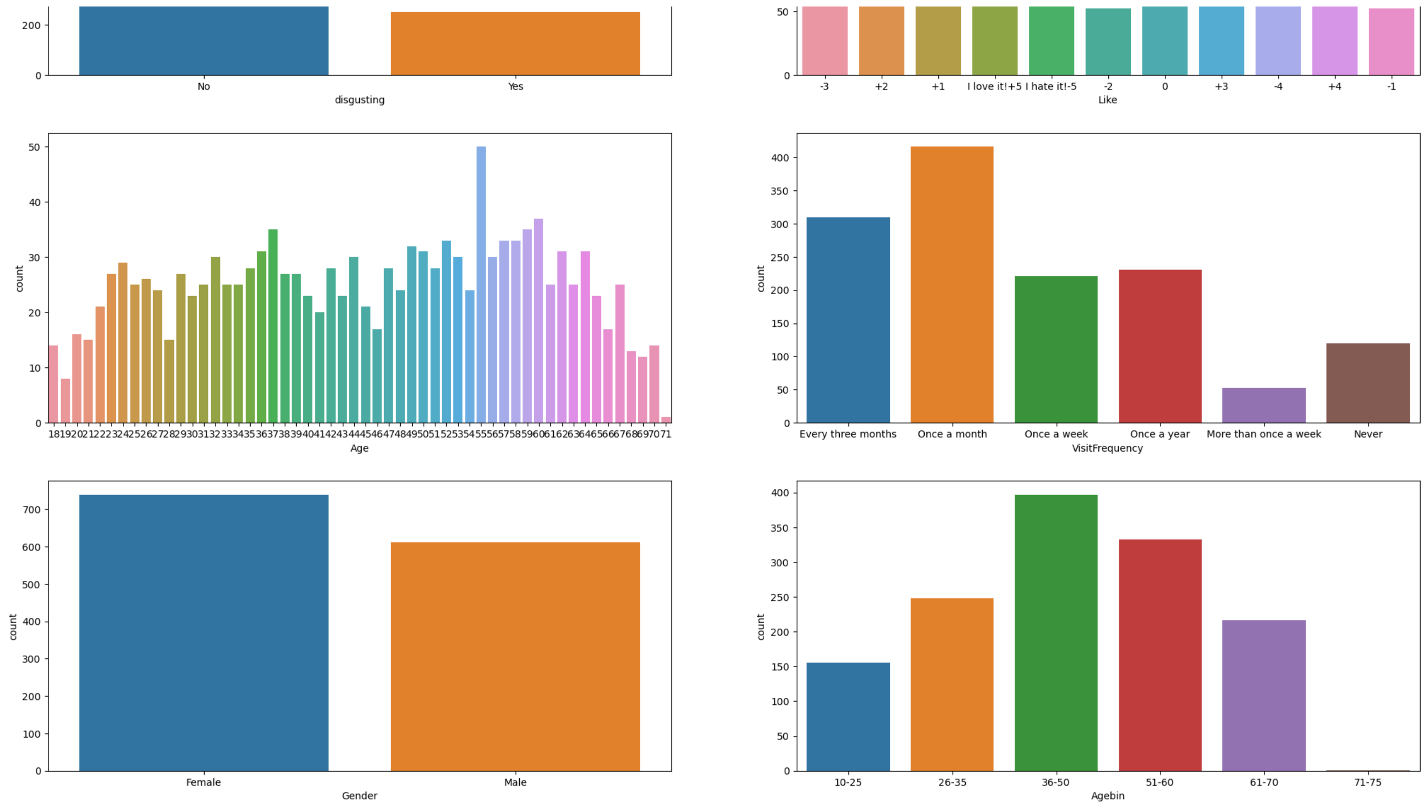
```
(1350, 15)
```

In [92]:

```
# Let's Create copy of the dataframe and creating bins for the 'Age' column

datacopy=data.copy()
datacopy['Agebin'] = pd.cut(datacopy['Age'], bins = [15,25, 35, 50, 60, 70, 75], labels
= ['10-25','26-35', '36-50', '51-60', '61-70','71-75'])
```

```
# Let's find the distribution of values in each and every columns to anlalyze the data

fig, axs = plt.subplots(8, 2, figsize=(25, 50))
axs = axs.flatten()
for x, col in enumerate(datacopy.columns):
    sns.countplot(x=col,data=datacopy,ax=axs[x])
```





In [94]:

```
#to get the propotionate values in the data

for i in data.columns:
    print(data[i].value_counts()/len(data)*100 )
```

```
Yes     54.666667
No      45.333333
Name: yummy, dtype: float64
Yes     90.518519
No       9.481481
Name: convenient, dtype: float64
No      91.555556
Yes      8.444444
Name: spicy, dtype: float64
Yes     86.074074
No      13.925926
Name: fattening, dtype: float64
Yes     50.074074
No      49.925926
Name: greasy, dtype: float64
Yes     89.925926
No      10.074074
Name: fast, dtype: float64
Yes     59.925926
No      40.074074
Name: cheap, dtype: float64
Yes     62.148148
No      37.851852
Name: tasty, dtype: float64
No      65.481481
Yes     34.518519
Name: expensive, dtype: float64
No      80.0
Yes     20.0
Name: healthy, dtype: float64
No      81.481481
Yes     18.518519
Name: disgusting, dtype: float64
+3              16.074074
+2              13.111111
0               11.333333
+4              11.333333
I hate it!-5    10.370370
```

```
+1               10.222222
I love it!+5     10.000000
-3                4.962963
-4                4.888889
-2                3.851852
-1                3.851852
Name: Like, dtype: float64
55    3.703704
60    2.740741
37    2.592593
59    2.592593
52    2.444444
58    2.444444
57    2.444444
49    2.370370
64    2.296296
36    2.296296
50    2.296296
62    2.296296
32    2.222222
53    2.222222
56    2.222222
44    2.222222
24    2.148148
51    2.074074
42    2.074074
47    2.074074
35    2.074074
29    2.000000
38    2.000000
39    2.000000
23    2.000000
26    1.925926
33    1.851852
63    1.851852
25    1.851852
61    1.851852
31    1.851852
34    1.851852
67    1.851852
54    1.777778
48    1.777778
27    1.777778
40    1.703704
65    1.703704
30    1.703704
43    1.703704
45    1.555556
22    1.555556
41    1.481481
66    1.259259
46    1.259259
20    1.185185
21    1.111111
28    1.111111
18    1.037037
70    1.037037
68    0.962963
69    0.888889
19    0.592593
71    0.074074
Name: Age, dtype: float64
Once a month              30.814815
Every three months        22.962963
Once a year               17.111111
Once a week               16.370370
Never                      8.888889
More than once a week      3.851852
Name: VisitFrequency, dtype: float64
Female    54.740741
Male      45.259259
Name: Gender, dtype: float64
```

By above observations we can conclude that: -more females visit Mcdonald's than males -more then 50% peoplpe visit in a month -34% of people conclude that it is expensive -80% of people believe that food is unhealthy -91% of them feel that the food is spicy

In [95]:

```
# Converting string values of the 'Like' column to numerical form

data=data.replace('-1',-1)
data=data.replace('-2',-2)
data=data.replace('-3',-3)
data=data.replace('-4',-4)
data=data.replace('+1',1)
data=data.replace('+2',2)
data=data.replace('+3',3)
data=data.replace('+4',4)
data=data.replace('0',0)
data=data.replace('I love it!+5',5)
data=data.replace('I hate it!-5',-5)
```

In [96]:

```
# The following pairs of variables essentially express the same idea in the data:
# (like, tasty),(like, disgusting) and (expensive, cheap)
# the columns 'expensive', 'disgusting' and 'like' can be dropped.

data.drop(['expensive', 'disgusting', 'Like'], inplace=True, axis=1)
```

In [97]:

```
data.head()
```

Out[97]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	healthy	Age	VisitFrequency	Gender
0	No	Yes	No	Yes	No	Yes	Yes	No	No	61	Every three months	Female
1	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	51	Every three months	Female
2	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	62	Every three months	Female
4	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	49	Once a month	Male
5	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No	55	Every three months	Male

In [98]:

```
# According to the data ,list of categorical value columns

objectList = data.select_dtypes(include = "object").columns
print (objectList)
```

```
Index(['yummy', 'convenient', 'spicy', 'fattening', 'greasy', 'fast', 'cheap',
       'tasty', 'healthy', 'VisitFrequency', 'Gender'],
      dtype='object')
```

