Market Segmentation

Fundamentals of Market Segmentation and McDonalds Case Study

By

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Marketing

Marketing is the set of activities a company undertakes to promote the buying or selling f a product and service. It may include advertising, promotion, delivering products to customers.

Marketing plan consists of various steps, Strategic planning, tactical planning.

- The strategic plan aims on long time goals of the organization.
- The tactical plan aims on short time goals of the organization.

SWOT analysis is done for marketing planning. S(strength) W(weakness) O(opportunities) T(threat)

Marketing Segmentation

Market Segmentation is the process of dividing a broad group of consumer or target market into sub groups of consumers based on demographics, needs, common interests, geographic locations, or psychographic behavior. Market segmentation is one of the key building blocks of strategic marketing. Market segmentation is essential for marketing success.

Benefits of Market segmentation

It helps in achieving long time goals that is market dominance in particular area which results from being best able to cater to the needs of a very specific market segment. It helps to yield a higher return on investment.

Cost of Market segmentation

Implementing market segmentation requires a large investment by the organization. A large number of people are needed for the market segmentation analysis. They have to spend a whole lot of time for this process. They have to monitor the market dynamics properly. In the worst case, if market segmentation is not implemented well, the entire exercise is a waste of resources.

Steps in Market Segment Analysis:

Deciding (not) to segment

We spent a handful of money in this market segmentation analysis for improving business. Before investing time and resources in a market segmentation analysis, it is very important to understand the strategy behind the market and decide whether to analyze it or not.

Segmenting a market is not free of cost. There are various costs for performing the research, surveys, contacting groups, communicating messages to them, designing solutions, designing advertisements, etc. It is highly recommended not to segment unless the expected increase in sales is sufficient to justify the analysis.

Barriers in Market segment analysis:

Implementing the market segmentation has so many barriers. We can't implement just like that easily. We have to plan correctly and implement them consistently.

There may be so many difficulties in implementing these plans. Few barriers are discussed here.

Lack of leadership, pro-active championing, commitment and involvement in the market segmentation process by senior leadership undermines the success of market segmentation.

Lack of market or consumer orientation, resistance to change and new ideas, lack of creative thinking, bad communication and lack of sharing of information and insights across organizational units, short-term thinking, unwillingness to make changes and office politics have been identified as preventing the successful implementation of market segmentation.

Another potential problem is lack of training.

Another obstacle may be objective restrictions faced by the organization, including lack of financial resources, or the inability to make the structural changes required.

Some key scenarios to ensure the market should be segmented or not are,

Checking whether the organization's culture is market-oriented or not.

Checking whether the organization is open to new ideas or not.

Checking whether the organization has sufficient financial resources to support market segmentation strategy.

Ensure that there is enough time to analyze the market and conduct market segmentations.

Specifying the ideal target segment

The second step of the market segmentation analysis depends on the user input. It is important to understand that for a market segmentation analysis, user input cannot be limited to either briefing at the start of the process or the development of a marketing mix at the end. Rather, the user needs to be involved in most stages, literally wrapping around the technical aspects of market segmentation analysis.

They need to check whether the following procedures and processes are followed.

- They have to discuss about the homogeneity, distinctness, size, match, identifiability and reachability.
- Individually study available criteria for the assessment of market segment attractiveness.
- Discuss the criteria with the other segmentation team members and agree on a subset of no more than six criteria.

- Individually distribute 100 points across the segment attractiveness criteria you have agreed upon with the segmentation team. Distribute them in a way that reflects the relative importance of each attractiveness criterion.
- Discuss weightings with other segmentation team members and agree on a weighting.
- Present the selected segment attractiveness criteria and the proposed weights assigned to each of them to the advisory

Collecting Data

In commonsense segmentation, the segmentation variable is typically one single characteristic of the consumers in the sample. Describing segments is critical to being able to develop an effective marketing mix targeting the segment. Typical descriptor variables include socio-demographics, but also information about media behavior. The correct description, in turn, makes it possible to develop a customized product, determine the most appropriate pricing strategy, select the best distribution channel, and the most effective communication channel for advertising and promotion.

Geographic Segmentation

Geographic information is segmentation criterion used for the purpose of market segmentation. when geographic segmentation is used – the consumer's location is considered.

Socio-Demographic Segmentation

Typical socio-demographic segmentation criteria include age, gender, income and education. Socio-demographic segments can be very useful in some industries.

Psychographic Segmentation

When people are grouped according to psychological criteria, such as their beliefs, interests, preferences, aspirations, or benefits sought when purchasing a product, the term psychographic segmentation is used. Psychographic criteria are, by nature, more complex than geographic or socio-demographic criteria because it is difficult to find a single characteristic of a person that will provide insight into the psychographic dimension of interest.

Behavioral Segmentation

Another approach to segment extraction is to search directly for similarities in behavior or reported behavior. A wide range of possible behaviors can be used for this purpose, including prior experience with the product, frequency of purchase, amount spent on purchasing the product on each occasion (or across multiple purchase occasions), and information search behavior.

Survey data is cheap and easy to collect. But survey data can be contaminated by a wide range of biases. Such biases can, in turn, negatively affect the quality of solutions derived from market segmentation analysis.

Carefully selecting the variables that are included as segmentation variable in common sense segmentation, or as segmentation variables in data-driven segmentation, is critical to the quality of the market segmentation solution. Developing a good questionnaire typically requires conducting exploratory or qualitative research.

Answer options provided to respondents in surveys determine the scale of the data available for subsequent analyses.

Survey data is prone to capturing biases. A response bias is a systematic tendency to respond to a range of questionnaire items on some basis other than the specific item content.

Increasingly organizations have access to substantial amounts of internal data that can be harvested for the purpose of market segmentation analysis. Typical examples are scanner data available to grocery stores, booking data available through airline loyalty programs, and online purchase data. The strength of such data lies in the fact that they represent actual behavior of consumers, rather than statements of consumers about their behavior or intentions, known to be affected by imperfect memory. The danger of using internal data is that it may be systematically biased by over-representing existing customers. What is missing is information about other consumers the organization may want to win as customers in future, which may differ systematically from current customers in their consumption patterns.

Exploring the data

After the data is collected, data is preprocessed, cleaned and exploratory data analysis is performed. It gives valuable insights for the extraction of meaningful market segments. Exploratory data analysis helps to identify the measurement level of variables, investigate the distribution of variables, and find relationship between variables. Results from the data exploration stage provide insights into the suitability of different segmentation methods for extracting market segments.

Data cleaning

First step is to clean the data. This includes checking if all columns and rows have been correctly recorded, categorical values are transformed into numerical. Similarly, levels of categorical variables can be checked to ensure they contain only permissible values.

Descriptive Analysis

Descriptive numeric and graphic representations provide insights into the data. Statistical software packages offer a wide variety of tools for descriptive analysis. The range, the quartiles, and the mean for numeric variables are calculated. Helpful graphical methods for numeric data are histograms, boxplots and scatter plots. Bar plots of frequency counts are useful for the visualization of categorical variables. Mosaic plots illustrate the association of multiple categorical variables. Histograms visualize the distribution of numeric variables.

Pre-Processing

Categorical Variables

Two pre-processing procedures are often used for categorical variables. One is merging levels of categorical variables before further analysis, the other one is converting categorical variables to numeric ones, if it makes sense to do so. Merging levels of categorical variables is useful if the original categories are too differentiated (too many).

Numeric Variables

The range of values of a segmentation variable affects its relative influence in distance-based methods of segment extraction. To balance the influence of segmentation variables on segmentation results, variables can be standardized. Standardizing variables means transforming them in a way that puts them on a common scale.

Principal Components Analysis

Principal components analysis (PCA) transforms a multivariate data set containing metric variables to a new data set with variables referred to as principal components which are uncorrelated and ordered by importance. The first variable (principal component) contains most of the variability, the second principal component contains the second most variability, and so on.

