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MGT7215: MARKETING ANALYTICS

ASSIGNMENT 2: PRODUCT DESIGN

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1.0 Introduction

Marketing researchers have done a lot of work to find and analyze the success of new product concepts before they are launched. This interest has been fueled most by consumer preference-based techniques such as conjoint analysis and multidimensional scaling (Kohli and Krishnamurti, 1987).

According to Kohli and Krishnamurti (1987), the proposed heuristic significantly outperforms a competing Lagrangian relaxation heuristic when simulating real problems in terms of processing time and best solution approximation. Laptops are designed in a way that can satisfy every desire of the consumers according to their defined set of preferences Shiau et al. (2007). Both laptop designers and users can benefit from a better understanding of these choices and preferences. Shiau et al. (2007)

This report aims to solve the challenge of designing a new laptop by identifying the right features of the product by analysing customers' preferences and deriving the value associated with each attribute to increasing profitability and market share using conjoint analysis and principal component analysis.

2.0 Methodology

Using a ranking survey dataset that includes 132 observations of customers who have ranked the 20 product profiles of the laptop and are planning to buy laptops. The 20 conjoint profiles contain attributes (Brand, Harddrive, RAM, Screensize and Price) with respective levels. The conjoint analysis was carried out to evaluate the relative importance of the attribute and the customer's utility for each level of the attribute. This was done using regression with dummy variables.

The independent variables are the rankings given by each respondent for a particular product profile and the dependent variables are the levels of each attribute which are incorporated using dummy variables. The 20 product profiles were checked for approval by calculating the correlation among attributes and levels.

Further baseline attributes were selected (Brand – Apple, Hard drive – 128, RAM – 2, Screensize – 12.1 and Price - 900) which have predefined values as 0 and these were not included in the regression. Using Tableau, the part worths of each level of the attributes were compared with baselines and ranges were calculated to obtain the relative importance between attributes and levels (Figures 1 and 2). Further, the willingness to pay by a customer was also calculated for each level and attribute to find the relative importance between attributes and levels (Figure 4). The utility scores were also calculated which were later used to calculate the market share using the maximum utility rule and the logit share of preference. The maximum utility rule determines the ratio of the number of customers with the highest utility product and the total number of customers that participated in the analysis and the logit share of preference rule determines a respondent's likelihood of selecting a given product configuration which is proportional to the utility of that configuration in comparison to utilities of all other configurations. These were later visualized using Tableau (Figure 5).

To obtain the perceptions of the attributes and levels of the selected 8 product profiles of laptops currently in the market, principal component analysis (PCA) was performed. PCA is used to transform the variables into a smaller set of variables called principal components which are extracted sequentially with the first principal component containing the most variance of data which is a normalized linear combination of features. The first principal component loading vector that defines the direction of the feature was calculated. Singular value decomposition that transforms correlated variables into a set of uncorrelated variables was also performed. The principal component scores are the projected values in this direction. These principal components and scores were later used to generate a perceptual map using Tableau. Further, the projection variance explained was also calculated to examine the strength of the two principal components.

3. 0 Results and Discussions

3.1 Product Profiles

According to Bradlow (2005), the product profiles should be selected in such a way that each profile contains a subset of the attributes. The 20 product profiles satisfy this condition. Figure 1 shows the selected 20-product profile.

(Wittink et. al, 1990 ; McCullough, 2002) states that a feature-rich product may have more total utility than a low-priced one simply because all the small utility weights of the various product features when summed, exceed the utility weight of the price attribute which can create a bias. (Wittink et. al, 1990; McCullough, 2002; Bradlow, 2005) state that the attribute level therefore should be smaller in nature ideally less than six. This condition is also satisfied by the selected product profiles. Figure 2 shows the calculated correlations between the attributes present in the 20 product profiles. The correlations satisfy the correlation conditions to be appropriate for carrying out conjoint analysis. They should be close to zero to avoid multicollinearity issues while performing regression.

According to Green and Srinivasan (1978), reducing the number of features to a reasonable amount that ensures the estimating techniques are accurate while also adequately accounting for customer preferences is the more challenging and frequently subjective task. The most suitable combination will likely vary depending on the type of product or market, the number of relevant features, the type of respondent, etc (Green and Srinivasan, 1978).

The conjoint analysis attempts to determine the product features and levels that most appeal to customers and capture the largest market share. By comparing the benefits produced by each attribute level and choosing the combination that gives the highest overall benefit, the best combination is found. It can be considered a good choice if the study results show that the synthesis of 20 product profiles generates a high level of overall utility and adequately represents the preferences of the target market (Kohli and Krishnamurti, 1989). It is crucial to remember that the best combination depends on a specific market and customer preferences, so testing a variety of combinations is recommended. A sensitivity analysis should also be performed to see how reliable the results are.

```
> design
   Profile    Hard   RAM Screen.Size   Price
1     Acer 512 GB  8 GB    17.3 in  $1,500
2    Apple 128 GB  2 GB     17.3 in $2,000
3     Dell 128 GB  8 GB     15.4 in $1,500
4   Lenovo 128 GB  2 GB     15.4 in $1,500
5     Acer 512 GB  4 GB     15.4 in $1,500
6     Dell 256 GB  8 GB     15.4 in $1,500
7   Lenovo 128 GB 16 GB     17.3 in $2,000
8    Apple 128 GB  4 GB     12.1 in $2,000
9     Dell 512 GB  4 GB     12.1 in $2,000
10    Dell 256 GB  4 GB     12.1 in $2,000
11    Acer 128 GB  8 GB     12.1 in $2,000
12    Acer 512 GB  2 GB     17.3 in $2,000
13   Apple 128 GB 16 GB    17.3 in  $1,200
14  Lenovo 128 GB 16 GB     15.4 in $2,000
15    Dell 512 GB  2 GB    17.3 in  $1,200
16    Dell 256 GB  4 GB     15.4 in $1,200
17  Lenovo 128 GB  8 GB     12.1 in $1,200
18  Lenovo 256 GB  8 GB     15.4 in $1,200
19   Apple 256 GB 16 GB     17.3 in $1,500
20    Acer 512 GB  2 GB     17.3 in $1,200
```

Figure 1: 20 Product Profiles

```
> print(cor(caEncodedDesign(design)))
                Profile       Hard         RAM Screen.Size      Price
Profile      1.00000000 -0.4382478 -0.04646616  -0.2806271 -0.1131734
Hard        -0.43824776  1.0000000  0.10317569   0.2858176 -0.1905429
RAM         -0.04646616  0.1031757  1.00000000  -0.4894689 -0.1249576
Screen.Size -0.28062709  0.2858176 -0.48946886   1.0000000 -0.3354075
Price       -0.11317343 -0.1905429 -0.12495756  -0.3354075  1.0000000
> 
```