In [99]:

```
# Converting categorical Columns to numeric
from sklearn import preprocessing
le=preprocessing.LabelEncoder()


#Converting all the categorical value columns to numeric columns

for i in objectList:
    data[i] = le.fit_transform(data[i])
```

```
print (data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1350 entries, 0 to 1452
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   yummy           1350 non-null   int32
 1   convenient      1350 non-null   int32
 2   spicy           1350 non-null   int32
 3   fattening       1350 non-null   int32
 4   greasy          1350 non-null   int32
 5   fast            1350 non-null   int32
 6   cheap           1350 non-null   int32
 7   tasty           1350 non-null   int32
 8   healthy         1350 non-null   int32
 9   Age             1350 non-null   int64
 10  VisitFrequency  1350 non-null   int32
 11  Gender          1350 non-null   int32
dtypes: int32(11), int64(1)
memory usage: 79.1 KB
None
```

In [131]:

```
data.head(3)
```

Out[131]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	healthy	Age	VisitFrequency	Gender
0	0	1	0	1	0	1	1	0	0	61	0	0
1	1	1	0	1	1	1	1	1	0	51	0	0
2	0	1	1	1	1	1	0	1	1	62	0	0

In [132]:

```
#We need to scale the data and perform futher process on scaled version of data
#let's apply scaling on both 'Age' and 'VisitFrequency' column


from sklearn.preprocessing import MinMaxScaler
scaled_df=data.copy()
scaled_df.iloc[:,9:11]=MinMaxScaler().fit_transform(scaled_df.iloc[:,9:11])
```

In [133]:

```
scaled_df.head(5)
```

Out[133]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	healthy	Age	VisitFrequency	Gender
0	0	1	0	1	0	1	1	0	0	0.811321	0.0	0
1	1	1	0	1	1	1	1	1	0	0.622642	0.0	0
2	0	1	1	1	1	1	0	1	1	0.830189	0.0	0
4	0	1	0	1	1	1	1	0	1	0.584906	0.6	1
5	1	1	0	1	0	1	1	1	0	0.698113	0.0	1

In [134]:

```
#Principal Component Analysis

from sklearn.decomposition import PCA
```

In [135]:

```
pca_compo=PCA(n_components=11).fit(scaled_df)
```

In [136]:

```
pca_compo.components_
```

Out[136]:

```
array([[-5.98874087e-01, -1.56606908e-01, -8.75384990e-03,
         1.27994355e-01,  3.25215203e-01, -1.00341670e-01,
        -2.32080520e-01, -5.88392285e-01, -2.56866452e-01,
         5.83130205e-02,  1.34932754e-02,  1.22073095e-01],
       [ 2.58461400e-02, -4.65885427e-02,  3.09830190e-02,
        -2.34791358e-01, -4.10241591e-01, -1.21039698e-01,
        -4.76134728e-01,  2.80217893e-02,  9.82760911e-02,
         6.88944264e-02, -4.21045777e-02,  7.17257873e-01],
       [-3.67861755e-01, -2.17915145e-02,  2.92724626e-03,
        -2.59576176e-01, -6.42188526e-01,  4.73388823e-02,
         3.83392195e-01, -3.01386874e-01,  2.04724814e-01,
         2.35519040e-01,  5.65655475e-03, -2.16634114e-01],
       [ 5.55088364e-02, -7.18895121e-02, -3.08206660e-02,
        -4.56445710e-02, -2.09846921e-01, -1.58982479e-01,
        -7.07585656e-01,  1.46386096e-03,  2.36905727e-02,
         3.04980362e-02, -3.37033087e-02, -6.45057577e-01],
       [-2.45950570e-02, -1.14502798e-01,  1.35581019e-01,
        -3.88387395e-01,  4.45302606e-01, -1.41515243e-01,
        -2.31881779e-02, -9.25717892e-02,  7.67426397e-01,
        -6.96227214e-03, -2.39885262e-03, -2.51297819e-02],
       [-1.66488184e-02,  8.03545409e-02,  9.36396941e-02,
         1.35102804e-02,  4.51158637e-02,  5.97270007e-02,
         1.88209987e-02, -3.60038595e-03, -1.58001340e-02,
         9.87544765e-02, -9.83989587e-01, -1.03680926e-02],
       [ 2.00584463e-01, -5.40623548e-01, -2.85552756e-01,
        -2.86935729e-01,  6.06102050e-04, -5.85140517e-01,
         2.41879656e-01, -1.26260777e-02, -2.73532368e-01,
        -1.17311474e-01, -1.16650090e-01, -1.93753445e-02],
       [-1.28547804e-01, -8.46162546e-02,  6.70795835e-01,
        -3.59366486e-01,  1.27450082e-01, -4.02954228e-02,
         1.94882350e-02,  3.17277761e-01, -3.57996053e-01,
         3.69214787e-01,  1.00225533e-01, -6.13687648e-02],
       [-3.16067486e-02, -1.32550177e-01,  3.39217625e-01,
         6.79720778e-01, -1.40699882e-01, -5.14096122e-01,
         9.16908230e-02,  9.27552380e-02,  2.66919353e-01,
         1.74713964e-01,  7.93582682e-03,  3.75049644e-02],
       [ 2.27311429e-01, -7.48826785e-01,  1.46374219e-01,
         1.71870304e-01, -5.26420371e-02,  5.52182369e-01,
        -4.06705034e-02, -1.25788382e-01,  7.38172147e-02,
         7.49921623e-02, -1.17504824e-02,  1.60906247e-02],
       [ 5.70824647e-01,  2.49897951e-01,  3.89778628e-01,
        -6.10310232e-02, -4.70776282e-02, -1.03758282e-01,
         4.11182865e-02, -6.49449960e-01, -1.13896399e-01,
        -7.23720263e-02,  3.63621340e-02, -8.22919040e-03]])
```

In [137]:

```
#we use explained variance ratio is used as metric to evalute the usefulness of PCA

pca_compo.explained_variance_ratio_
```

Out[137]:

```
array([0.25677724, 0.13775668, 0.13409026, 0.11029037, 0.07749798,
       0.06270064, 0.04770758, 0.04357158, 0.0391985 , 0.03257548,
       0.03205534])
```

Let's reassign the columns name to the dataframe

In [138]:

```
pca_df = pd.DataFrame(data=pca_compo.components_ , columns=["PCA1","PCA2","PCA3","PCA4",
"PCA5","PCA6","PCA7","PCA8","PCA9","PCA10","PCA11","PCA12"])
pca_df.head(10)
```

Out[138]:

	PCA1	PCA2	PCA3	PCA4	PCA5	PCA6	PCA7	PCA8	PCA9	PCA10	PCA11	PCA12
0	-0.598874	-0.156607	-0.008754	0.127994	0.325215	-0.100342	-0.232081	-0.588392	-0.256866	0.058313	0.013493	0.122073
1	0.025846	-0.046589	0.030983	-0.234791	-0.410242	-0.121040	-0.476135	0.028022	0.098276	0.068894	-0.042105	0.717258
2	-0.367862	-0.021792	0.002927	-0.259576	-0.642189	0.047339	0.383392	-0.301387	0.204725	0.235519	0.005657	-0.216634
3	0.055509	-0.071890	-0.030821	-0.045645	-0.209847	-0.158982	-0.707586	0.001464	0.023691	0.030498	-0.033703	-0.645058
4	-0.024595	-0.114503	0.135581	-0.388387	0.445303	-0.141515	-0.023188	-0.092572	0.767426	-0.006962	-0.002399	-0.025130
5	-0.016649	0.080355	0.093640	0.013510	0.045116	0.059727	0.018821	-0.003600	-0.015800	0.098754	-0.983990	-0.010368
6	0.200584	-0.540624	-0.285553	-0.286936	0.000606	-0.585141	0.241880	-0.012626	-0.273532	-0.117311	-0.116650	-0.019375
7	-0.128548	-0.084616	0.670796	-0.359366	0.127450	-0.040295	0.019488	0.317278	-0.357996	0.369215	0.100226	-0.061369
8	-0.031607	-0.132550	0.339218	0.679721	-0.140700	-0.514096	0.091691	0.092755	0.266919	0.174714	0.007936	0.037505
9	0.227311	-0.748827	0.146374	0.171870	-0.052642	0.552182	-0.040671	-0.125788	0.073817	0.074992	-0.011750	0.016091

In [139]:

```
cumulative_variance = np.cumsum(pca_compo.explained_variance_ratio_)

cumulative_variance
```

Out[139]:

```
array([0.25677724, 0.39453392, 0.52862418, 0.63891456, 0.71641254,
       0.77911318, 0.82682076, 0.87039234, 0.90959083, 0.94216631,
       0.97422165])
```

In [140]:

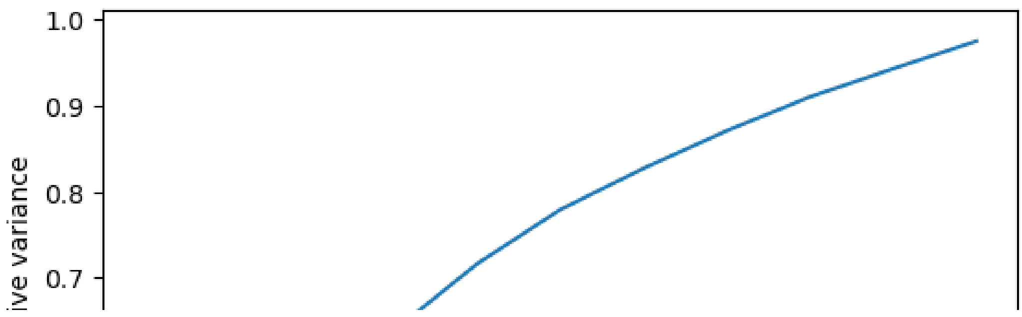
```
# By Observing the cumulative variance, 90% of the variance is explained by the first 9 p
rincipal components.

final_pca_comp=PCA(n_components=9).fit_transform(scaled_df)
```

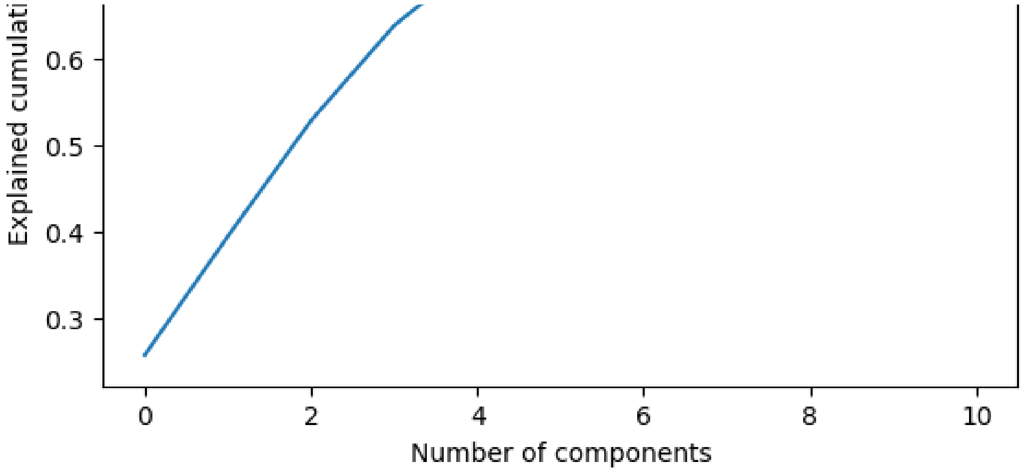
In [141]:

```
data_pca=pd.DataFrame(final_pca_comp, columns=["PCA1","PCA2","PCA3","PCA4","PCA5","PCA6"
,"PCA7","PCA8","PCA9"])
```

In [142]:

```
plt.plot(cumulative_variance)
plt.xlabel('Number of components')
plt.ylabel('Explained cumulative variance')
plt.show()
```





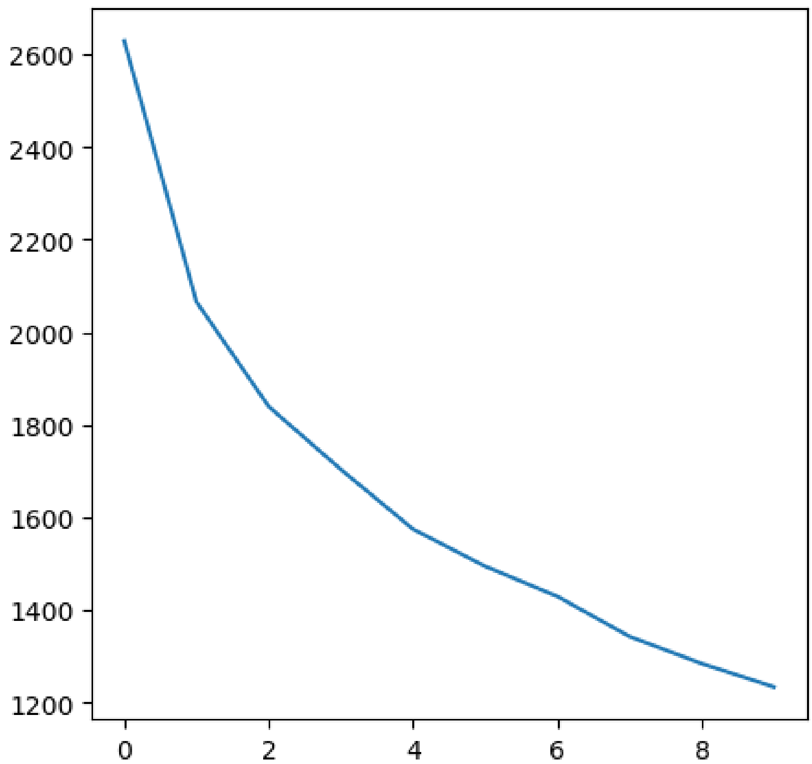
In [143]:

```
#since clustering can be done on large data set
# Determining the number of clusters

from sklearn.cluster import KMeans

count=list(range(1,11))
distance=list([0]*10)
for x in count:
    clustr_res=KMeans(n_clusters=x).fit(scaled_df)
    distance[x-1]=clustr_res.inertia_
plt.figure(figsize=(5,5))
plt.plot(distance)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036: UserWarning:
KMeans is known to have a memory leak on Windows with MKL, when there are less chunks tha
n available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS
=6.
  warnings.warn(
```

Out[143]:

```
[<matplotlib.lines.Line2D at 0x218da032670>]
```



When k-means comes into picture plotting elbow plot is very important to identify the number of clusters/k value to be taken according to the obsevation,we can say that elbow is at k=4,so we divide the data into 4 clusters.

In [145]:

```
# Extracting segments from the scaled data
#performing inertia will measure how well the dataset is clustered by K-Means


final_cluster=KMeans(n_clusters=4).fit(scaled_df)

final_cluster.inertia_
```

Out[145]:

```
1693.937582469573
```

In [146]:

```
scaled_df['cluster'] = final_cluster.labels_
```

In [147]:

```
# cluster size

from collections import Counter
Counter(final_cluster.labels_)
```

Out[147]:

```
Counter({3: 283, 2: 299, 0: 295, 1: 473})
```

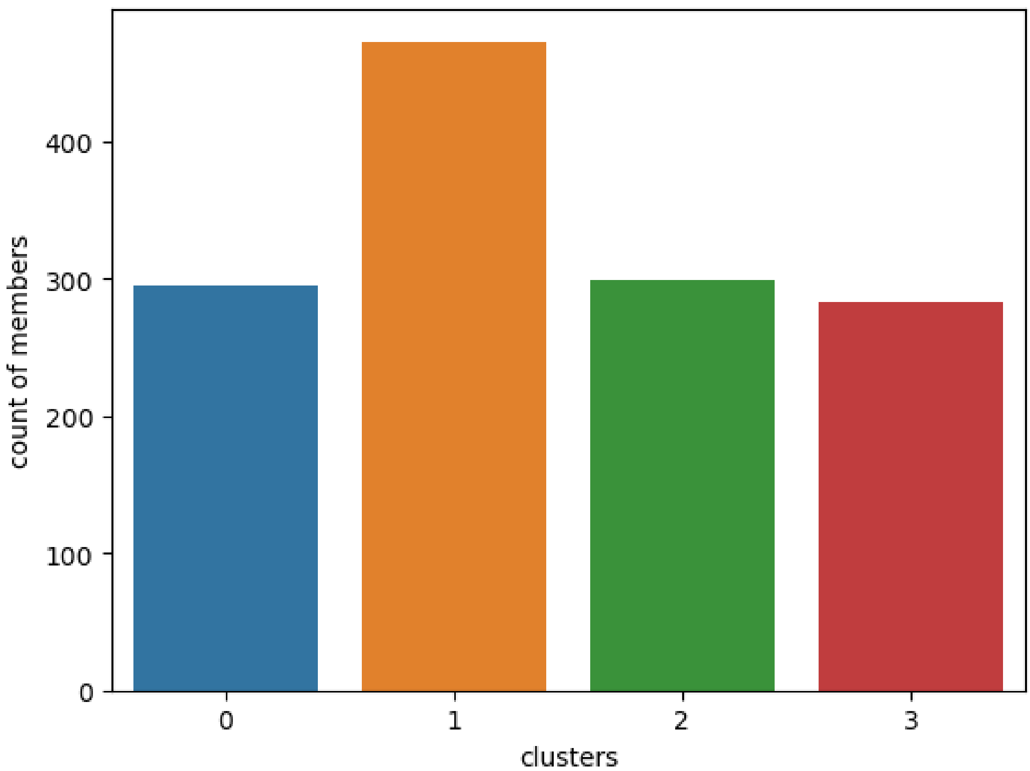
By above observation we can say that : cluster 0 has 295 peoples cluster 1 has 473 peoples cluster 2 has 299 peoples cluster 3 has 283 peoples