After transformation, observations (consumers) still have the same relative positions to one another, and the dimensionality of the new data set is the same because principal components analysis generates as many new variables as there were old ones.

Principal components analysis basically keeps the data space unchanged, but looks at it from a different angle. Principal components analysis works off the covariance or correlation matrix of several numeric variables. In most cases, the transformation obtained from principal components analysis is used to project high-dimensional data into lower dimensions for plotting purposes.

Extracting Segments

Data-driven market segmentation analysis is exploratory by nature. Consumer data sets are typically not well structured. Consumers come in all shapes and forms; a two-dimensional plot of consumers' product preferences typically does not contain clear groups of consumers. Rather, consumer preferences are spread across the entire plot. The combination of exploratory methods and unstructured consumer data means that results from any method used to extract market segments from such data will strongly depend on the assumptions made on the structure of the segments implied by the method. The result of a market segmentation analysis, therefore, is determined as much by the underlying data as it is by the extraction

Profiling Segments

The aim of the profiling step is to get to know the market segments resulting from the extraction step. Profiling is only required when data-driven market segmentation is used. For commonsense segmentation, the profiles of the segments are predefined. If, for example, age is used as the segmentation variable for the commonsense segmentation, it is obvious that the resulting segments will be age groups.

Describing Segments

Segment profiling is about understanding differences in segmentation variables across market segments. Segmentation variables are chosen early in the market segmentation analysis process: conceptually in Step 2 (specifying the ideal target segment), and empirically in Step 3 (collecting data). Segmentation variables form the basis for extracting market segments from empirical data.

Selecting the Target Segment(s):

The Targeting Decision - which of the many possible market segments will be selected for targeting?

In this, one or more of those market segments (which we obtained in step 5,6,7) need to be selected for targeting.

The first task in this step, therefore, is to ensure that all the market segments that are still under consideration to be selected as target markets have well and truly passed the knock-out criteria test.

The segmentation team has to ask a number of questions which fall into two broad categories:

1. Which of the market segments would the organization most like to target? Which segment would the organisation like to commit to?

2. Which of the organizations offering the same product would each of the segments most like to buy from?

How likely is it that our organization would be chosen?

How likely is it that each segment would commit to us?

Answering these two questions forms the basis of the target segment decision

Market Segment Evaluation

Many versions of decision matrices have been proposed in the past, and many names are used to describe them.

Whichever variation is chosen, the two criteria plotted along the axes cover two dimensions: Segment attractiveness, and Relative organisational competitiveness specific to each of the segments.

Segment attractiveness- How attractive is the segment to us? (X-axis)

Relative organizational competitiveness- How attractive are we to the segment? (Y-axis)

If you intend to target more than one segment: make sure that the

selected target segments are compatible with one another.

Customizing the Marketing Mix

Commonly the marketing mix is understood as consisting of the 4Ps: Product, Price, Promotion and Place. Market segmentation does not stand independently as a marketing strategy. Rather, it goes hand in hand with the other areas of strategic marketing, most importantly: positioning and competition.

Product - One of the key decisions an organization needs to make when developing the product dimension of the marketing mix, is to specify the product in view of customer needs. Other marketing mix decisions that fall under the product dimension are: naming the product, packaging it, offering or not offering warranties, and after sales support services.

Price - Typical decisions an organization needs to make when developing the price dimension of the marketing mix include setting the price for a product, and deciding on discounts to be offered.

Place - The key decision relating to the place dimension of the marketing mix is how to distribute the product to the customers. This includes answering questions such as: should the product be made available for purchase online or offline only or both; should the manufacturer sell directly to customers; or should a wholesaler or a retailer or both be used.

Promotion - developing an advertising message that will resonate with the target market, and identifying the most effective way of communicating this message. Other tools in the promotion category of the marketing mix include public relations, personal selling, and sponsorship.

Implementation

Data Sources :

We have gathered some datasets which are somehow related to the case. The link of the dataset is given below https://drive.google.com/file/d/1AOrLenQP1mqcKJnbzPxf-3Ud6a6rGQe9/view?usp=sharing.

Packages and Tools used :

- Numpy
- Pandas
- Matplotlib
- Seaborn
- Plotly
- Sklearn
- Scipy

The dataset is based on the previous stat of the customer review and behaviour about the Online food, here we have taken the case of "Mcdonalds".

Uploading packages and Tools :

```
In [94]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         import plotly as py
         import plotly.graph_objs as go
         import plotly.figure_factory as ff
         import plotly.graph_objects as go
         import plotly.express as px
         from plotly.subplots import make_subplots
```

Uploading dataset :

```
In [95]: df = pd.read_csv('C:\\Users\\SUSNATA BISWAS\\OneDrive\\Desktop\\mcdonalds.csv')
```

```
In [96]: # path_1 = "/content/drive/MyDrive/mcdonalds.csv"
         # df = pd.read_csv(path_1)
         df.head(10)
```

Out[96]:

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

Data Pre-processing :

- Checking is there any null values in the data set :

In [97]:
```
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 our data set we have 1453 rows and 15 columns. By applying df.info (), we can see that we have no null values.

- **Removing duplicates** :

In [123]:
```python
print('Duplicated value(s) on the dataset1 : ', df.duplicated().sum())
```

```
Duplicated value(s) on the dataset1 :  22
```

In [124]:
```python
df.drop_duplicates(keep="first", inplace=True)
```

In [125]:
```python
df
```

Out[125]:

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	healthy	disgusting	Like	Age	VisitFrequency	Gender
0	No	Yes	No	Yes	No	Yes	Yes	No	Yes	No	No	-3	61	Every three months	Female
1	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	+2	51	Every three months	Female
2	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	No	+1	62	Every three months	Female
3	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No	Yes	+4	69	Once a week	Female
4	No	Yes	No	Yes	Yes	Yes	Yes	No	No	Yes	No	+2	49	Once a month	Male
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1448	No	Yes	No	Yes	Yes	No	No	No	Yes	No	Yes	I hate it!-5	47	Once a year	Male
1449	Yes	Yes	No	Yes	No	No	Yes	Yes	No	Yes	No	+2	36	Once a week	Female
1450	Yes	Yes	No	Yes	No	Yes	No	Yes	Yes	No	No	+3	52	Once a month	Female
1451	Yes	Yes	No	No	No	Yes	Yes	Yes	No	Yes	No	+4	41	Every three months	Male
1452	No	Yes	No	Yes	Yes	No	No	No	Yes	No	Yes	-3	30	Every three months	Male

1431 rows × 15 columns

After this operation of the duplicacy test, we found that 22 rows were similar with each other, So, we have removed it. After removing, the total number of rows we have is (1453 - 22) = 1431.

Before removing duplicates no. of rows = 1453
After removing duplicates no. of rows = 1431

- **Handling categorical features** :

We have manually transformed all the categorical features to all numerical values.