Figure 2: Correlation between attributes

Using the conjoint analysis method, the part – worths or values of the attributes and levels were found and the relative importance of attributes and levels was also found (shown in Figure 3).

```
> part_worths
   intercept Apple Lenovo   Dell   Acer X128   X256   X512 X2     X4     X8    X16 X12.1  X15.4  X17.3 X900  X1200  X1500  X2000
1     20.953     0  0.270  6.325  6.909    0 -0.066 -5.202  0  0.589 12.470 10.977     0 -0.220 16.175    0 -7.856  0.370 -3.936
2     10.621     0 -3.465 -3.453 -3.517    0  1.103 -5.219  0 -1.030  3.047  8.750     0  2.120  7.258    0 -2.651 -3.248 -0.464
3      5.194     0 -3.063 -6.661 -6.124    0  2.338 -1.582  0 -1.108 -3.490  2.678     0  1.523 -2.507    0 -0.114 -4.080  0.850
4      9.958     0 -3.151 -0.369 -1.584    0 -1.598 -4.712  0  0.239  3.261  4.592     0  0.363  6.469    0 -8.070  4.276 -1.756
5      5.194     0 -3.063 -6.661 -6.124    0  2.338 -1.582  0 -1.108 -3.490  2.678     0  1.523 -2.507    0 -0.114 -4.080  0.850
6     22.286     0  1.021  6.688  7.880    0  0.526 -4.816  0  0.793 13.206 11.601     0  0.281 16.582    0 -7.263 -1.309 -4.018
7      6.174     0 -3.351 -6.067 -5.917    0  2.097 -2.509  0 -1.175 -2.318  4.017     0  1.637 -0.325    0 -0.952 -3.344  0.699
8     15.768     0 -1.298 -0.241 -0.129    0  0.851 -4.361  0 -1.350  5.827  9.204     0  2.140 10.204    0  3.899 -5.489  0.414
9      3.469     0 -3.113 -6.786 -6.581    0  1.708 -1.128  0 -1.087 -4.678  0.974     0  1.172 -4.548    0 -1.329 -2.760  0.657
10    13.522     0 -2.786 -0.785 -0.532    0  0.788 -5.976  0 -0.534  6.732 10.634     0  1.691 11.279    0 -5.460 -1.909 -1.772
11    14.443     0 -1.852 -2.047 -1.676    0  1.425 -4.139  0 -1.410  4.286  9.072     0  2.525  8.904    0  3.808 -5.383  1.009
12     2.819     0 -2.810 -7.232 -6.755    0  1.934 -0.309  0 -0.780 -5.788 -0.120     0  1.322 -6.230    0 -1.593 -2.625  0.831
13    14.821     0 -2.628 -0.325 -0.074    0  0.837 -6.153  0 -0.565  7.390 11.131     0  1.718 12.129    0 -5.093 -2.186 -1.799
14    11.302     0 -3.628 -0.910 -1.514    0 -0.492 -5.605  0  0.327  4.583  6.733     0  0.681  8.643    0 -7.472  2.654 -1.779
15     6.633     0 -3.624 -3.492 -3.928    0 -0.480 -3.264  0  0.347 -0.333  2.294     0  0.622  1.627    0 -7.263  3.368 -0.950
16    10.430     0 -2.349  0.080 -0.939    0 -1.529 -4.216  0  0.170  3.238  4.544     0  0.589  6.571    0 -8.473  4.292 -1.870
17    11.532     0 -3.129 -0.151 -0.952    0 -1.108 -5.134  0  0.381  4.548  6.147     0  0.573  8.452    0 -8.015  3.637 -1.855
18     5.370     0 -2.820 -6.939 -6.229    0  2.410 -1.132  0 -1.416 -3.812  2.708     0  1.591 -2.798    0  1.085 -4.419  1.288
19    10.621     0 -3.465 -3.453 -3.517    0  1.103 -5.219  0 -1.030  3.047  8.750     0  2.120  7.258    0 -2.651 -3.248 -0.464
20    11.452     0 -2.338 -4.238 -3.484    0  1.653 -3.431  0 -1.727  2.029  7.718     0  2.594  5.454    0  3.724 -6.094  1.182
21    14.189     0 -2.589 -1.682 -0.941    0  1.407 -5.592  0 -0.623  5.983 10.911     0  2.065 10.161    0 -1.747 -3.879 -0.530
22     4.302     0 -3.427 -6.099 -6.199    0  1.327 -2.023  0 -0.991 -3.407  2.163     0  1.146 -2.422    0 -2.328 -2.343  0.213
23    13.820     0 -2.732 -0.970 -0.882    0  1.069 -6.040  0 -0.859  6.533 10.934     0  1.972 11.392    0 -3.138 -3.269 -1.186
24    11.532     0 -3.129 -0.151 -0.952    0 -1.108 -5.134  0  0.381  4.548  6.147     0  0.573  8.452    0 -8.015  3.637 -1.855
25    14.048     0 -1.084 -2.116 -1.460    0  1.352 -3.332  0 -1.378  3.536  7.994     0  2.910  7.037    0  5.147 -5.803  1.466

26    13.635     0 -1.245 -2.032 -1.776    0  1.414 -3.175  0 -1.710  3.041  7.321     0  2.394  6.492    0  5.486 -5.714  1.497
27     9.958     0 -3.151 -0.369 -1.584    0 -1.598 -4.712  0  0.239  3.261  4.592     0  0.363  6.469    0 -8.070  4.276 -1.756
28     8.303     0 -3.721 -2.325 -3.165    0 -1.008 -4.380  0 -0.061  1.658  4.215     0  0.485  4.669    0 -7.060  3.509 -1.185
29    12.161     0 -1.826 -3.746 -3.148    0  1.848 -2.921  0 -1.607  1.600  7.039     0  2.639  5.136    0  5.233 -5.928  1.799
30    14.443     0 -1.852 -2.047 -1.676    0  1.425 -4.139  0 -1.410  4.286  9.072     0  2.525  8.904    0  3.808 -5.383  1.009
31    13.611     0 -1.538 -2.735 -2.059    0  1.806 -3.243  0 -1.506  3.014  7.883     0  2.551  6.778    0  4.806 -5.801  1.451
32    10.623     0 -3.362 -2.808 -2.710    0  0.872 -5.332  0 -0.735  3.904  8.948     0  1.866  7.995    0 -4.605 -2.163 -1.077
33    13.635     0 -1.245 -2.032 -1.776    0  1.414 -3.175  0 -1.710  3.041  7.321     0  2.394  6.492    0  5.486 -5.714  1.497
34     7.854     0 -3.137 -1.827 -2.848    0 -1.330 -3.572  0  0.443  0.735  2.654     0  0.600  3.144    0 -7.906  4.285 -1.233
35     8.303     0 -3.721 -2.325 -3.165    0 -1.008 -4.380  0 -0.061  1.658  4.215     0  0.485  4.669    0 -7.060  3.509 -1.185
36    14.443     0 -1.852 -2.047 -1.676    0  1.425 -4.139  0 -1.410  4.286  9.072     0  2.525  8.904    0  3.808 -5.383  1.009
37    20.966     0  0.532  6.687  7.318    0  0.077 -5.147  0  0.527 12.536 11.589     0  0.491 17.075    0 -7.689 -1.065 -3.888
38    12.161     0 -1.826 -3.746 -3.148    0  1.848 -2.921  0 -1.607  1.600  7.039     0  2.639  5.136    0  5.233 -5.928  1.799
39    14.443     0 -1.852 -2.047 -1.676    0  1.425 -4.139  0 -1.410  4.286  9.072     0  2.525  8.904    0  3.808 -5.383  1.009
40    12.606     0 -1.793 -3.444 -2.639    0  1.718 -3.221  0 -1.622  2.525  7.481     0  2.597  6.101    0  5.241 -5.664  1.308
41    13.223     0 -2.943 -1.244 -0.989    0  0.739 -5.799  0 -0.502  6.076 10.138     0  1.664 10.430    0 -5.827 -1.633 -1.745
42     8.508     0 -3.439 -1.380 -2.673    0 -1.556 -4.390  0  0.137  1.846  3.749     0  0.451  4.827    0 -7.643  4.149 -1.408
43    12.219     0 -3.151 -2.534 -2.603    0  1.202 -5.573  0 -1.093  4.362  9.743     0  2.173  8.957    0 -1.917 -3.801 -0.519
44    11.532     0 -3.129 -0.151 -0.952    0 -1.108 -5.134  0  0.381  4.548  6.147     0  0.573  8.452    0 -8.015  3.637 -1.855
45    20.234     0 -0.535  4.564  5.267    0  0.289 -5.854  0 -0.019 12.038 12.649     0  0.415 16.665    0 -6.196 -1.774 -3.433
46    22.286     0  1.021  6.688  7.880    0  0.526 -4.816  0  0.793 13.206 11.601     0  0.281 16.582    0 -7.263 -1.309 -4.018
47    20.869     0 -0.172  5.798  6.258    0  0.003 -5.886  0  0.380 12.759 12.197     0  0.280 17.105    0 -7.145 -1.282 -3.942
48     4.302     0 -3.427 -6.099 -6.199    0  1.327 -2.023  0 -0.991 -3.407  2.163     0  1.146 -2.422    0 -2.328 -2.343  0.213
49    13.735     0 -2.363 -2.538 -2.011    0  1.229 -4.649  0 -1.530  4.715  9.751     0  2.481  9.222    0  2.298 -5.549  0.392
50    22.286     0  1.021  6.688  7.880    0  0.526 -4.816  0  0.793 13.206 11.601     0  0.281 16.582    0 -7.263 -1.309 -4.018
51    13.670     0 -2.863 -1.523 -1.514    0  1.160 -5.894  0 -0.991  5.776 10.587     0  2.086 10.599    0 -2.343 -3.673 -0.866
52    11.216     0 -2.443 -4.220 -3.889    0  1.525 -3.385  0 -1.850  1.396  7.141     0  2.437  5.120    0  4.763 -5.511  1.678
 [ reached 'max' / getOption("max.print") -- omitted 80 rows ]
```

Figure 3: Part- Worths of attributes and levels

The willingness to pay obtained further demonstrates the relative importance of the attributes and the levels. Using the dummy variable coefficients resulting from regression, a comparison was done with the set baseline levels and interpreted as discussed in the following paragraphs.

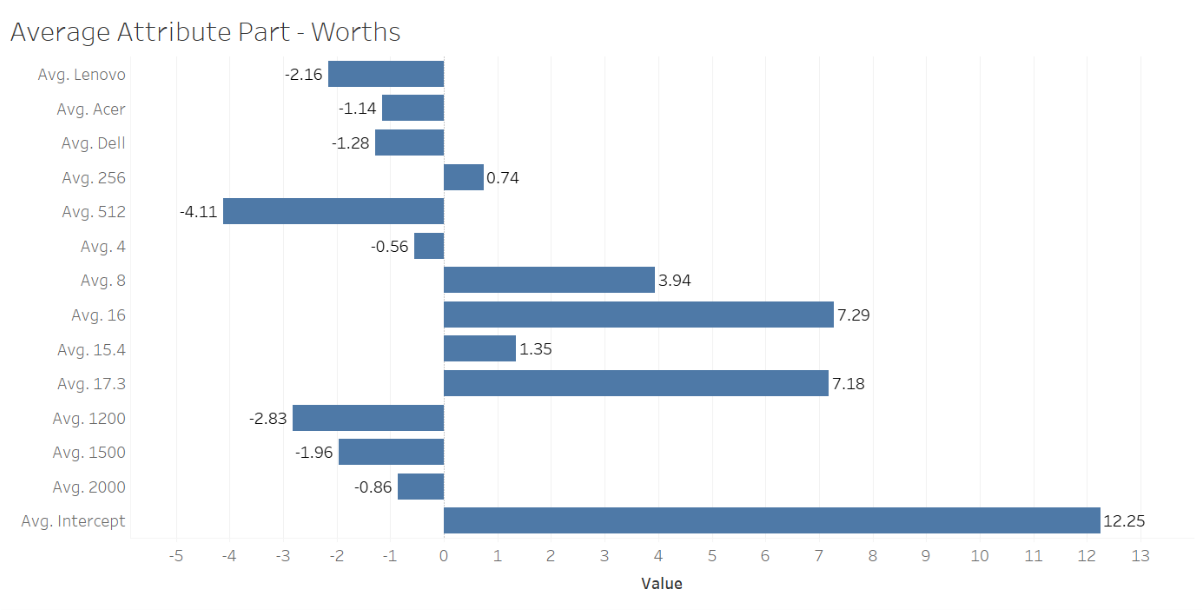

Figure 4: Average Attribute Part–Worths

Figure 4 shows the average value or part worths of the attributes of the laptop. Following the comparison of attributes with the baseline attributes (Apple, 128, 2, 12.1 and 900), it was found that Apple has the highest preference followed by Acer, Dell and Lenovo. In terms of RAM, 16 GB is most valued followed by 8. 4 GB is the least preferred. For screens, 17.3 is the most valued followed by 15.4 and 12.1. In terms of price, 900 is the most valued followed by 2000, 1500 and 1200 by the consumers.