In [148]:

```
sns.countplot(x=scaled_df['cluster'])
plt.xlabel("clusters")
plt.ylabel("count of members")
```

Out[148]:

```
Text(0, 0.5, 'count of members')
```



In [149]:

```
#finding the range of the 'age' column
age_range=data['Age'].max()-data['Age'].min()
age_range
```

```
# Finding the minimum value in the 'Age'column
x=data['Age'].min()
x
```

Out[149]:

```
18
```

In [150]:

```
scaled_df
```

Out[150]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	healthy	Age	VisitFrequency	Gender	cluster
0	0	1	0	1	0	1	1	0	0	0.811321	0.0	0	3
1	1	1	0	1	1	1	1	1	0	0.622642	0.0	0	2
2	0	1	1	1	1	1	0	1	1	0.830189	0.0	0	0
4	0	1	0	1	1	1	1	0	1	0.584906	0.6	1	3
5	1	1	0	1	0	1	1	1	0	0.698113	0.0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1448	0	1	0	1	1	0	0	0	0	0.547170	1.0	1	0
1449	1	1	0	1	0	0	1	1	1	0.339623	0.8	0	1
1450	1	1	0	1	0	1	0	1	0	0.641509	0.6	0	1
1451	1	1	0	0	0	1	1	1	1	0.433962	0.0	1	1
1452	0	1	0	1	1	0	0	0	0	0.226415	0.0	1	0

1350 rows × 13 columns

In [151]:

```
#Restoring the original values to columns for us to analyse the data while doing clusteri
ng

scaled_df['yummy']=scaled_df['yummy'].map({0:'No',1:'Yes'})
scaled_df['convenient']=scaled_df['convenient'].map({0:'No',1:'Yes'})
scaled_df['spicy']=scaled_df['spicy'].map({0:'No',1:'Yes'})
scaled_df['fattening']=scaled_df['fattening'].map({0:'No',1:'Yes'})
scaled_df['greasy']=scaled_df['greasy'].map({0:'No',1:'Yes'})
scaled_df['fast']=scaled_df['fast'].map({0:'No',1:'Yes'})
scaled_df['cheap']=scaled_df['cheap'].map({0:'No',1:'Yes'})
scaled_df['tasty']=scaled_df['tasty'].map({0:'No',1:'Yes'})
scaled_df['healthy']=scaled_df['healthy'].map({0:'No',1:'Yes'})
scaled_df['Age']=scaled_df['Age']*age_range+x
scaled_df['VisitFrequency']=scaled_df['VisitFrequency'].map({0.0:'Every three months', 0.
8:'once a week', 0.6:'once a month', 1.0:'once a year', 0.4:'Never',0.2:'More than once
a week'})
scaled_df['Gender']=scaled_df['Gender'].map({0:'Female',1:'Male'})
```

In [152]:

```
scaled_df
```

Out[152]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	healthy	Age	VisitFrequency	Gender	cluster
0	No	Yes	No	Yes	No	Yes	Yes	No	No	61.0	Every three months	Female	3
1	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	51.0	Every three months	Female	2
2	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	62.0	Every three months	Female	0

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	healthy	Age	VisitFrequency	Gender	cluster
4	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	49.0	NaN	Male	3
5	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No	55.0	Every three months	Male	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1448	No	Yes	No	Yes	Yes	No	No	No	No	47.0	once a year	Male	0
1449	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	36.0	once a week	Female	1
1450	Yes	Yes	No	Yes	No	Yes	No	Yes	No	52.0	NaN	Female	1
1451	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	41.0	Every three months	Male	1
1452	No	Yes	No	Yes	Yes	No	No	No	No	30.0	Every three months	Male	0

1350 rows × 13 columns

In [154]:

```
scaled_df.fillna(value={'VisitFrequency':'once a month'}, inplace=True)
```

In [156]:

```
scaled_df
```

Out[156]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	healthy	Age	VisitFrequency	Gender	cluster
0	No	Yes	No	Yes	No	Yes	Yes	No	No	61.0	Every three months	Female	3
1	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	51.0	Every three months	Female	2
2	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	62.0	Every three months	Female	0
4	No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	49.0	once a month	Male	3
5	Yes	Yes	No	Yes	No	Yes	Yes	Yes	No	55.0	Every three months	Male	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1448	No	Yes	No	Yes	Yes	No	No	No	No	47.0	once a year	Male	0
1449	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	36.0	once a week	Female	1
1450	Yes	Yes	No	Yes	No	Yes	No	Yes	No	52.0	once a month	Female	1
1451	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	41.0	Every three months	Male	1
1452	No	Yes	No	Yes	Yes	No	No	No	No	30.0	Every three months	Male	0

1350 rows × 13 columns

In [158]:

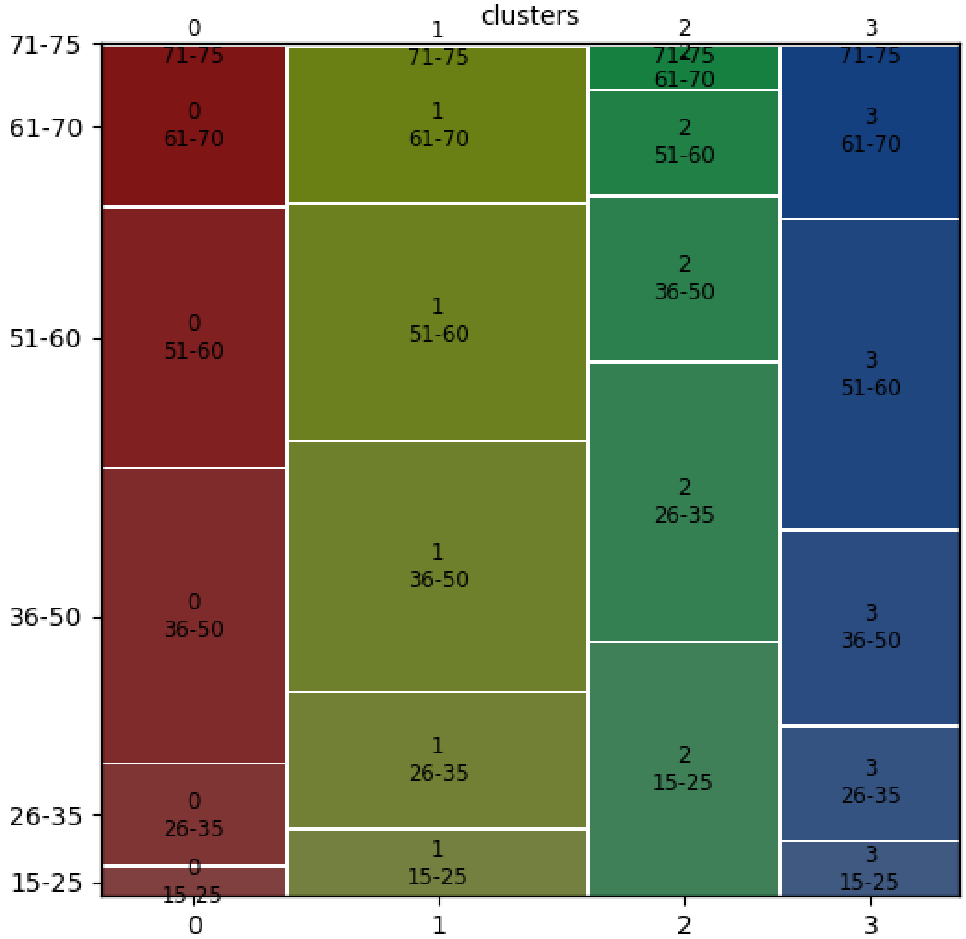
```
#age wise clusters

cluster_age =pd.crosstab(scaled_df['cluster'],scaled_df['Age'])
cluster_age


datacopy2=scaled_df.copy()
datacopy2['Agebin'] = pd.cut(datacopy2['Age'], bins = [15,25, 35, 50, 60, 70, 75], label
s = ['15-25','26-35', '36-50', '51-60', '61-70','71-75'])
cluster_agebin =pd.crosstab(datacopy2['cluster'],datacopy2['Agebin'])
cluster_agebin
```

Out[158]:

Agebin	15-25	26-35	36-50	51-60	61-70	71-75
cluster						
0	10	35	103	91	56	0
1	37	76	140	132	87	1
2	90	99	58	37	15	0
3	18	38	65	104	58	0

In [190]:

```
#MOSAIC PLOT

from statsmodels.graphics.mosaicplot import mosaic

plt.rcParams['figure.figsize'] = (6,6)
mosaic(cluster_agebin.stack())
plt.xlabel('clusters')
plt.show()
```



Observations: more then 50 percent of the people in cluster 0 and cluster 1 are 50 years of age In cluster2 more then 50% of the people are more then 35 years of age