```
In [141]: df['Gender'] = df['Gender'].replace({'Male':1, 'Female':0})
          df['yummy'] = df['yummy'].replace({'Yes':1, 'No':0})
          df['convenient'] = df['convenient'].replace({'Yes':1, 'No':0})
          df['spicy'] = df['spicy'].replace({'Yes':1, 'No':0})
          df['fattening'] = df['fattening'].replace({'Yes':1, 'No':0})
          df['greasy'] = df['greasy'].replace({'Yes':1, 'No':0})
          df['fast'] = df['fast'].replace({'Yes':1, 'No':0})
          df['cheap'] = df['cheap'].replace({'Yes':1, 'No':0})
          df['tasty'] = df['tasty'].replace({'Yes':1, 'No':0})
          df['expensive'] = df['expensive'].replace({'Yes':1, 'No':0})
          df['healthy'] = df['healthy'].replace({'Yes':1, 'No':0})
          df['disgusting'] = df['disgusting'].replace({'Yes':1, 'No':0})
          df['VisitFrequency'] = df['VisitFrequency'].replace({'Never':0, 'Once a year':1, 'Every three months':2, 'Once a month':3, 'Once
          df['Like']= df['Like'].replace({'I hate it!-5': -5, 'I love it!+5': 5,'+4': 4, '+3': 3,'+2': 2, '+1': 1})
```

After transforming, it looks like :