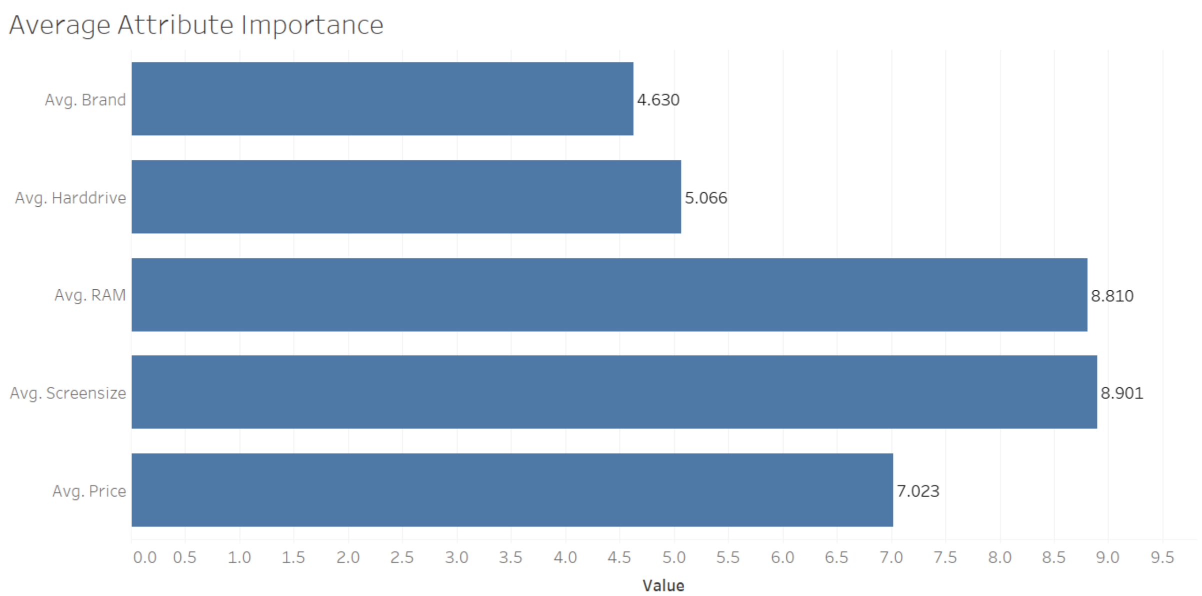

Figure 5: Average Attribute Importance

Figure 5 shows the average importance given by customers to each attribute. Here, the highest importance is given to Screensize (8.901) and the least importance to Brand(4.630). The distribution of percentages of the importance of attributes is shown in Figure 6.

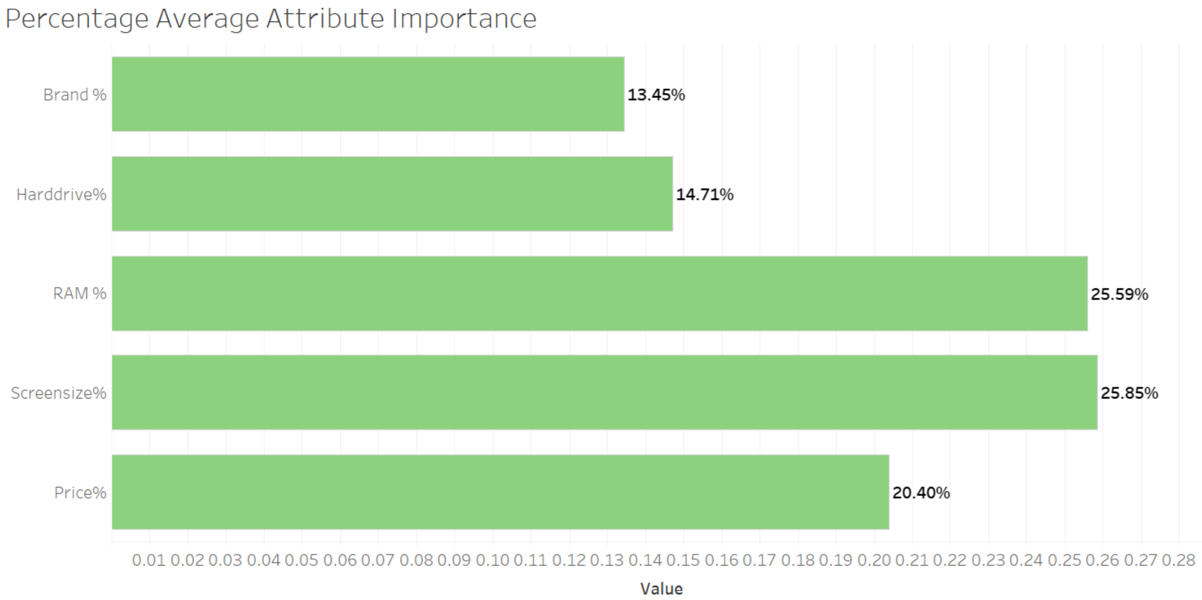

Figure 6: Percentages of Attribute Importance

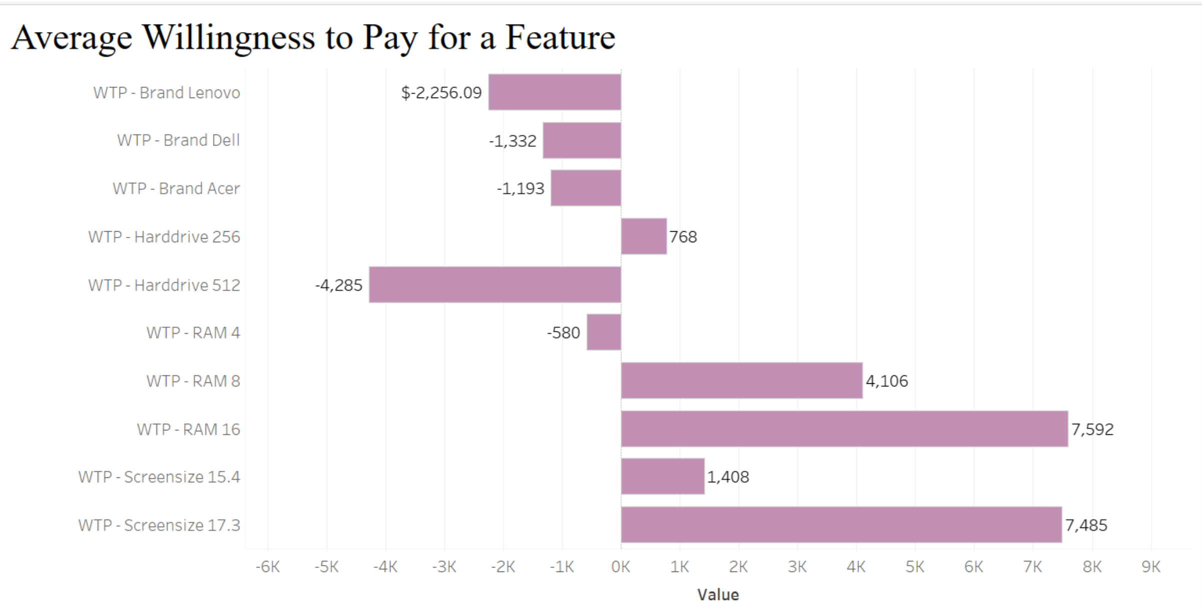

Figure 7: Average Willingness to pay for attributes

Figure 7 shows the average willingness to pay a customer for various attributes of the laptop. According to the distribution, the customer is highly likely to pay for Apple followed by Dell, Acer and Lenovo. For hard drives, 256 GB is the most preferred followed by 128 GB and the least preferred is 512 GB. For RAM, 16 GB RAM is the most preferred followed by 8, 4 and 2 GB. The screen size 17.3 in is the most preferred followed by 15.4 and 12.1 in.

3.2 Distribution of Market Share

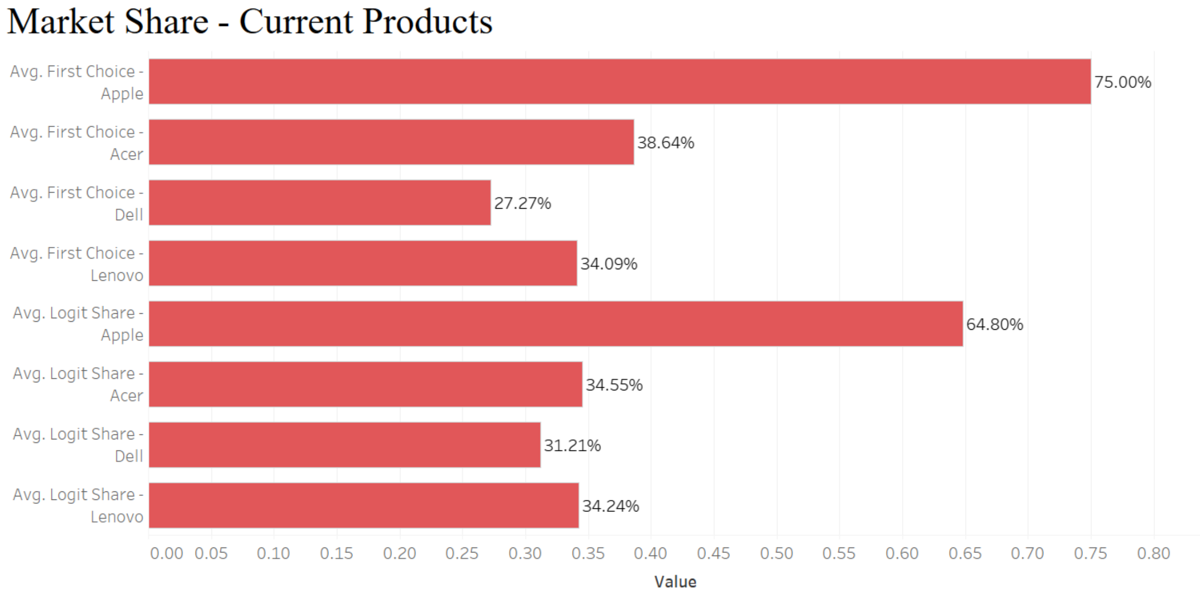

Figure 8: Market Share for current products

Figure 5 shows that the most preferred brand is Apple with a 75 % market share calculated using the maximum utility rule and 64.80% using Logit share. Acer has a slightly higher market share than Lenovo and the least market share is of Dell.