In [159]:

```
cluster_vfreq =pd.crosstab(scaled_df['cluster'],scaled_df['VisitFrequency'])
cluster_vfreq
```

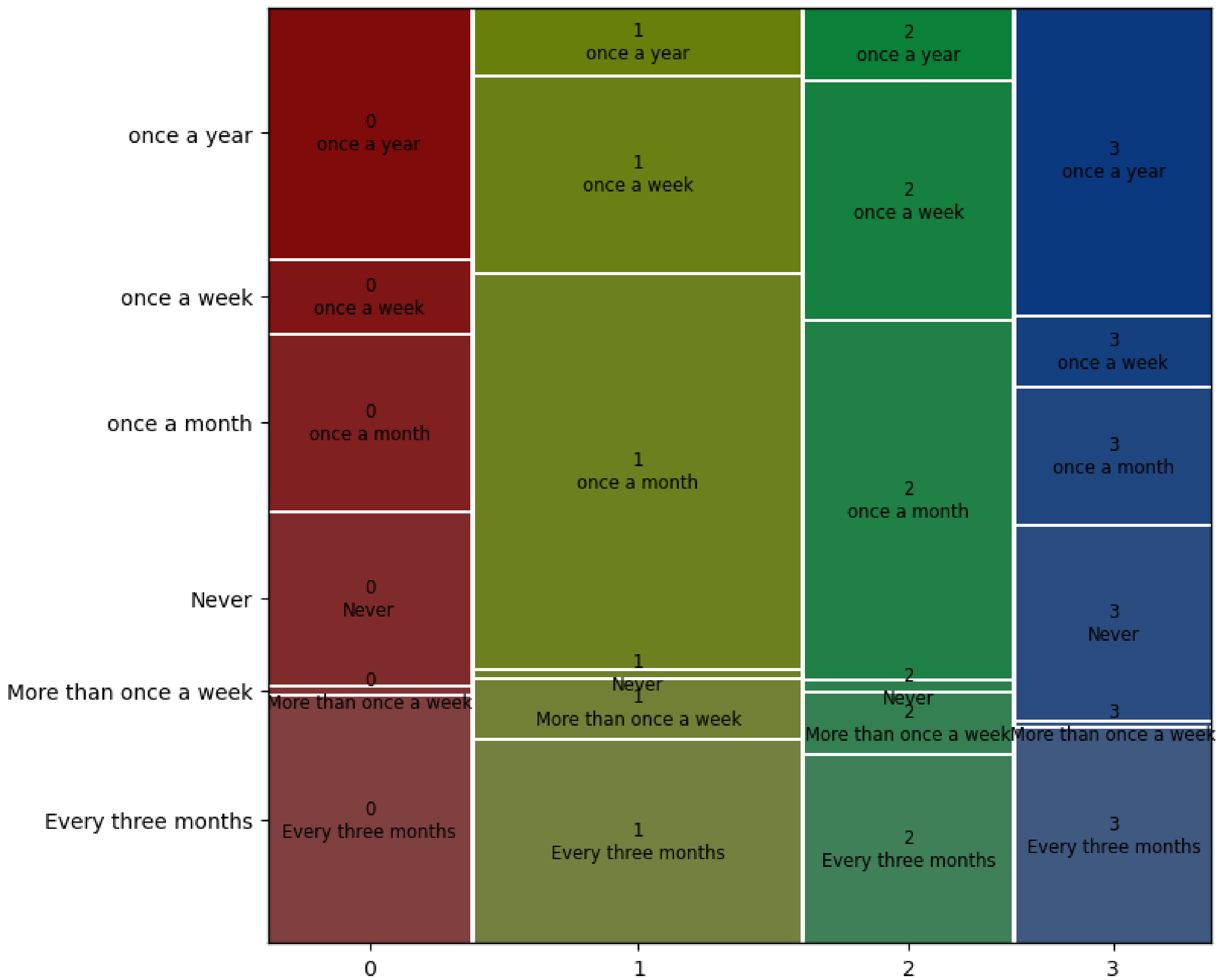
Out[159]:

VisitFrequency	Every three months	More than once a week	Never	once a month	once a week	once a year
cluster						
0	79	2	55	56	23	80
1	104	30	3	202	100	34

VisitFrequency	Every three months	More than once a week	Never	once a month	once a week	once a year
2	61	19	3	116	77	23
3	66	1	59	42	21	94

In [168]:

```
from statsmodels.graphics.mosaicplot import mosaic


plt.rcParams['figure.figsize'] = (8,8)
mosaic(cluster_vfreq.stack())
plt.show()
```



In [197]:

```
#calculating proportions

cluster_vfreq_prop = cluster_vfreq.apply(lambda x: 100*x/x.sum(), axis=1)
print(cluster_vfreq_prop)
```

```
VisitFrequency  Every three months  More than once a week      Never  \
cluster
0                        26.779661               0.677966  18.644068
1                        21.987315               6.342495   0.634249
2                        20.401338               6.354515   1.003344
3                        23.321555               0.353357  20.848057

VisitFrequency  once a month  once a week  once a year
cluster
0                  18.983051     7.796610    27.118644
1                  42.706131    21.141649     7.188161
2                  38.795987    25.752508     7.692308
3                  14.840989     7.420495    33.215548
```

In [ ]:

```

```

Insights: -In cluster 1 and cluster 2,just 1% have 'Never' visited the store

In [195]:

```
cluster_gender =pd.crosstab(scaled_df['cluster'],scaled_df['Gender'])
cluster_gender
```

Out[195]:

Gender	Female	Male
cluster		
0	124	171
1	278	195
2	174	125
3	163	120

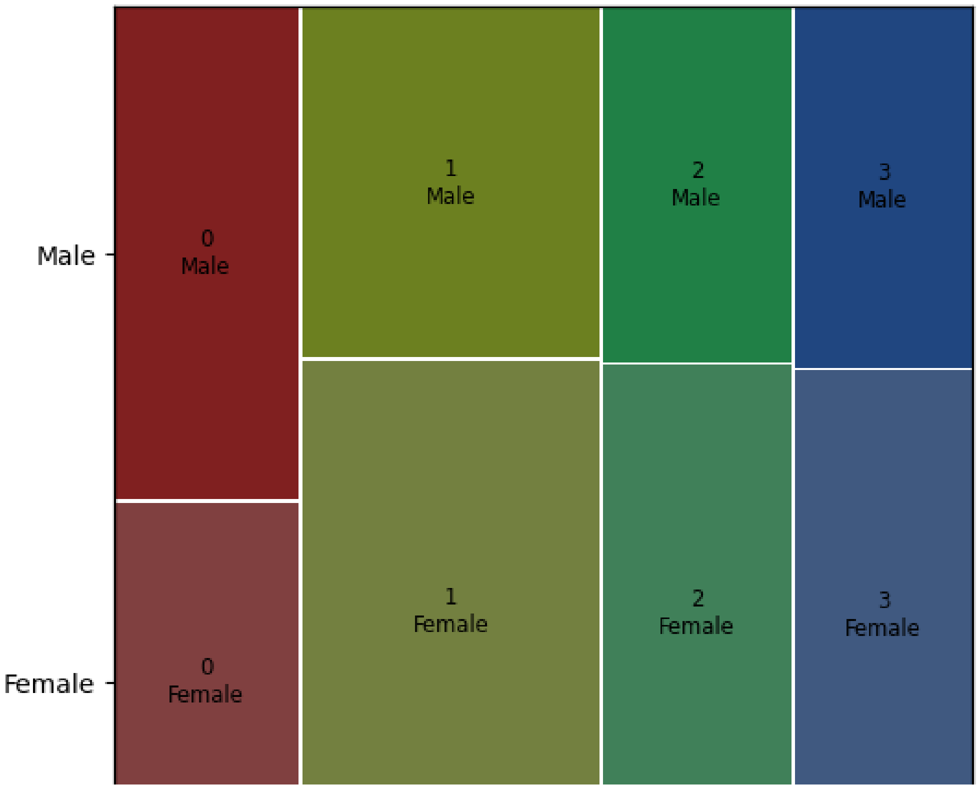
In [198]:

```
#calculating gender proportions

cluster_gender_prop = cluster_gender.apply(lambda x: 100*x/x.sum(), axis=1)
print(cluster_gender_prop)
```

```
Gender      Female       Male
cluster
0        42.033898  57.966102
1        58.773784  41.226216
2        58.193980  41.806020
3        57.597173  42.402827
```

In [164]:

```
from statsmodels.graphics.mosaicplot import mosaic

plt.rcParams['figure.figsize'] = (6,6)
mosaic(cluster_gender.stack())
plt.show()
```



observation: Here we can observe that males and femalesa re equally distibuted in every clusters

In [169]:

```
cluster_tasty =pd.crosstab(scaled_df['cluster'],scaled_df['tasty'])
cluster_tasty
```