```
In [142]: df
```

Out[142]:

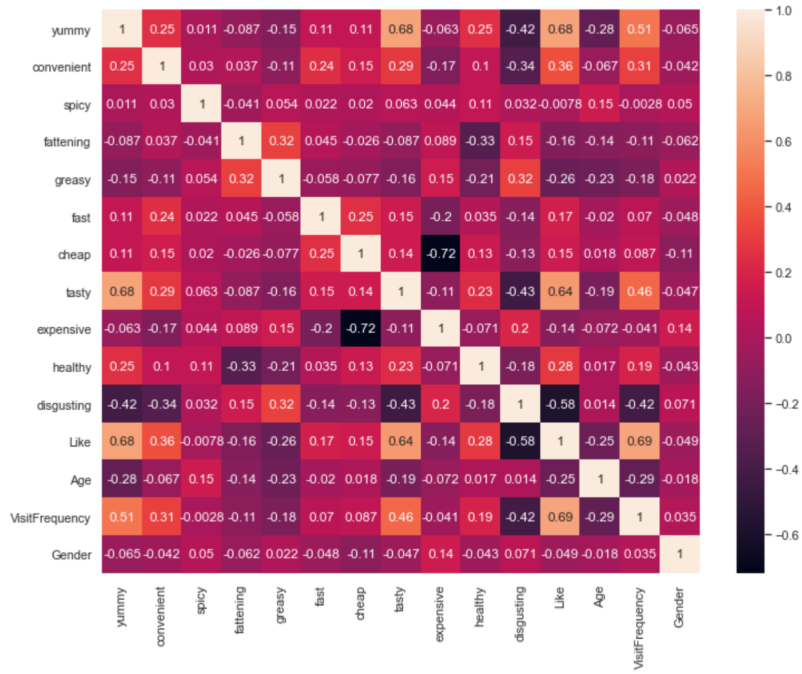
	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	healthy	disgusting	Like	Age	VisitFrequency	Gender
0	0	1	0	1	0	1	1	0	1	0	0	-3	61	2	0
1	1	1	0	1	1	1	1	1	1	0	0	2	51	2	0
2	0	1	1	1	1	1	0	1	1	1	0	1	62	2	0
3	1	1	0	1	1	1	1	1	0	0	1	4	69	4	0
4	0	1	0	1	1	1	1	0	0	1	0	2	49	3	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1448	0	1	0	1	1	0	0	0	1	0	1	-5	47	1	1
1449	1	1	0	1	0	0	1	1	0	1	0	2	36	4	0
1450	1	1	0	1	0	1	0	1	1	0	0	3	52	3	0
1451	1	1	0	0	0	1	1	1	0	1	0	4	41	2	1
1452	0	1	0	1	1	0	0	0	1	0	1	-3	30	2	1

1431 rows × 15 columns

Analysis :

- **Correlation Matrix** :

In [145]:
```
plt.figure(figsize = (12,9))
s=sns.heatmap (df.corr(),
               annot = True
               )
#                cmap = 'Rdbu',
#                vmain = -1,
#                vmax = +1)
# s.set_yticklabels(s.get_yticklabels(), rotation = 0, fontsize = 12)
# s.set_xticklabels(s.get_xticklabels(), rotation = 90, fontsize = 12)
# plt.title('Correlation Heatmap')
# plt.show()
```



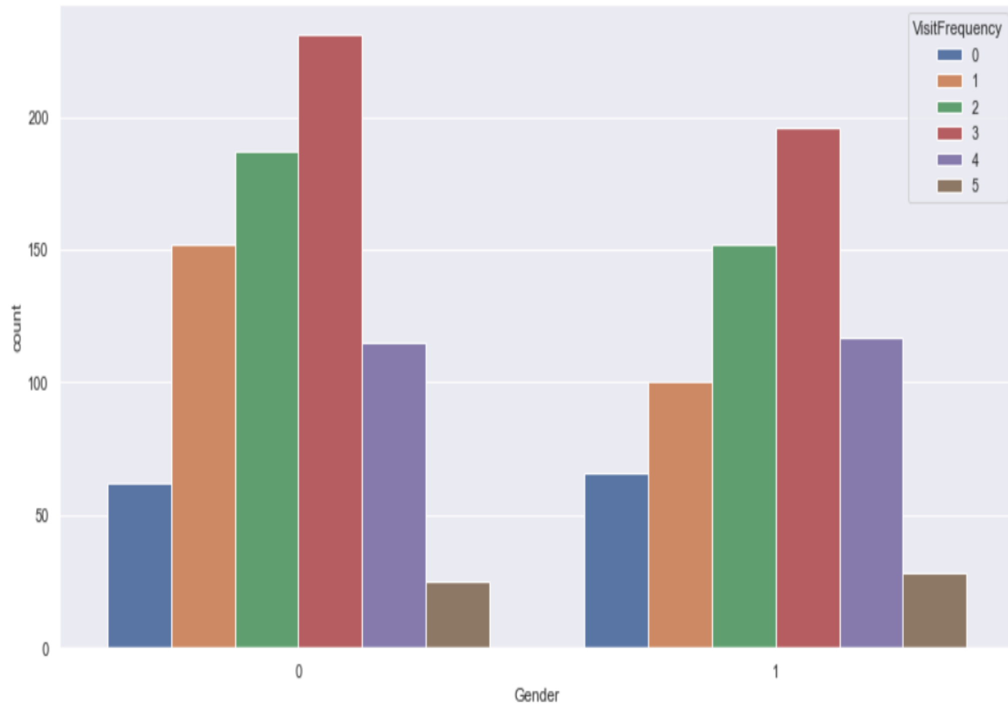
From the Correlation Matrix we see that the columns ‘VisitFrequency’ and ‘Like’ features are more likely connected as they have the correlation coefficient of 0.69.

Expensive and Cheap have correlation coefficients of -0.72, that is obvious.

- **Demographic Analysis** :

1. **Gender**

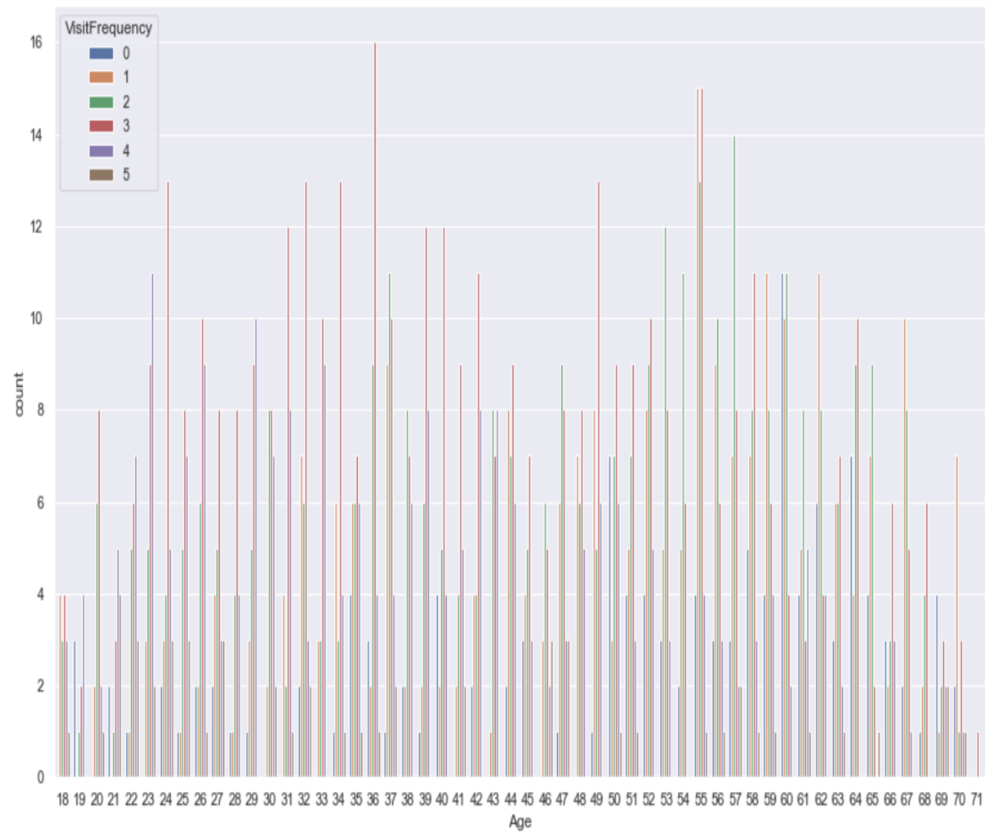
```
In [159]: plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(x= 'Gender', data=df, hue = 'VisitFrequency')
```



From the graph plot it is clear that females are more attracted to Mcdonalds. A large portion of the community, both men and women regularly visit Mcdonalds once in a month.

2. Age

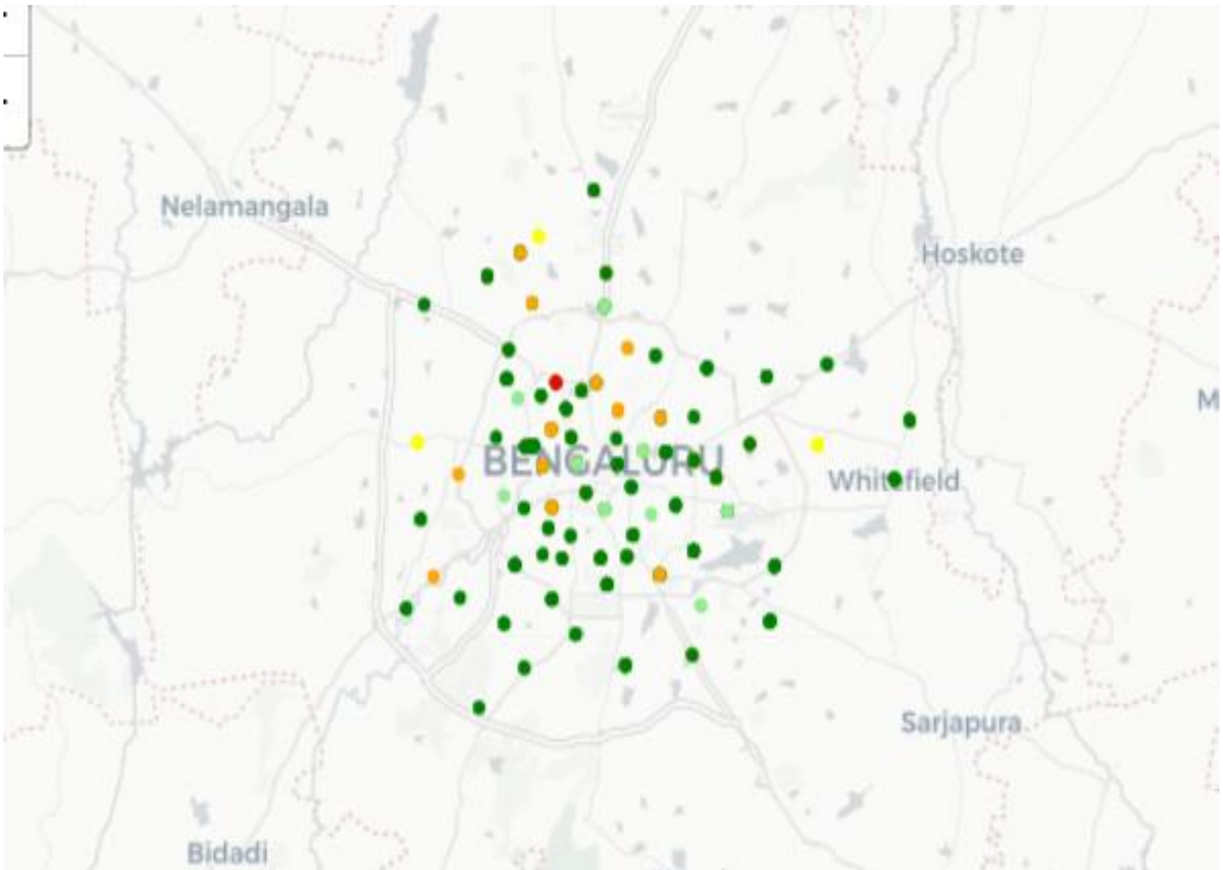
In [163]:
```
plt.figure(1 , figsize = (15 , 9))
sns.set(style="darkgrid")
ax = sns.countplot(x= 'Age', data=df, hue = 'VisitFrequency')
```



The graph is quite messy due to the presence of 5 factors in VisitFrequency features. Though if we try to observe, we can see that aged people are likely to avoid Mcdonalds. And the optimal target age group should be 25 to 39. This is our main Target Customer.

Geographical Analysis :

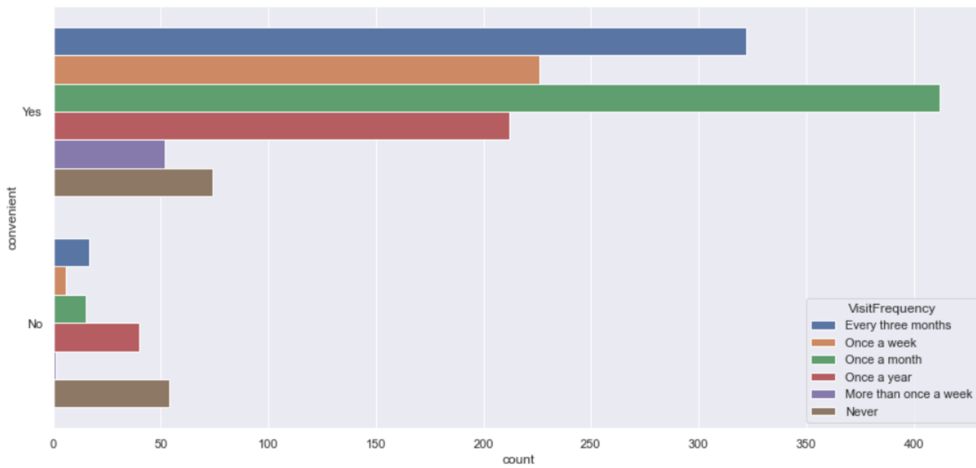
As we don't have a good datasets to describe geographic segmentation so, we have considered the customer churn datasets where we are analysing the location with the ease and a convenience question.



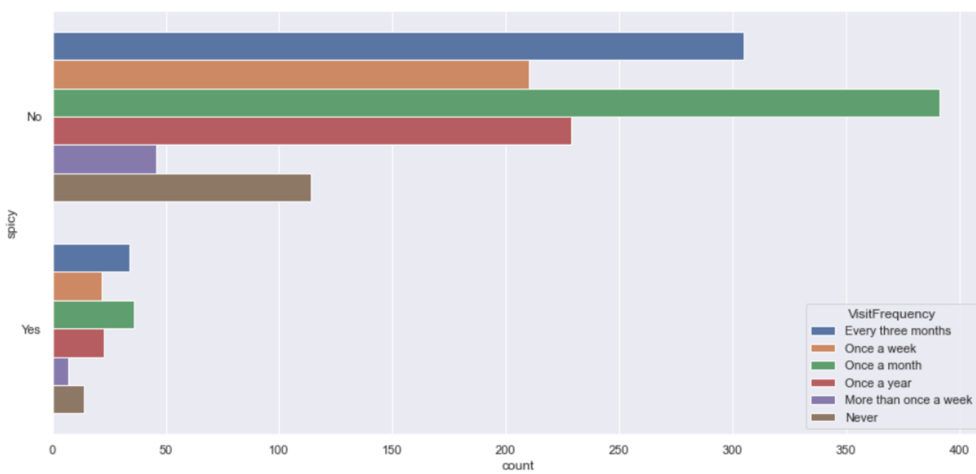
Psychographic Analysis :

Here we took a dataset and have plotted different survey questions related to Mcdonald's food survay .

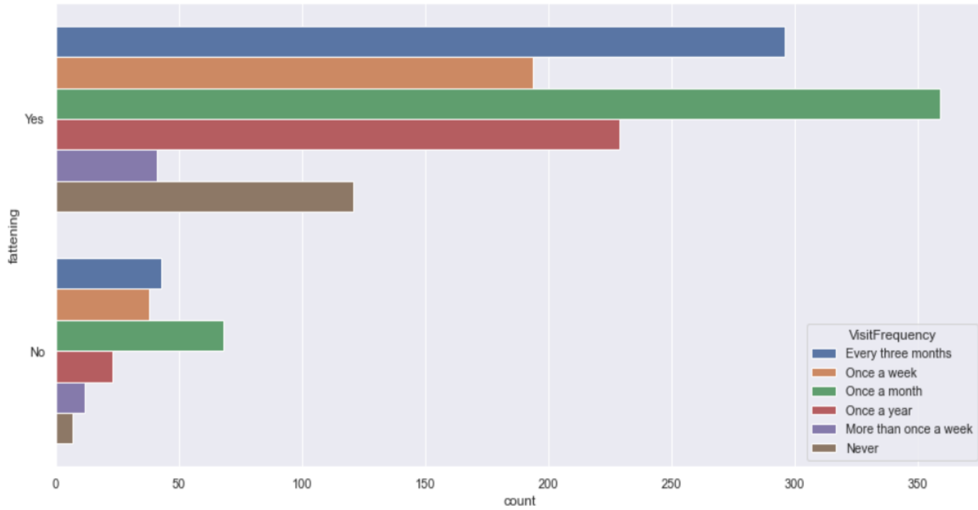
In [128]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="convenient", data=df, hue = 'VisitFrequency' )
```