3.3 Perceptual Maps

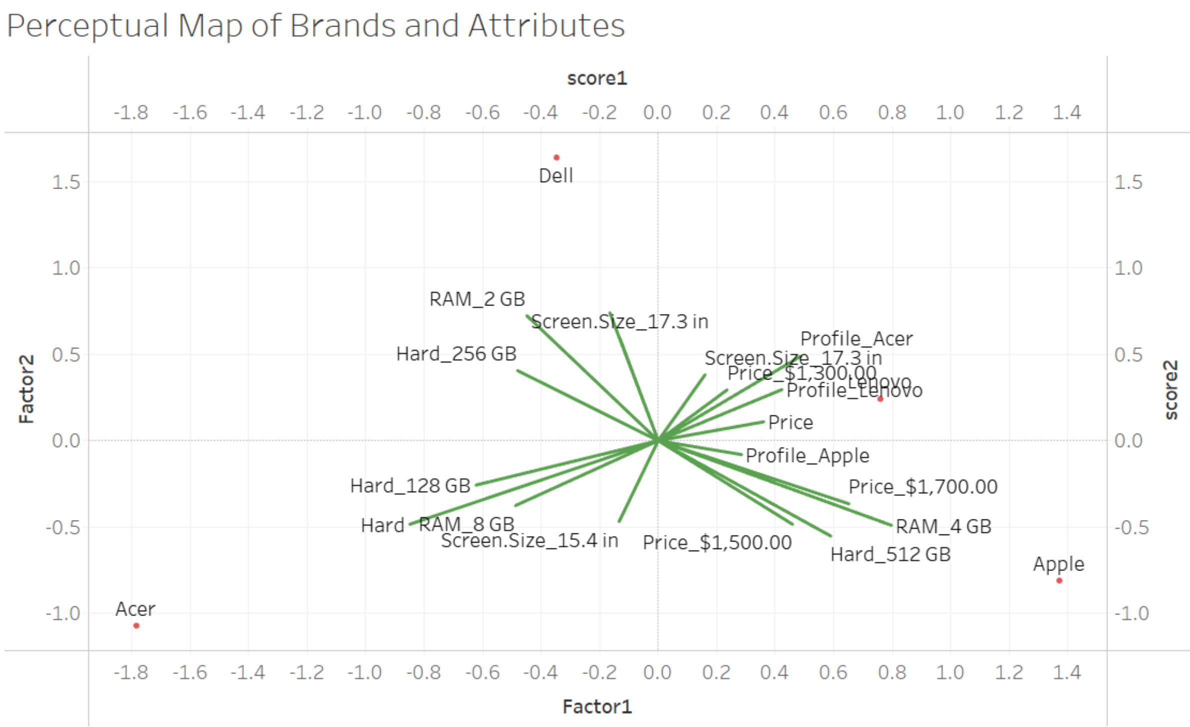

Figure 6: Perceptual Map

Figure 6 shows the perceptual map created using PCA to determine the positioning of the attributes and the brands of the laptop in the market. Factor 1 and Factor 2 are the principal components 1 and 2 respectively. From Figure 6, it can be seen that Apple has performed well in terms of price, hard drives and 4 GB RAM but has performed poorly in screen sizes. However, Acer and Dell perform poorly in terms of the level of prices and perform fairly well in hard drives, screen size and RAMs. Lenovo has performed well in both prices and screen sizes**.**

3.4 Conjoint Analysis in Market Segmentation

The notion of segmentation can be implemented in different ways, mainly depending on the type of segmentation basis used (Vriensf, 1994). Conjoint methods have been used in several practical marketing research studies since they were first introduced (Rao, 2010). The responsiveness condition is undoubtedly met when segments are created using Partworth utilities (Vriensf, 1994).

Conjoint analysis has been used in the transportation sector. According to Silver (2018), using detailed profiles of service offerings, this technique allows respondents to identify their preferences. The next step examines how the sample population can be partitioned into homogeneous subsets that roughly correspond to market categories (Silver, 2018).

According to Vriensf (1994), some underlying criteria should be followed for performing target segmentation. These include substantiality, accessibility and actionability. The use of benefits beats alternative segmentation bases, as evidenced by the literature, as this foundation is the only one that can meet all of the aforementioned requirements (Wedel, 1990). Conjoint analysis is the most popular method for operationalizing the idea of benefits Vriensf (1994). These benefit segments are formulated in stages that include calculating part – worths and then the segments are created using a clustering algorithm based on the similarity of benefits (Vriensf, 1994). Lopes et. al (2009) state that as conjoint analysis allows researchers to understand the structure of consumer preferences, and cluster analysis allows these customers to be classified according to their preferences, these two together can be very beneficial. Consequently, they further state that segmenting markets based on consumer preferences allows researchers and industry professionals to more accurately assess actual preferences and develop marketing strategies that better match consumers' interests showing enormous potential in the tourism market.

Green and Krieger (1991) state that recent developments such as user-friendly software packages and developments in product line positioning algorithms also pave the way to performing conjoint analysis in market segmentation. However, there are some limitations involved such as errors subject to the parameter estimations. According to Cattin and Wittink (1982), there are difficulties in the interpretation of brand and prices in the conjoint analysis as several other attributes can cover various aspects of the brand name while price can be seen as a product quality indicator which makes it controversial.

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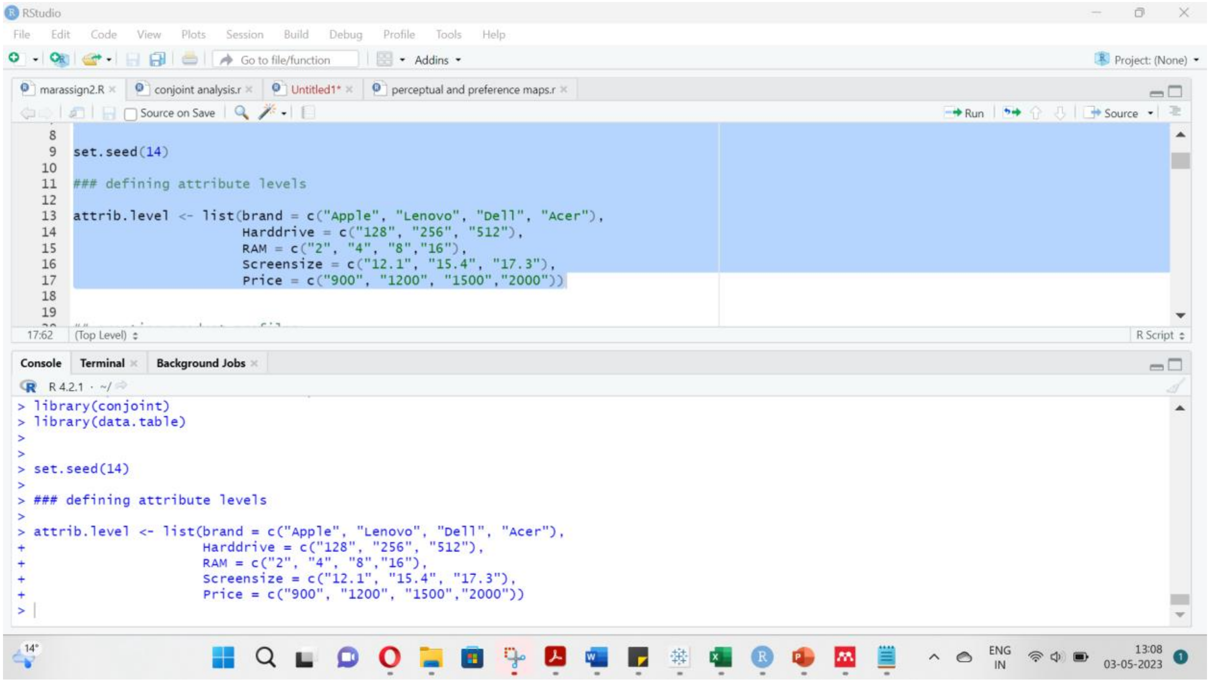
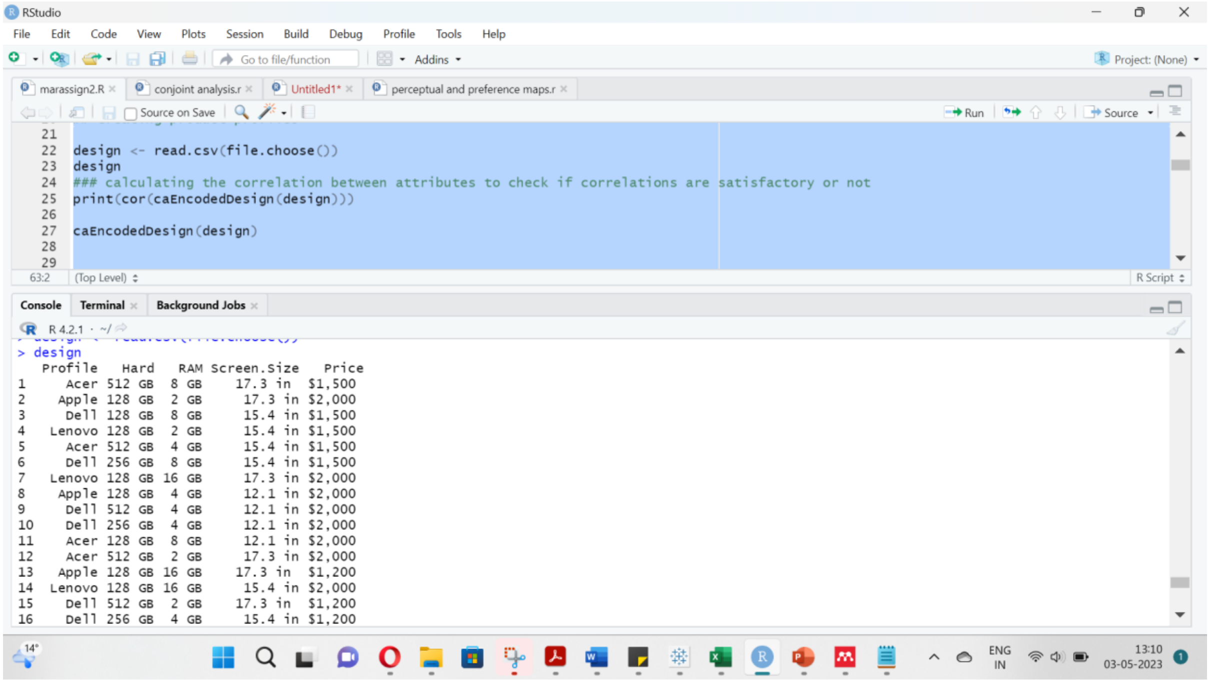
5.0 Appendix – R Code

```
## installing and importing packages

install.packages("conjoint")
install.packages("data.table")
library(conjoint)
library(data.table)


set.seed(14)

### defining attribute levels

attrib.level <- list(brand = c("Apple", "Lenovo", "Dell", "Acer"),
                     Harddrive = c("128", "256", "512"),
                     RAM = c("2", "4", "8","16"),
                     Screensize = c("12.1", "15.4", "17.3"),
                     Price = c("900", "1200", "1500","2000"))
```