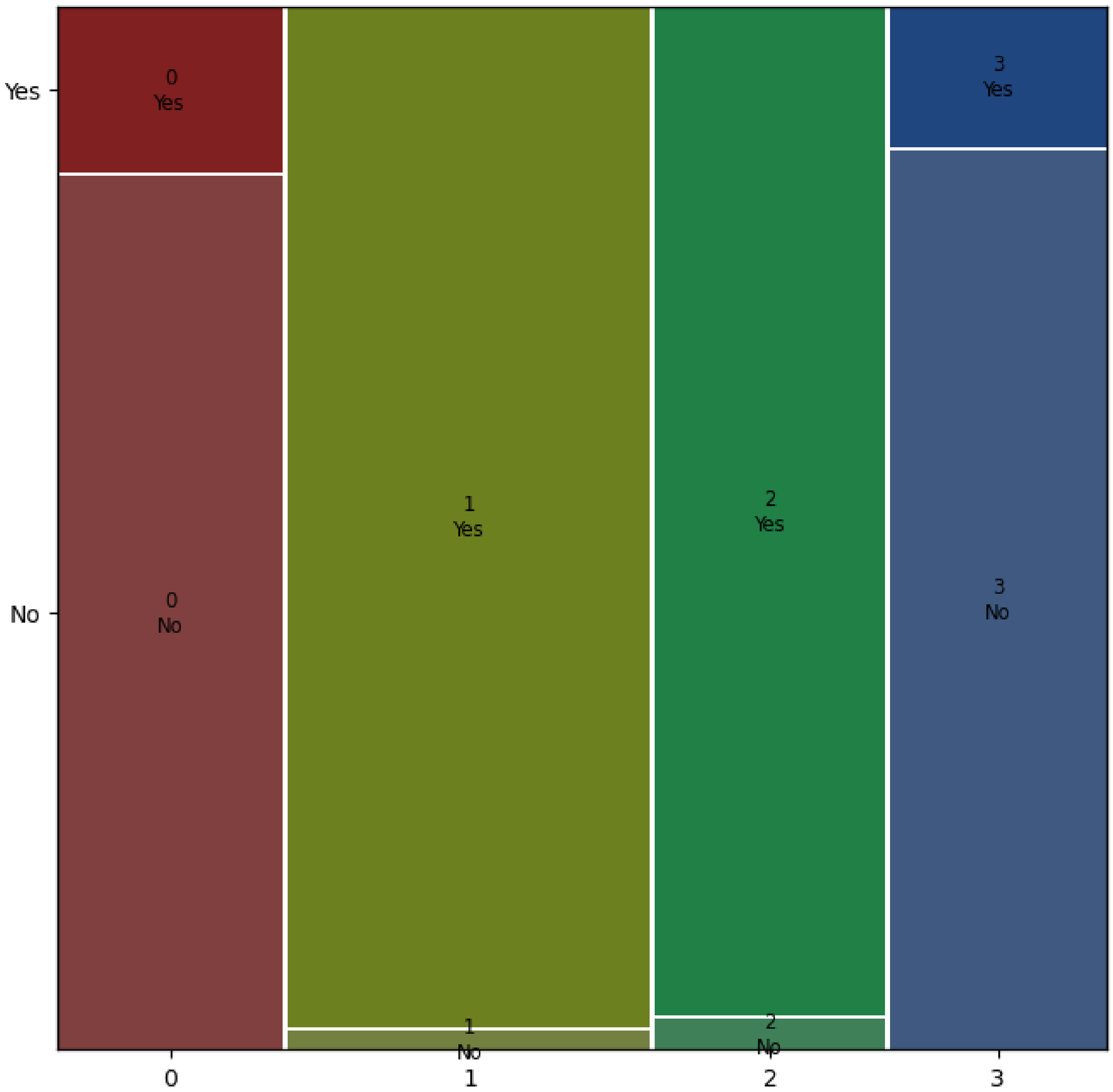
Out[169]:

tasty	No	Yes
cluster		
0	248	47
1	9	464
2	9	290
3	245	38

Insights: .majority of people from cluster 0 and cluster 3 find food not to be tasty .whereas people from cluster 2 and cluster 1 found it to be tasty.

In [171]:

```
plt.rcParams['figure.figsize'] = (8,8)
mosaic(cluster_tasty.stack())
plt.show()
```



In [174]:

```
cluster_healthy =pd.crosstab(scaled_df['cluster'],scaled_df['healthy'])
cluster_healthy
```

Out[174]:

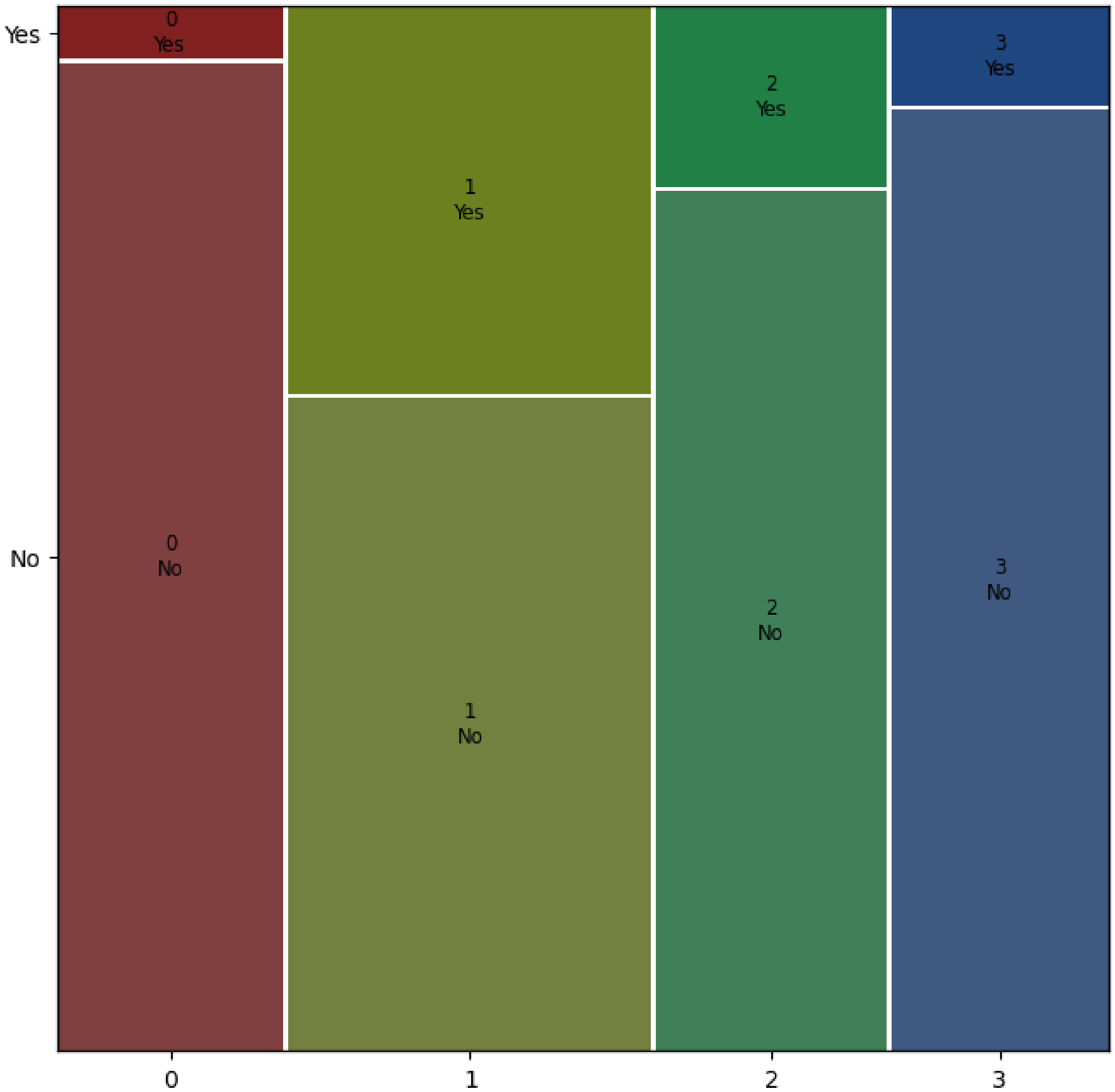
healthy	No	Yes
cluster		
0	280	15
1	297	176
2	247	52
3	256	27

observations:

.majority of people from clusters 0,2 and 3 find food to be unhealthy .few percentage of cluster 1 members think that the food is healthy

In [175]:

```
plt.rcParams['figure.figsize'] = (8,8)
mosaic(cluster_healthy.stack())
plt.show()
```



In [177]:

```
cluster_con =pd.crosstab(scaled_df['cluster'],scaled_df['convenient'])
cluster_con
```