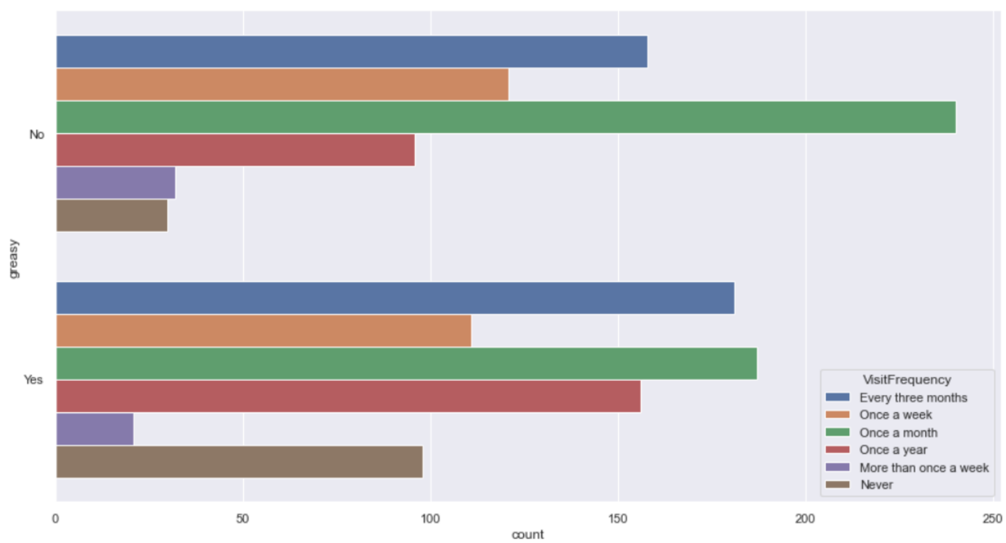
In [129]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="spicy", data=df, hue = 'VisitFrequency')
```



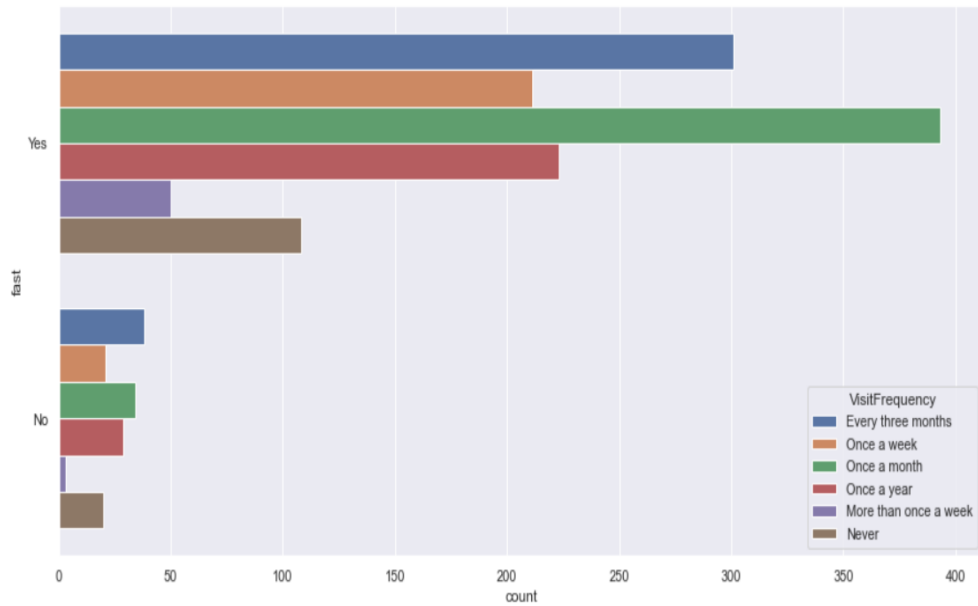
In [130]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="fattening", data=df, hue = 'VisitFrequency' )
```