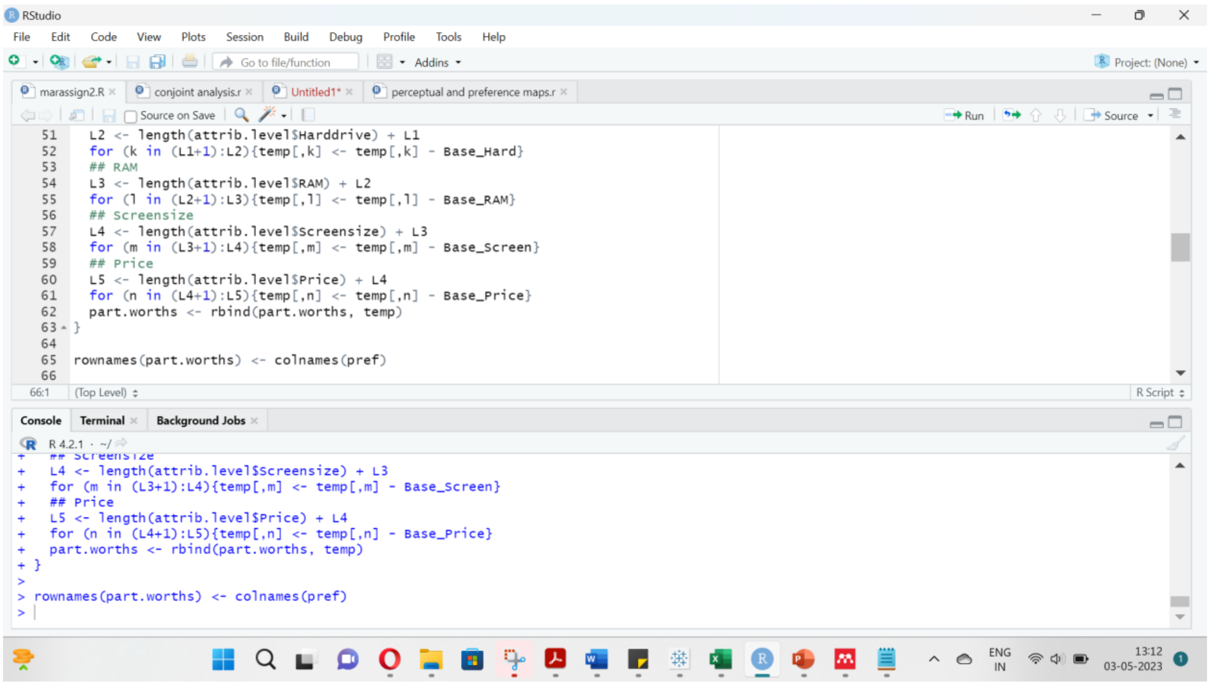



```
## creating product profiles


design <- read.csv(file.choose())

design

### calculating the correlation between attributes to check if correlations are satisfactory or not

print(cor(caEncodedDesign(design)))


caEncodedDesign(design)




### Importing customer rankings

pref <- read.csv(file.choose())


### creating a column vector containing all attribute levels

attrib.vector <- data.frame(unlist(attrib.level,use.names=FALSE))

colnames(attrib.vector) <- c("levels")

part.worths <- NULL
```




```
for (i in 1:ncol(pref)){
 temp <- caPartUtilities(pref[,i], design, attrib.vector)
 ## Pick the baseline case
 Base_Brand <- temp[,"Apple"]; Base_Hard <- temp[,"128"]; Base_RAM <- temp[,"2"];
 Base_Screen <- temp[,"12.1"]; Base_Price <- temp[,"900"]
 ## Adjust Intercept
 temp[,"intercept"] <- temp[,"intercept"] - Base_Brand - Base_Hard - Base_RAM -
   Base_Screen - Base_Price
 ## Adjust Coefficients
 ## Brand
 L1 <- length(attrib.level$brand) + 1 ## Add 1 for the intercept
 for (j in 2:L1){temp[,j] <- temp[,j] - Base_Brand}
 ## Harddrive
 L2 <- length(attrib.level$Harddrive) + L1
 for (k in (L1+1):L2){temp[,k] <- temp[,k] - Base_Hard}
 ## RAM
 L3 <- length(attrib.level$RAM) + L2
```

```
  for (l in (L2+1):L3){temp[,l] <- temp[,l] - Base_RAM}
  ## Screensize
  L4 <- length(attrib.level$Screensize) + L3
  for (m in (L3+1):L4){temp[,m] <- temp[,m] - Base_Screen}
  ## Price
  L5 <- length(attrib.level$Price) + L4
  for (n in (L4+1):L5){temp[,n] <- temp[,n] - Base_Price}
  part.worths <- rbind(part.worths, temp)
}

rownames(part.worths) <- colnames(pref)
```




```
##Export part-worths from analysis
write.csv(part.worths, file.choose(new=TRUE), row.names = FALSE)

summary(part_worths)
```

Principal Component Analysis and Perceptual Maps

Load Packages and Set Seed

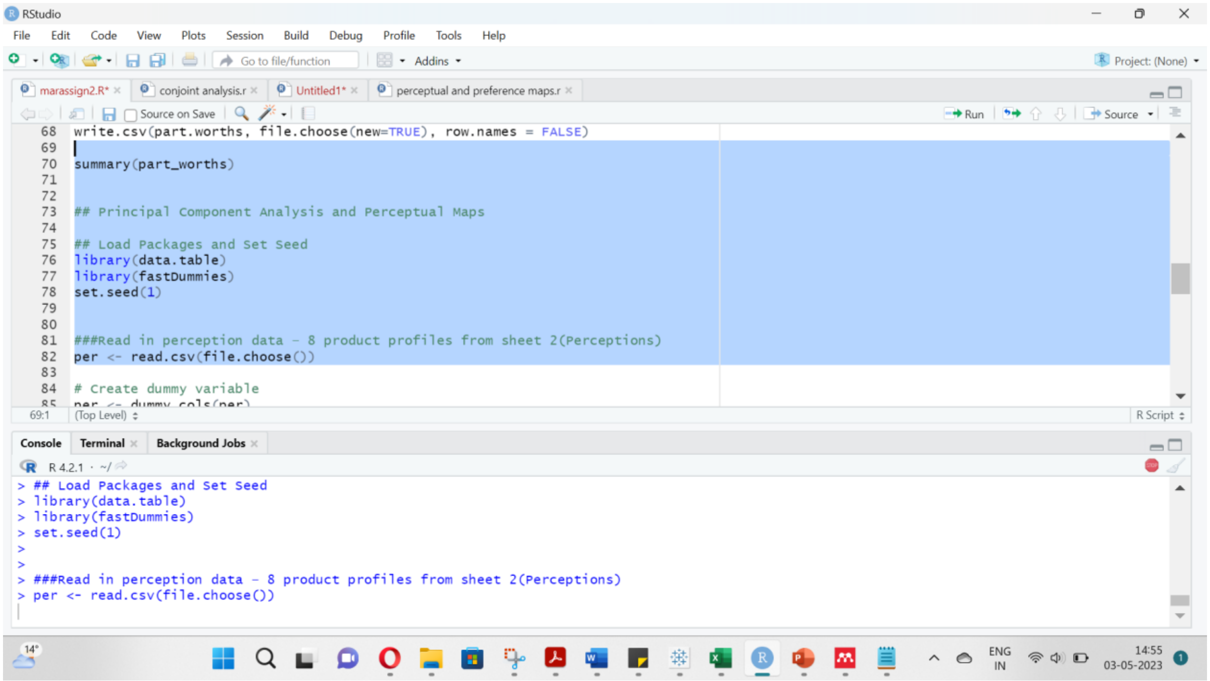
library(data.table)

library(fastDummies)

set.seed(1)

Read in perception data – 8 product profiles from sheet 2(Perceptions)

per <- read.csv(file.choose()) ## Choose perceptions.csv file



Create dummy variable

per <- dummy_cols(per)

per

Run Principle Components Analysis on Perceptions

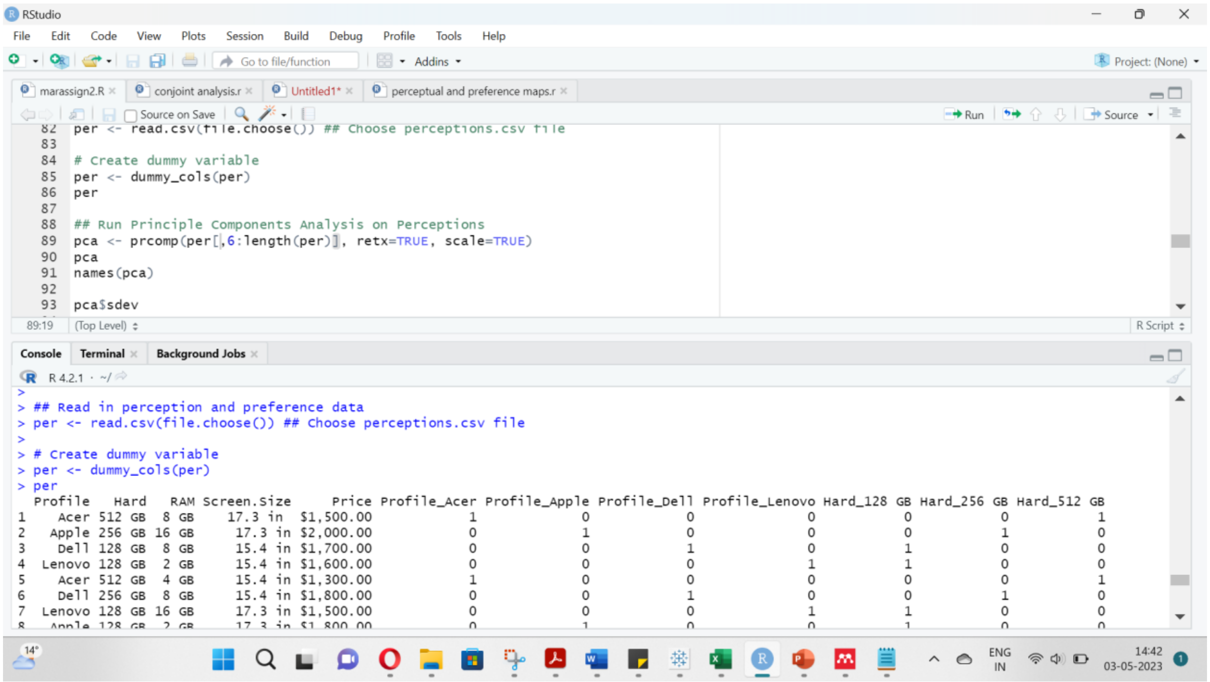
pca <- prcomp(per[,6:length(per)], retx=TRUE, scale=TRUE) pca