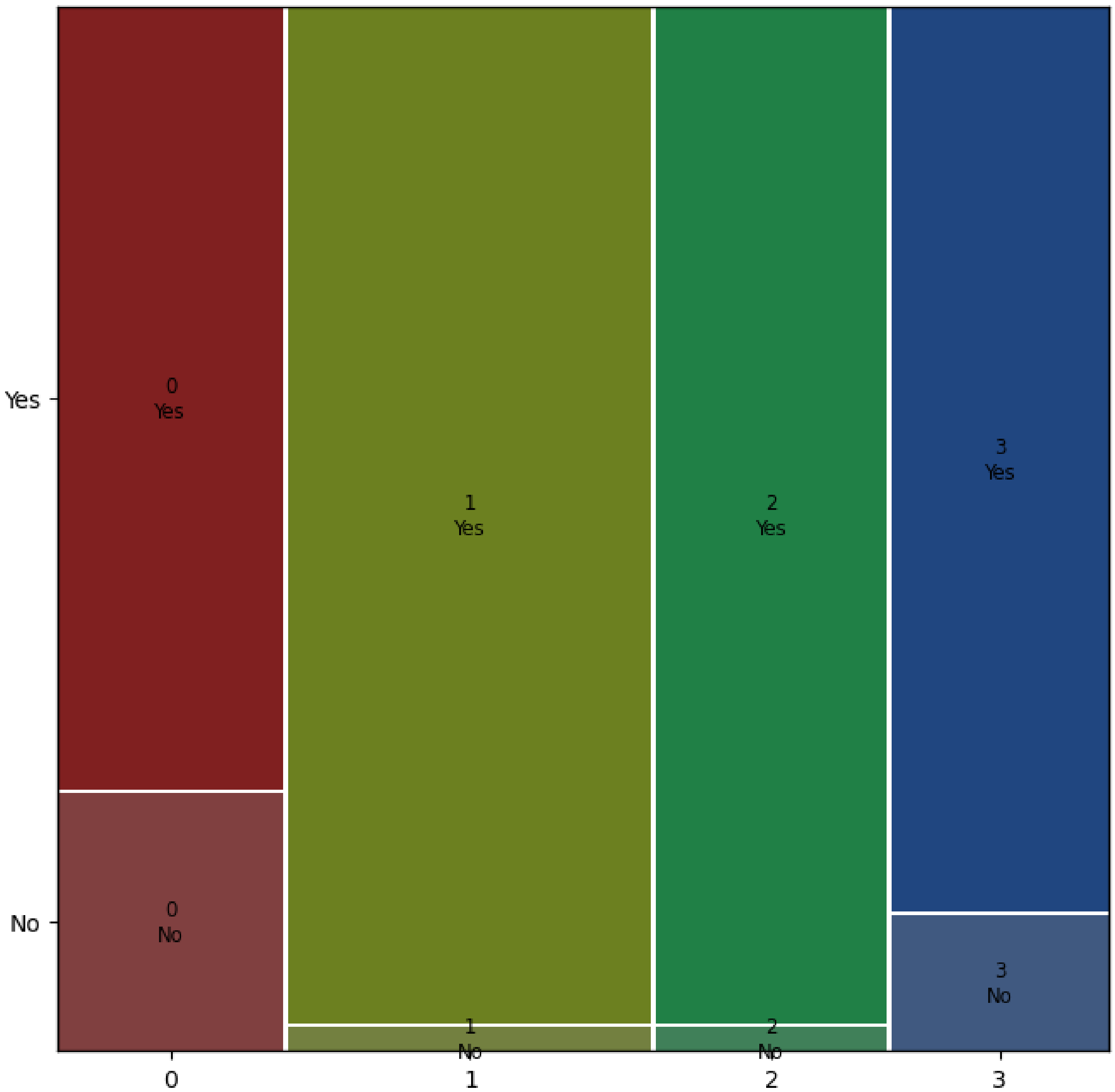
Out[177]:

convenient	No	Yes
cluster		
0	73	222
1	11	462
2	7	292
3	37	246

observations: .almost all clusters finds store to be convenient

In [178]:

```
plt.rcParams['figure.figsize'] = (8,8)
mosaic(cluster_c.stack())
plt.show()
```



In [179]:

```
cluster_fat=pd.crosstab(scaled_df['cluster'],scaled_df['fattening'])
cluster_fat
```

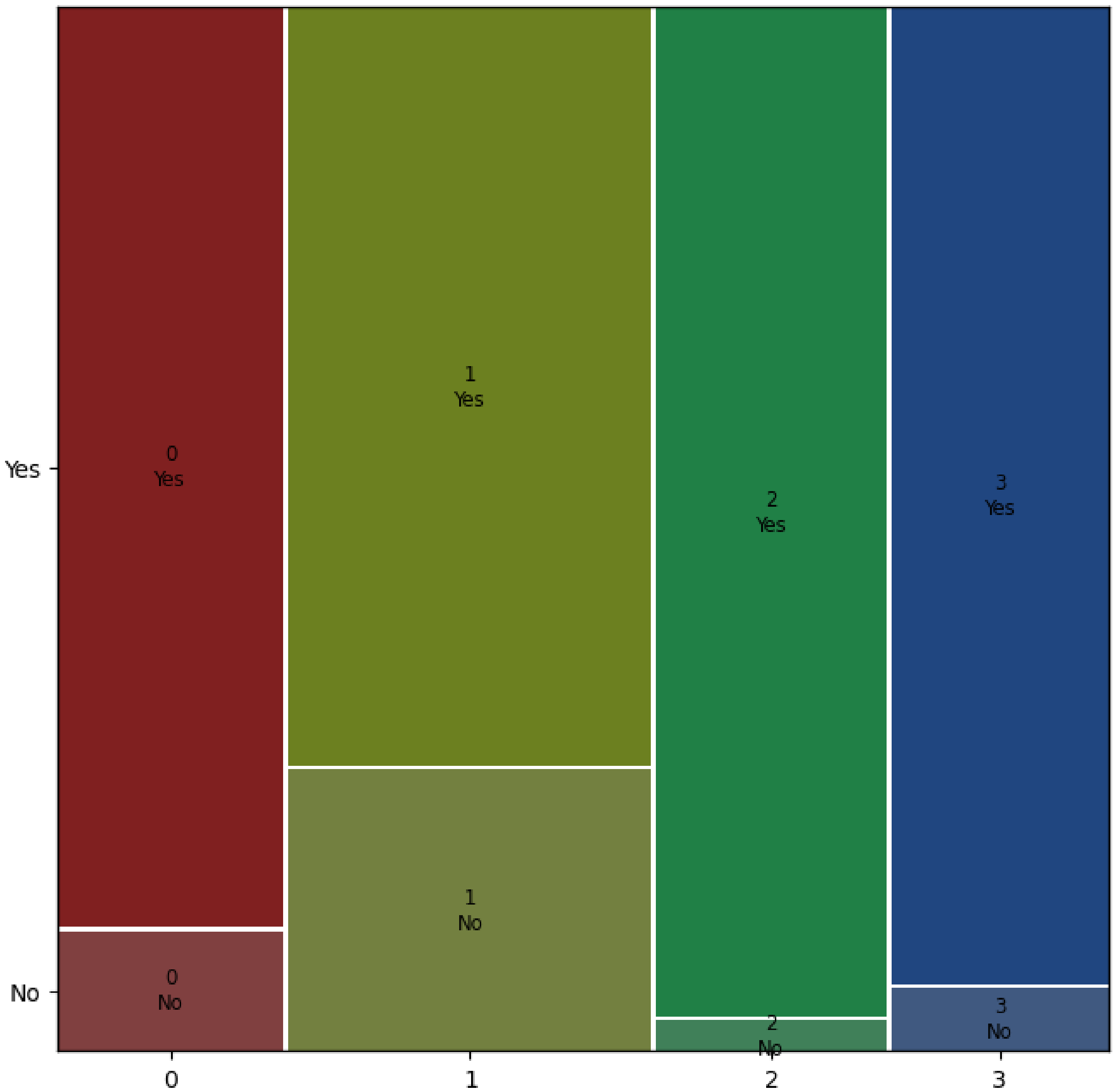
Out[179]:

fattening	No	Yes
cluster		
0	34	261
1	128	345
2	9	290
3	17	266

Vast majority of across all clusters are of the opinion that the food is fattening. Though cluster 1 seems to be a bit less concerned.