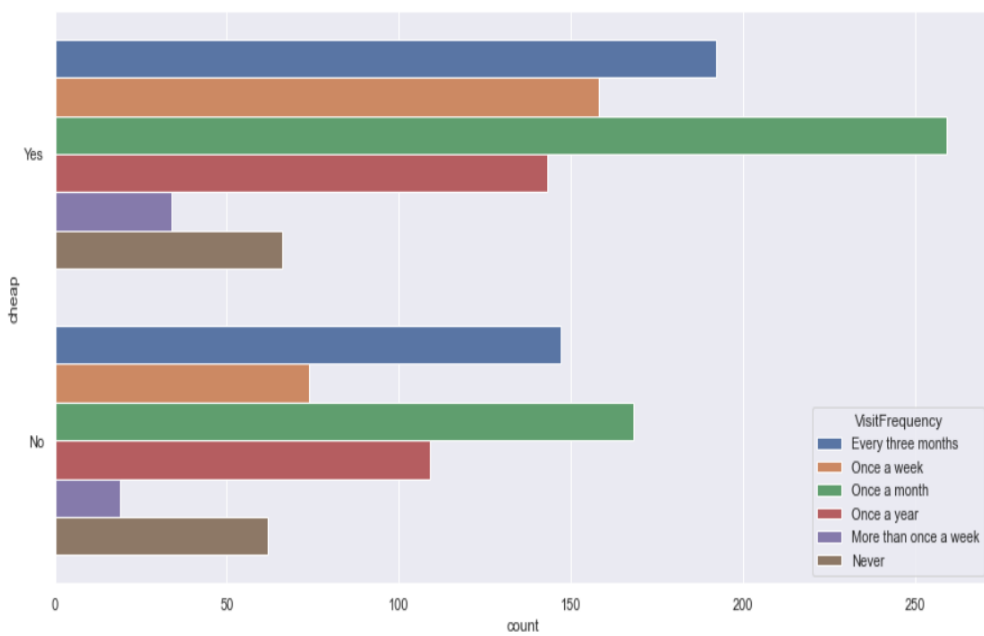
In [131]:
```
plt.figure(1 , figsize = (15 , 8))
sns.set(style="darkgrid")
ax = sns.countplot(y="greasy", data=df, hue = 'VisitFrequency' )
```



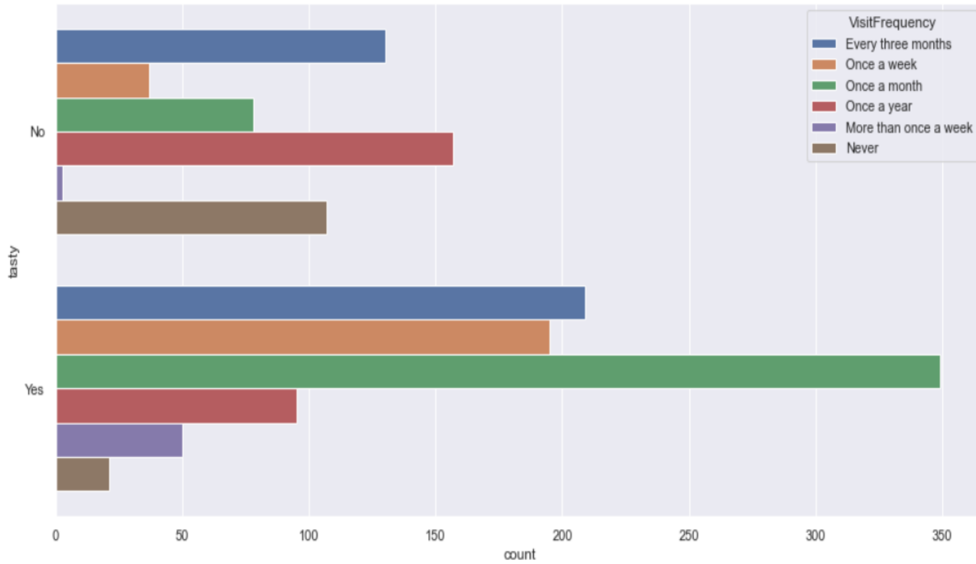
In [132]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="fast", data=df , hue = 'VisitFrequency')
```



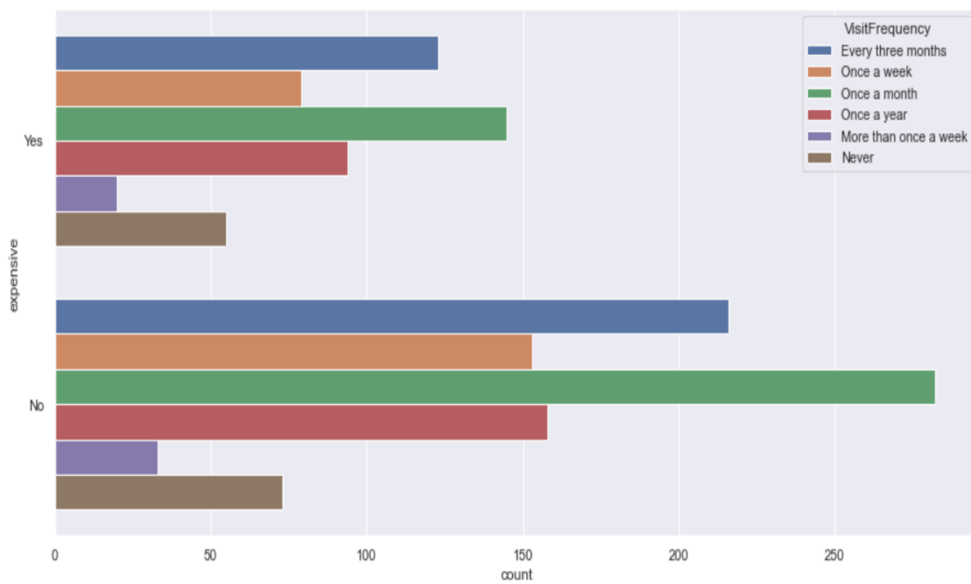
In [133]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="cheap", data=df , hue = 'VisitFrequency')
```



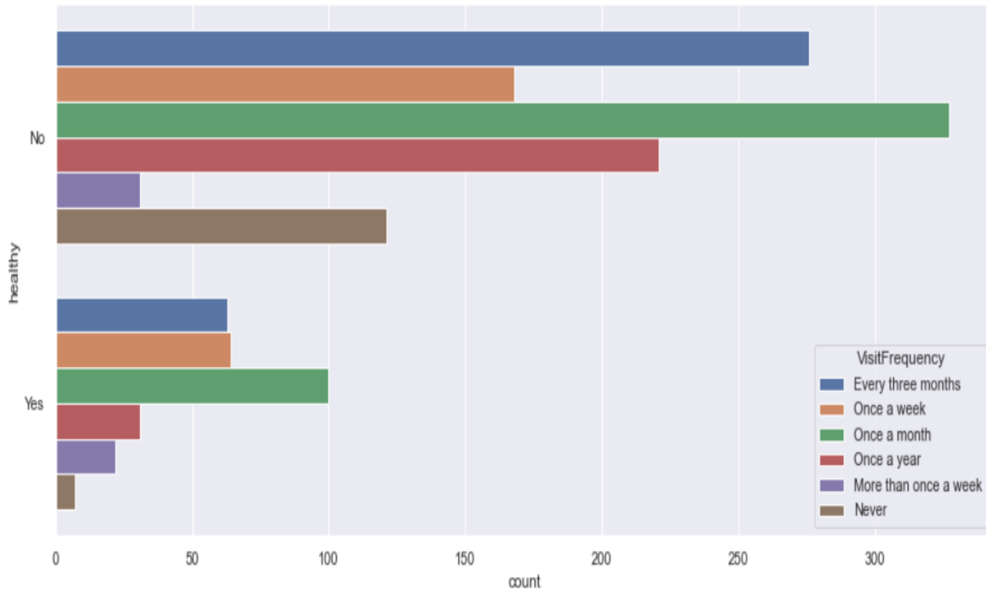
In [134]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="tasty", data=df, hue = 'VisitFrequency' )
```



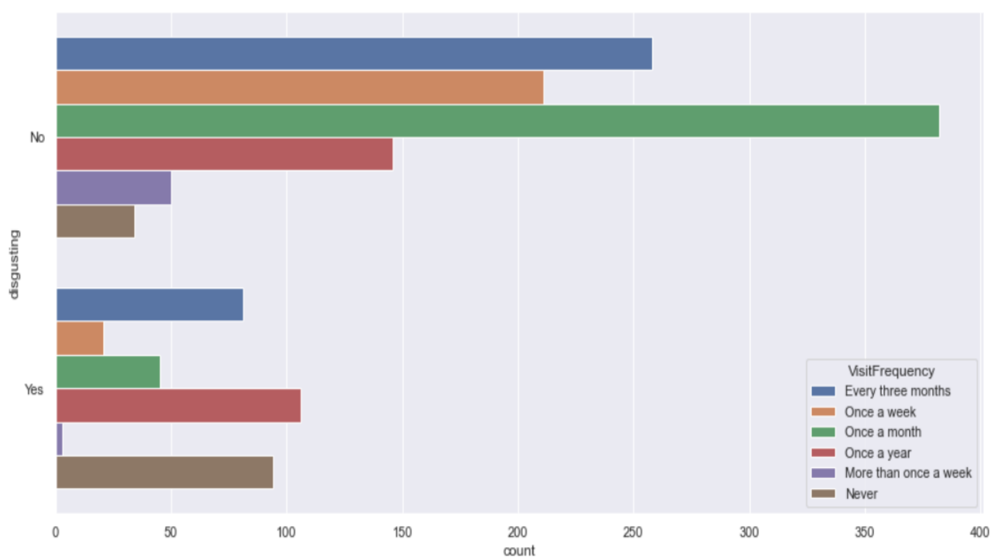
In [135]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="expensive", data=df , hue = 'VisitFrequency')
```