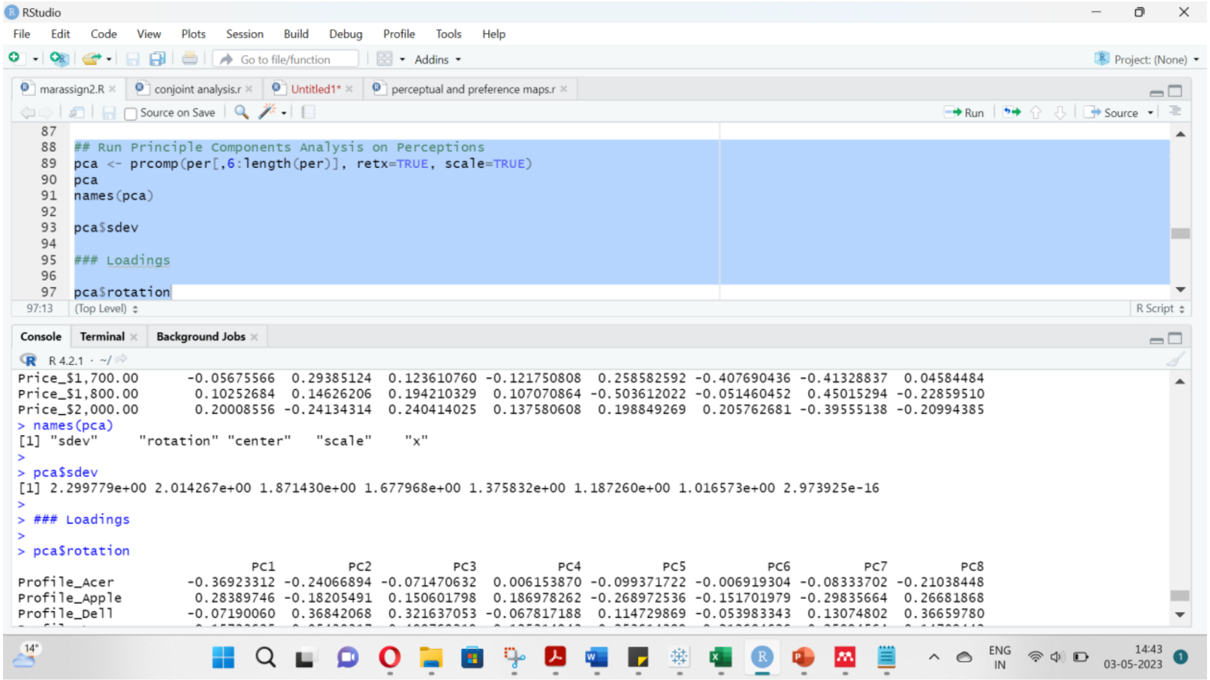
names(pca)

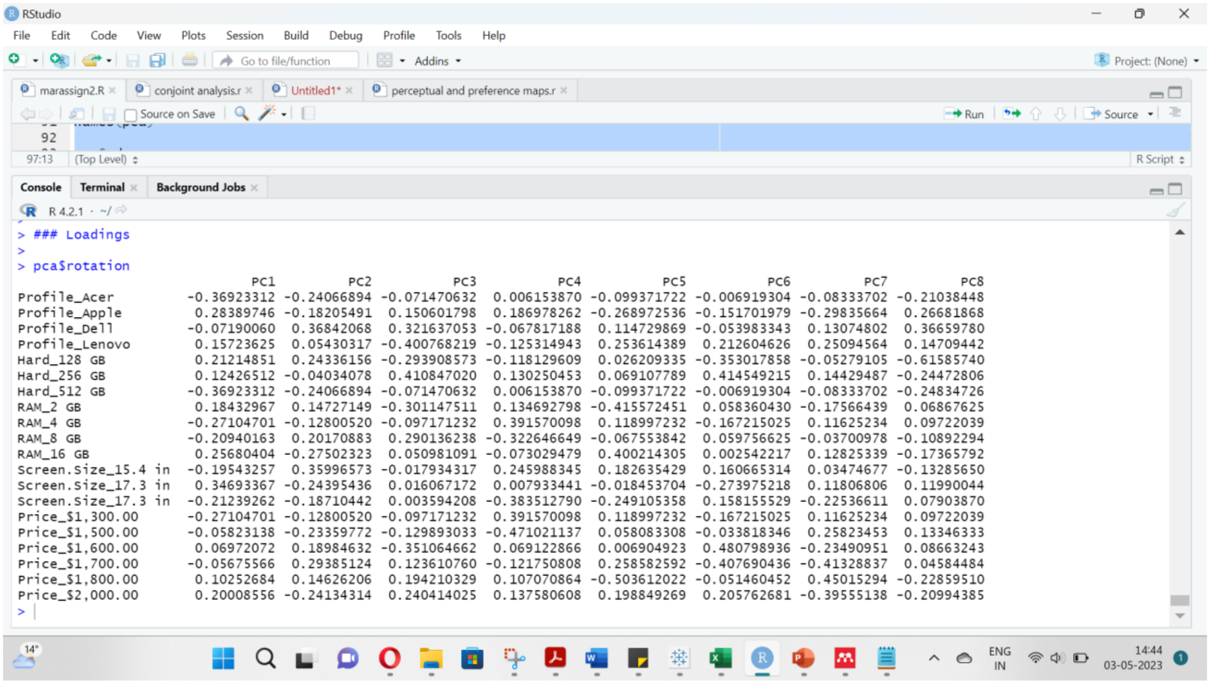
pca$sdev

Loadings

pca$rotation







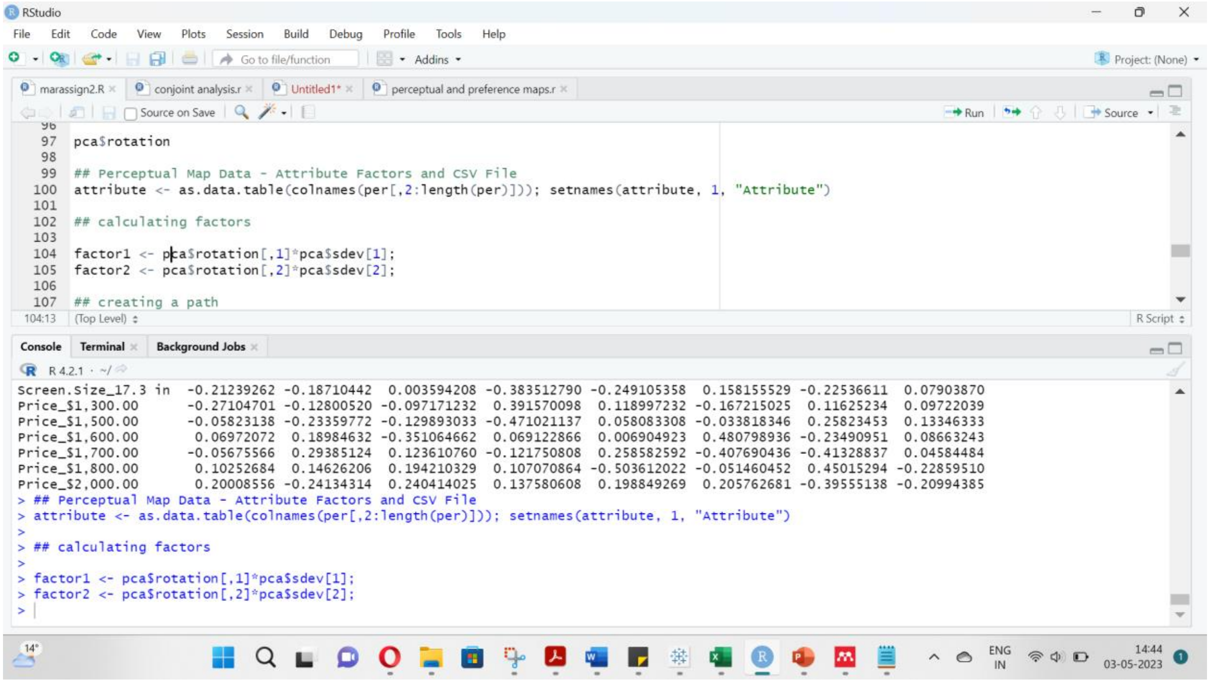
Perceptual Map Data - Attribute Factors and CSV File

attribute <- as.data.table(colnames(per[,2:length(per)])); setnames(attribute, 1, "Attribute")

calculating factors

factor1 <- pca$rotation[,1]*pca$sdev[1];

factor2 <- pca$rotation[,2]*pca$sdev[2];