In [182]:

```
plt.rcParams['figure.figsize'] = (8,8)
mosaic(cluster_fat.stack())
plt.show()
```



In [180]:

```
cluster_f=pd.crosstab(scaled_df['cluster'],scaled_df['fast'])
cluster_f
```

Out[180]:

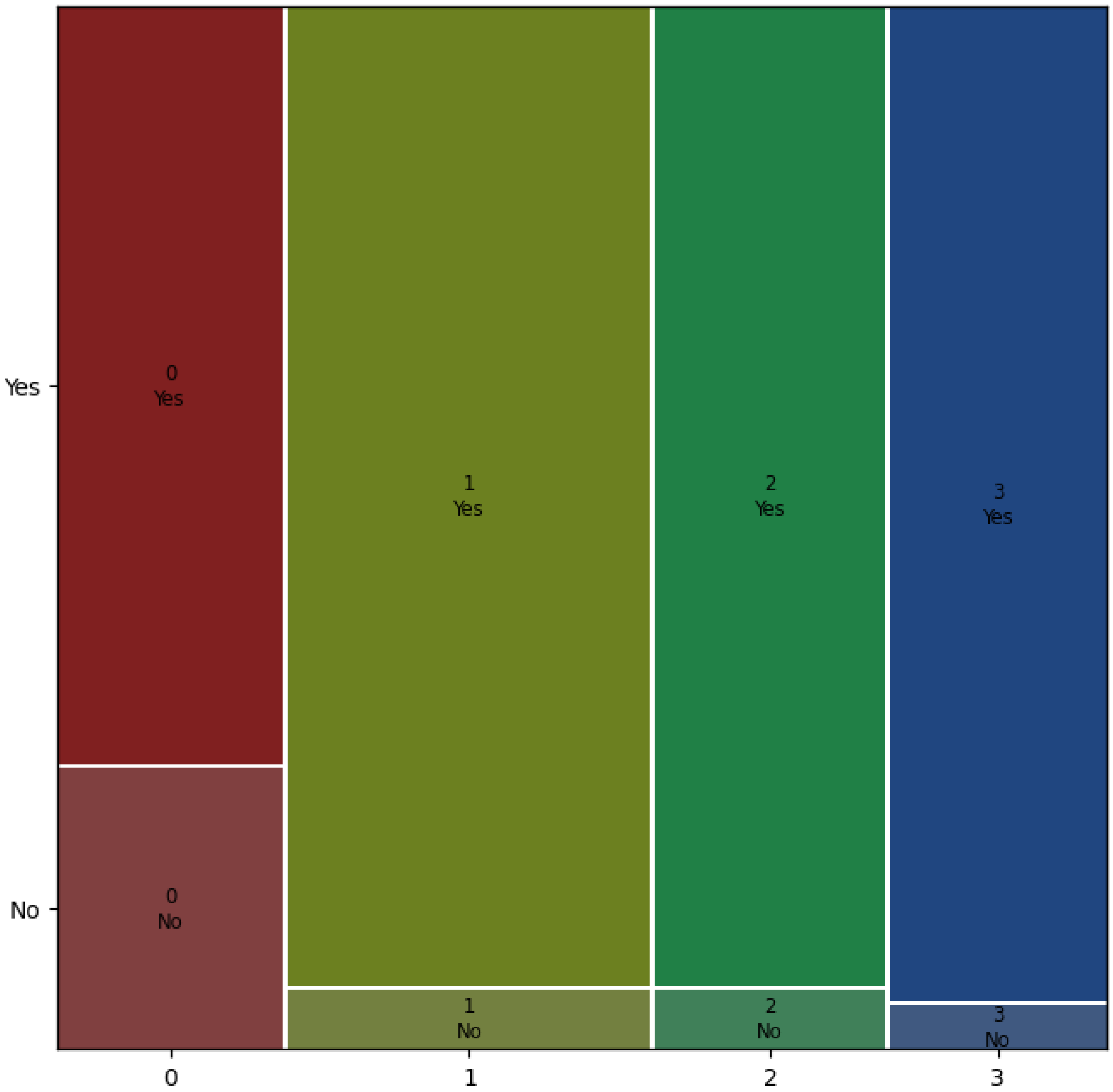
fast	No	Yes
cluster		
0	80	215

fast	No	Yes
cluster		
0	[illegible]	[illegible]
1	27	446
2	17	282
3	12	271

Here it is observed that almost every clusters seems that service is very fast.

In [183]:

```
plt.rcParams['figure.figsize'] = (8,8)
mosaic(cluster_f.stack())
plt.show()
```



In [184]:

```
cluster_cheap =pd.crosstab(scaled_df['cluster'],scaled_df['cheap'])
cluster_cheap
```

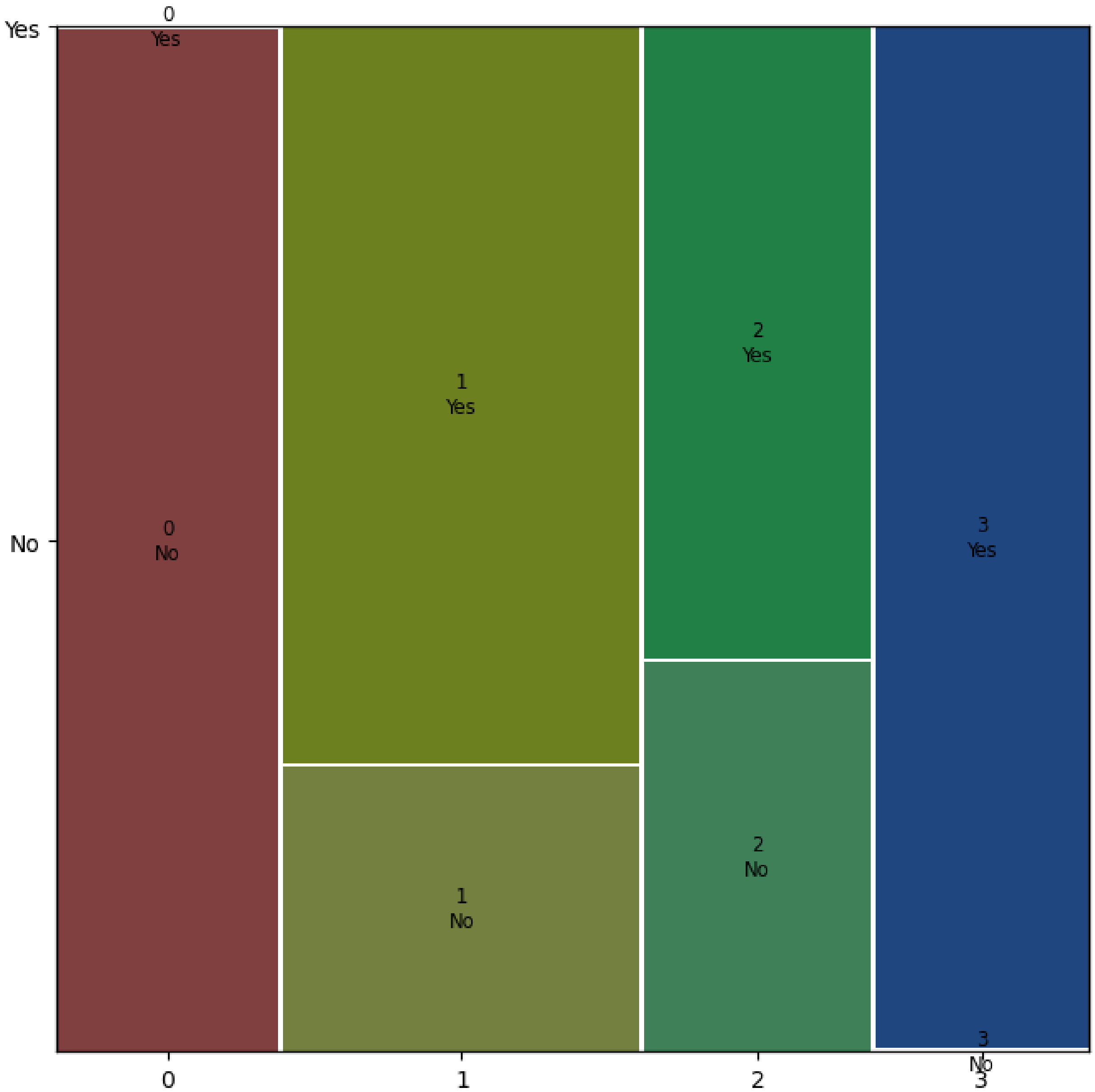
Out[184]:

cheap	No	Yes
cluster		
0	295	0
1	132	341
2	114	185
3	0	283

It is observed that price is a concern only within cluster 0. Most people in cluster 1,2 and 3 feels that its cheap.

In [186]:

```
plt.rcParams['figure.figsize'] = (8,8)
mosaic(cluster_cheap.stack())
plt.show()
```



CONCLUSION: Since we know that Demographic, psychographic, geographic and behavioral are the four pillars of market segmentation.considering the above dataset where we need to analyse and perform various data cleaning inorder to get the insights of the data. Changes can occur within existing market segments. But changes can also occur in the larger marketplace, for example, if new competitors enter the market. All potential sources of change have to be monitored in order to detect changes which require McDonald's management to adjust their strategic or tactical marketing in view of new market circumstances.