In [136]:
```
plt.figure(1 , figsize = (15 , 6))
sns.set(style="darkgrid")
ax = sns.countplot(y="healthy", data=df, hue = 'VisitFrequency')
```



In [137]:
```
plt.figure(1 , figsize = (15 , 7))
sns.set(style="darkgrid")
ax = sns.countplot(y="disgusting", data=df, hue = 'VisitFrequency' )
```



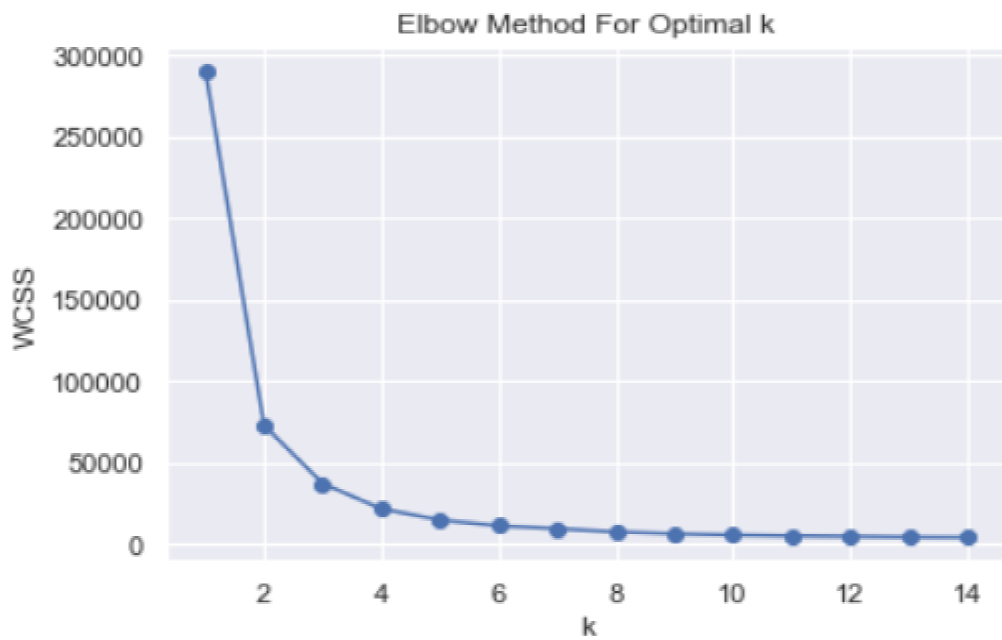
<u>Segmentation</u> :

Using K Means:

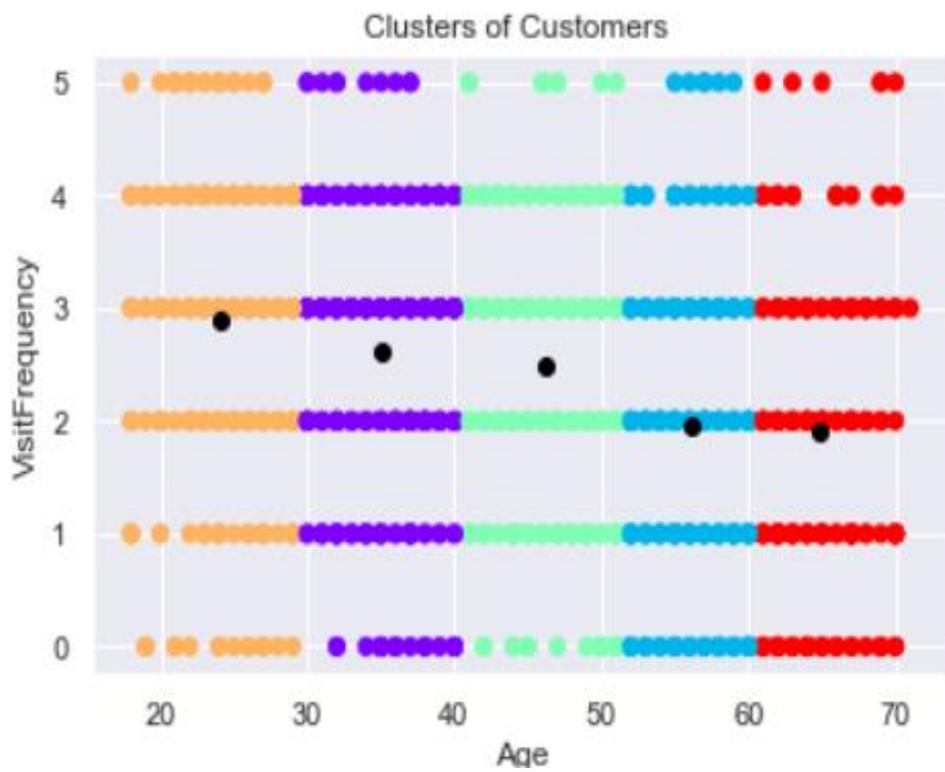
Age and Visit Frequency:

```
In [ ]: X1 = df.iloc[:, [12, 13]].values
        # selecting the columns number 12 ; Age and column number 13 ;
        # for our clustering.
```

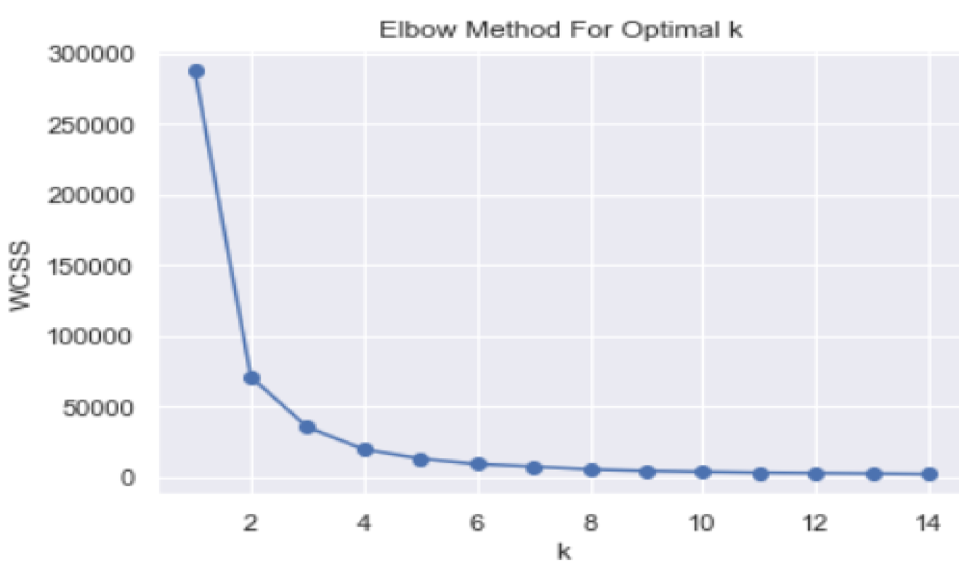
And we can use the Elbow method to find the optimum K value. For this our plot is something like this.