creating a path

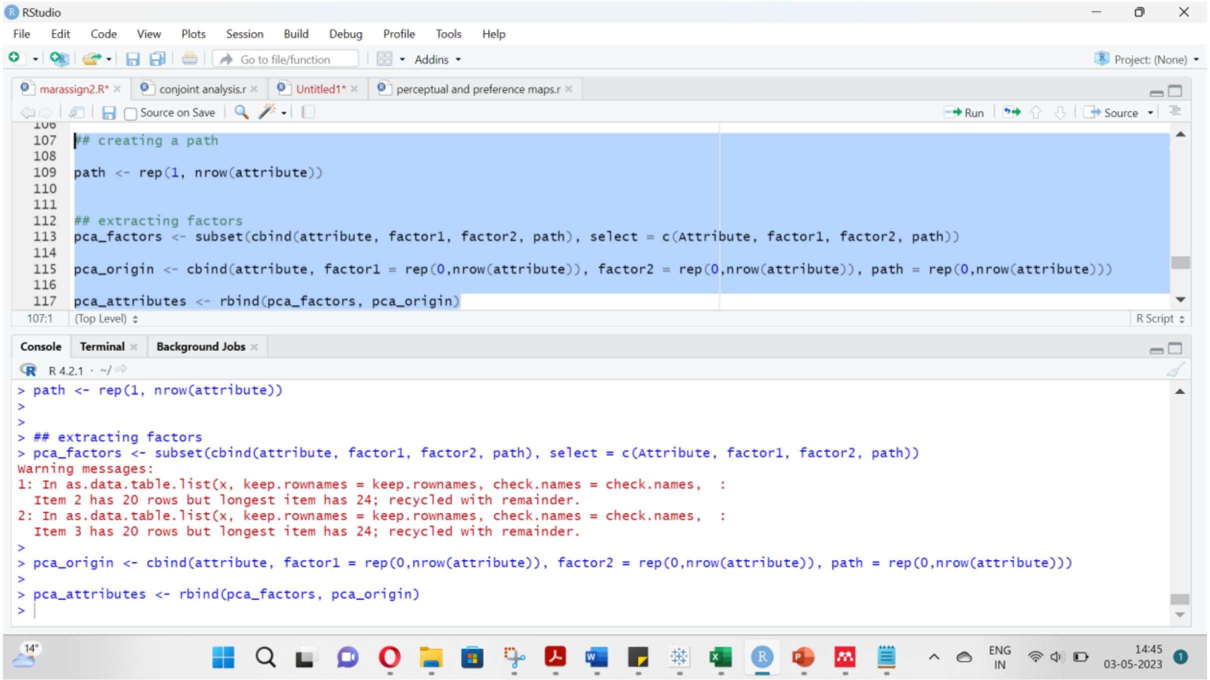
path <- rep(1, nrow(attribute))

extracting factors

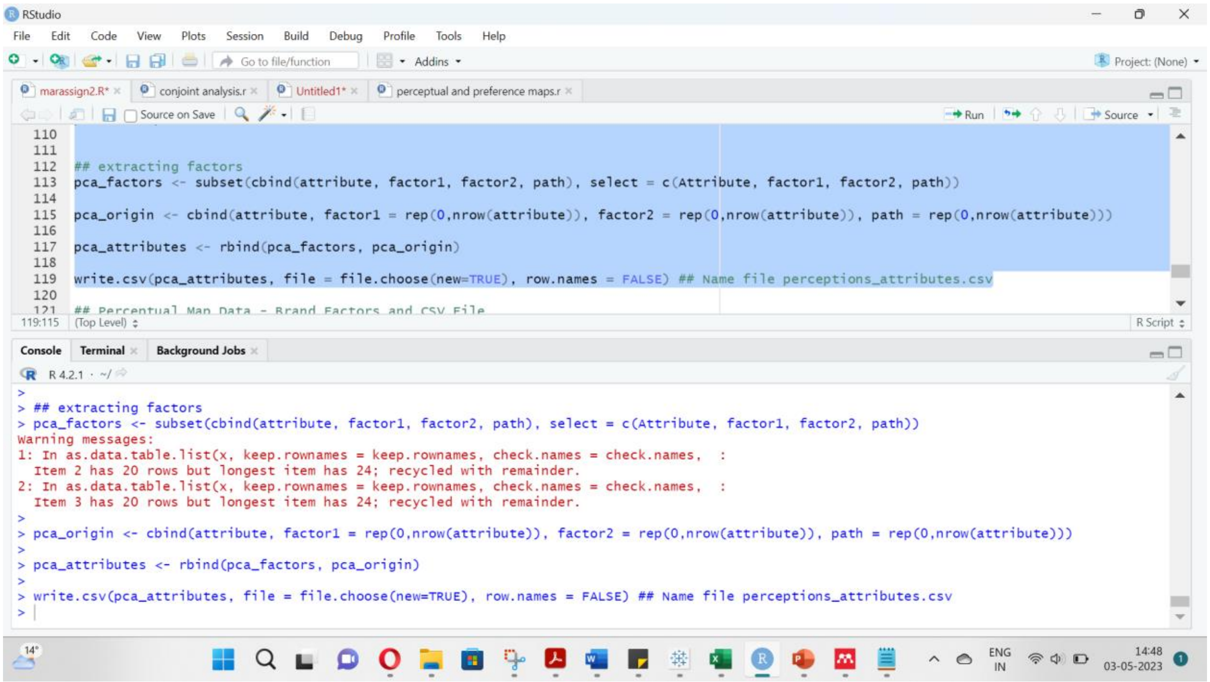
pca_factors <- subset(cbind(attribute, factor1, factor2, path), select = c(Attribute, factor1, factor2, path))

pca_origin <- cbind(attribute, factor1 = rep(0,nrow(attribute)), factor2 = rep(0,nrow(attribute)), path = rep(0,nrow(attribute)))

pca_attributes <- rbind(pca_factors, pca_origin)



write.csv(pca_attributes, file = file.choose(new=TRUE), row.names = FALSE) ## Name file perceptions_attributes.csv



Perceptual Map Data - Brand Factors and CSV File

score1 <- (pca$x[,1]/apply(abs(pca$x),2,max)[1])

score2 <- (pca$x[,2]/apply(abs(pca$x),2,max)[2]) pca_scores <- subset(cbind(per, score1, score2), select = c(Profile, score1, score2))

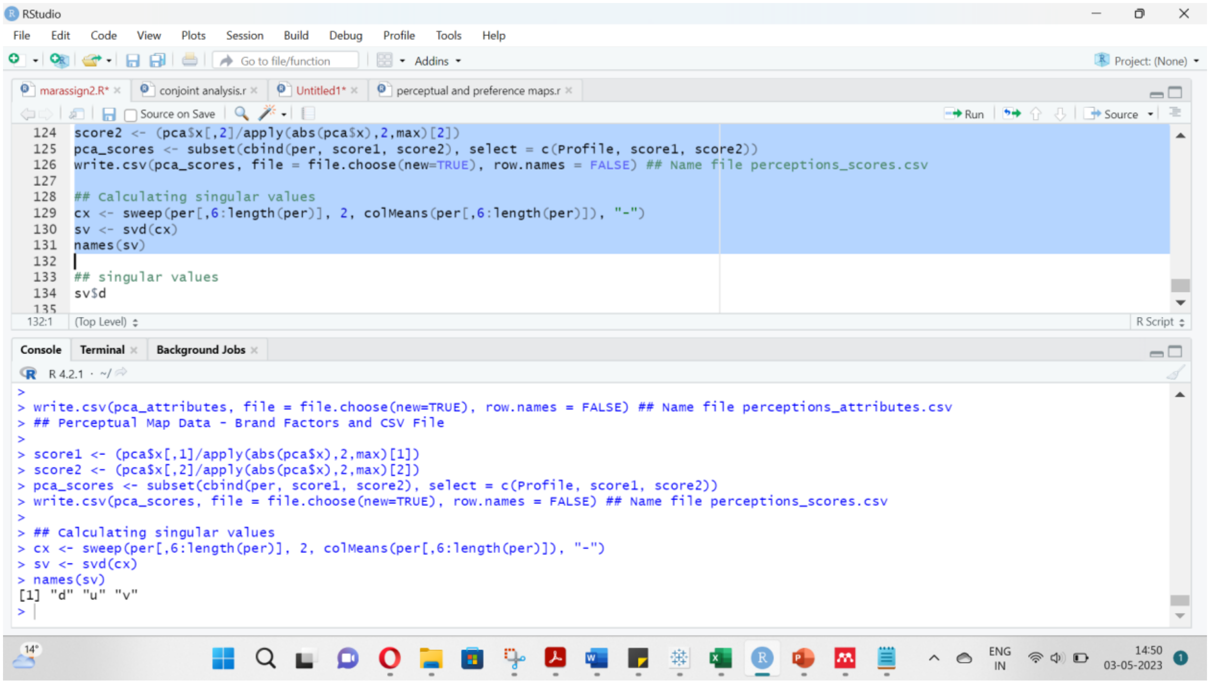
write.csv(pca_scores, file = file.choose(new=TRUE), row.names = FALSE) ## Name file perceptions_scores.csv

Calculating singular values

cx <- sweep(per[,6:length(per)], 2, colMeans(per[,6:length(per)]), "-")

sv <- svd(cx)

names(sv)