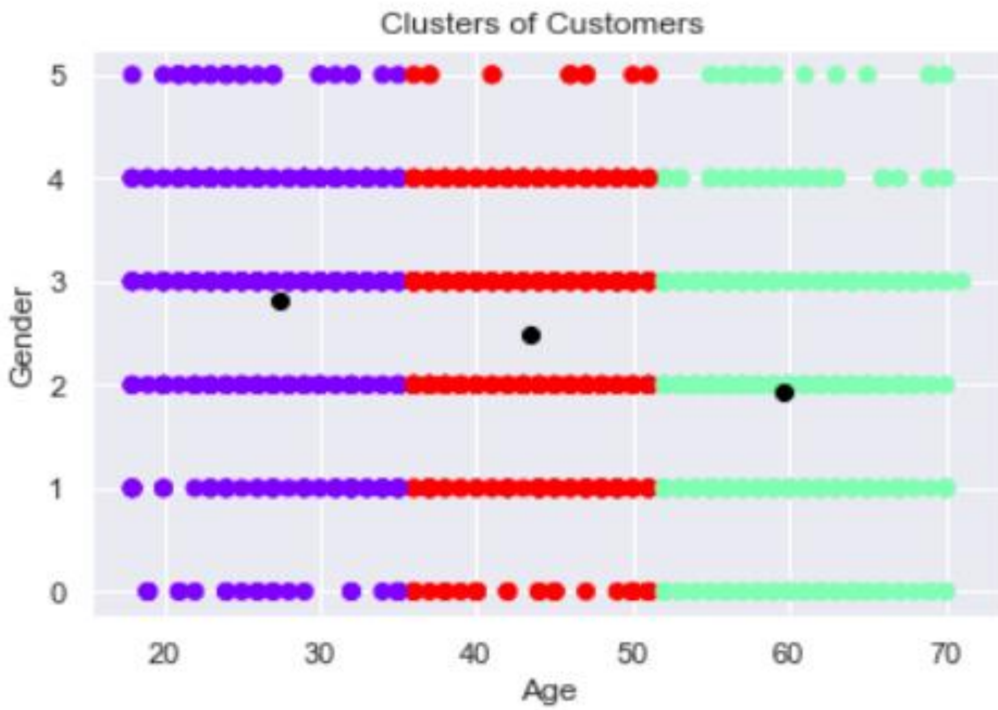


Here we can see that after the value of k is 5 the slope of the curve is increasing rapidly. So, we assume the optimal value of K is 5.



Age and Gender :

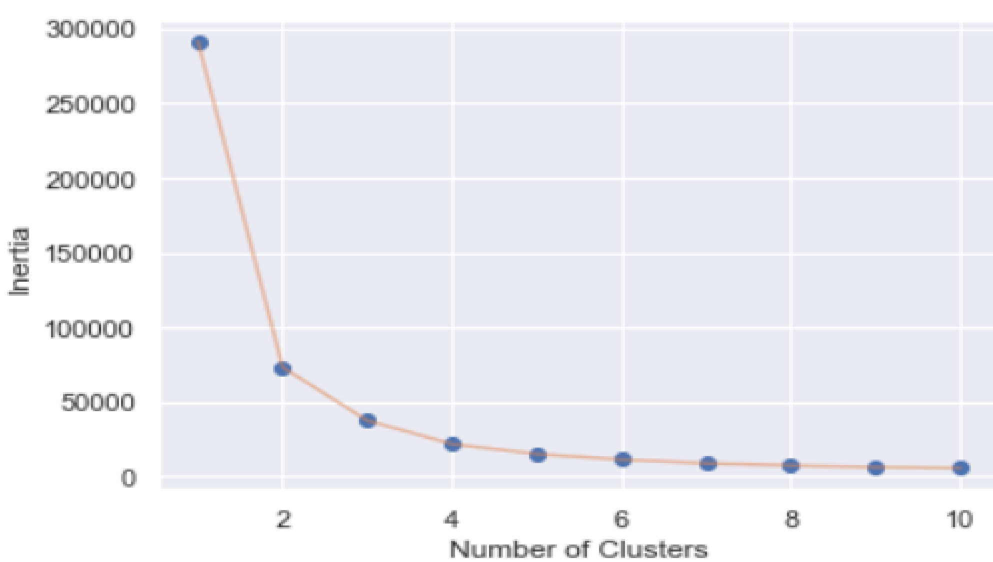


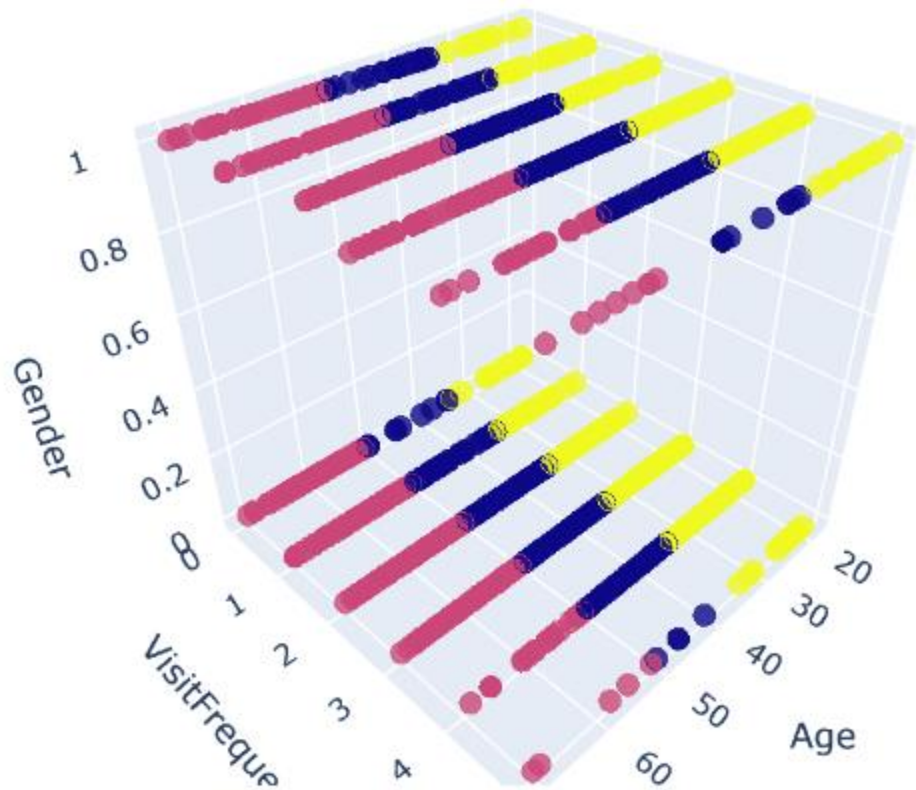


That helps a lot also.

Age, Gender and VisitFrequency :

Now considering 3 features we plot the elbow curve.





Here we can see 3 clusters based on **ages, Visit frequencies and Gender** .

Target segment :
So from the analysis we can see that the optimum customer base or the targeted customers should be of age bracket [20-37] with visit frequency once at a time in a month.

Code:

https://github.com/illiyas-sha/Feynn-Labs-Intern/blob/main/Task-1/Corvus_Task_1_Market_Segmentation_.ipynb

https://drive.google.com/file/d/1a9FLrDryr5bJom8KURMXnltGYgvcf4sJ/view?usp=sharing