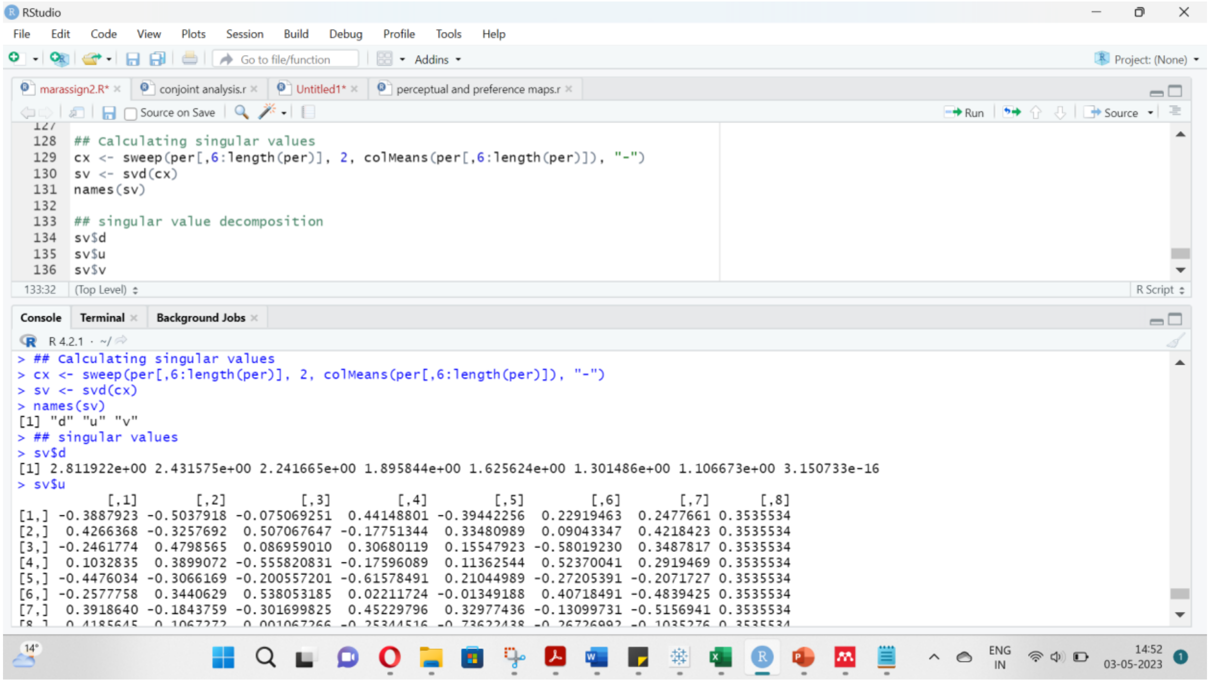


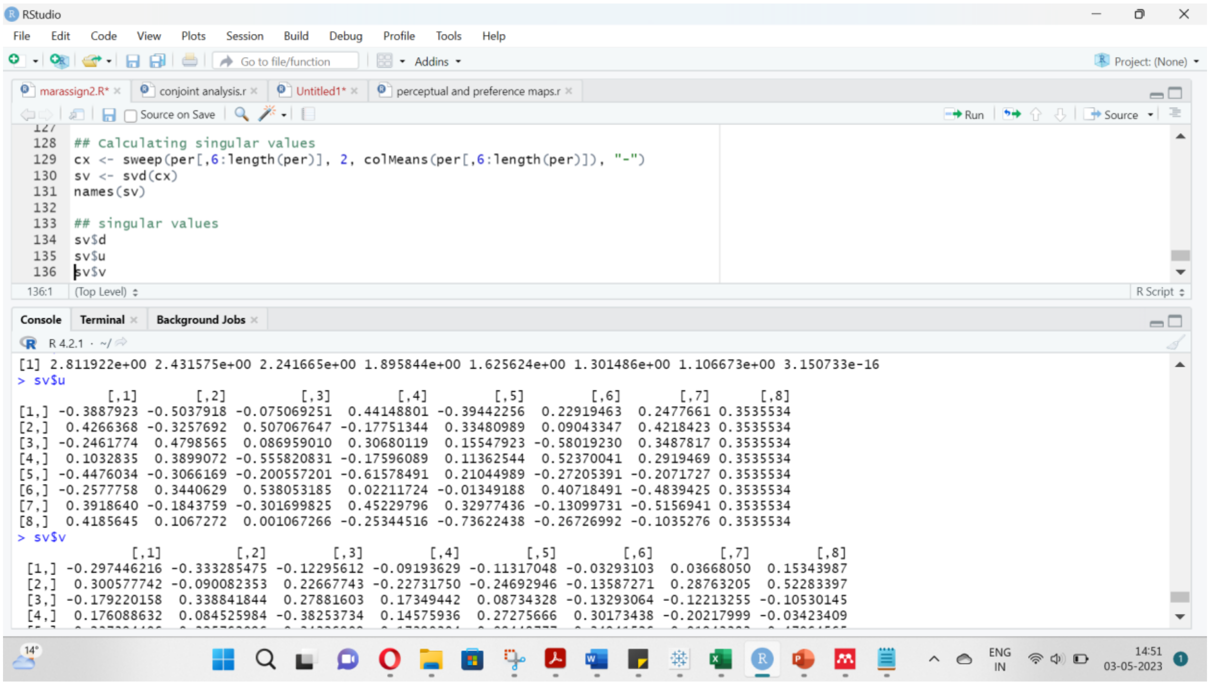
singular value decomposition

sv$d

sv$u

sv$v





##########Calculating PVE###########

###https://rpubs.com/cbolch/531355

Create a function that creates a new data frame with centered variables

center_apply <- function(x) {

apply(x, 2, function(y) y - mean(y))

}

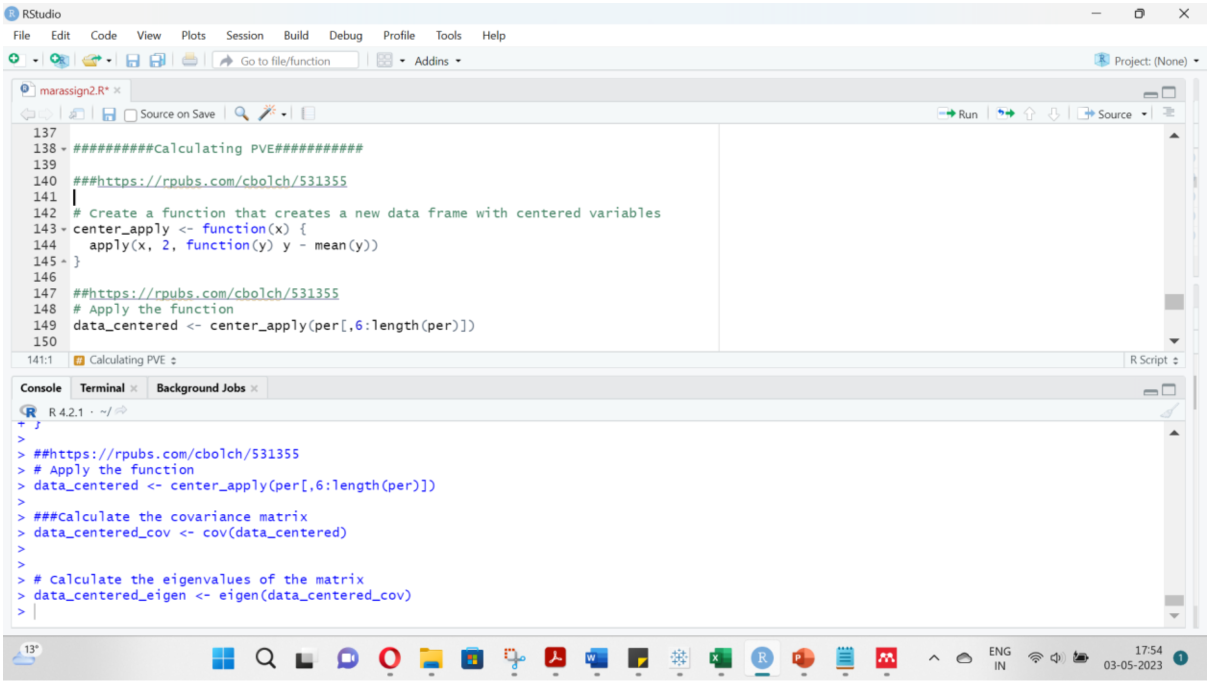
##https://rpubs.com/cbolch/531355

Apply the function

data_centered <- center_apply(per[,6:length(per)])

###Calculate the covariance matrix

data_centered_cov <- cov(data_centered)



Calculate the eigenvalues of the matrix

data_centered_eigen <- eigen(data_centered_cov)

##https://rpubs.com/cbolch/531355

Structure of the object contains the ordered eigenvalues and the corresponding eigenvector matrix

str(data_centered_eigen)

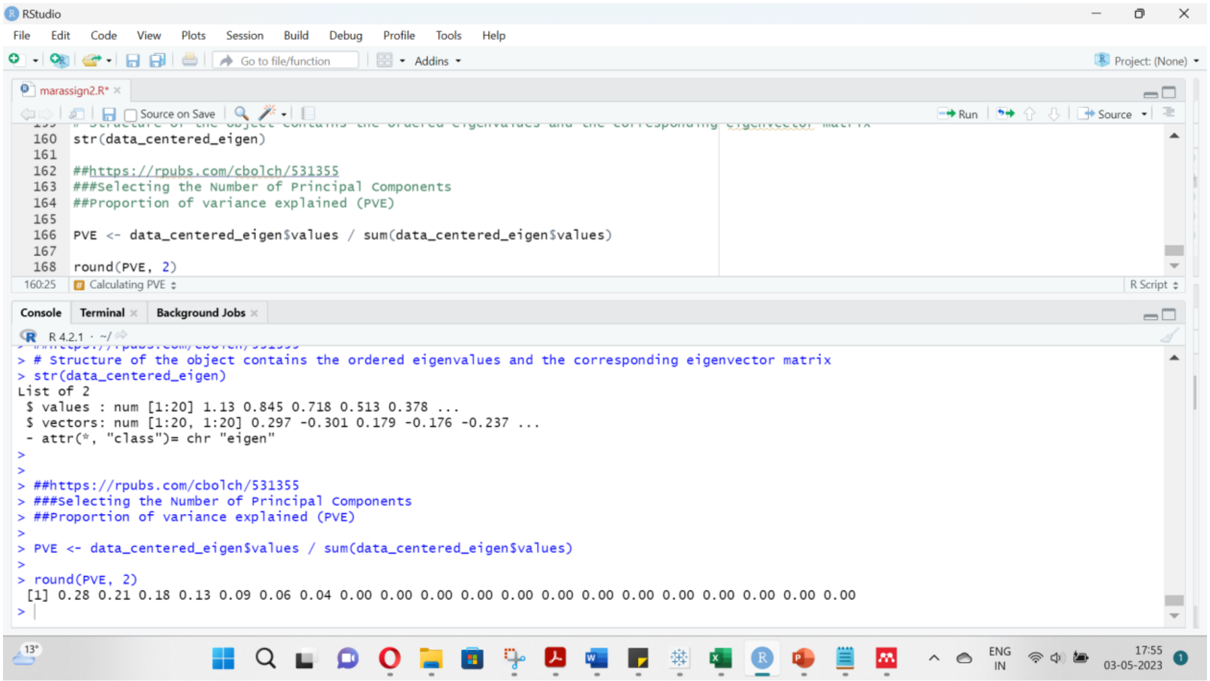
##https://rpubs.com/cbolch/531355

###Selecting the Number of Principal Components

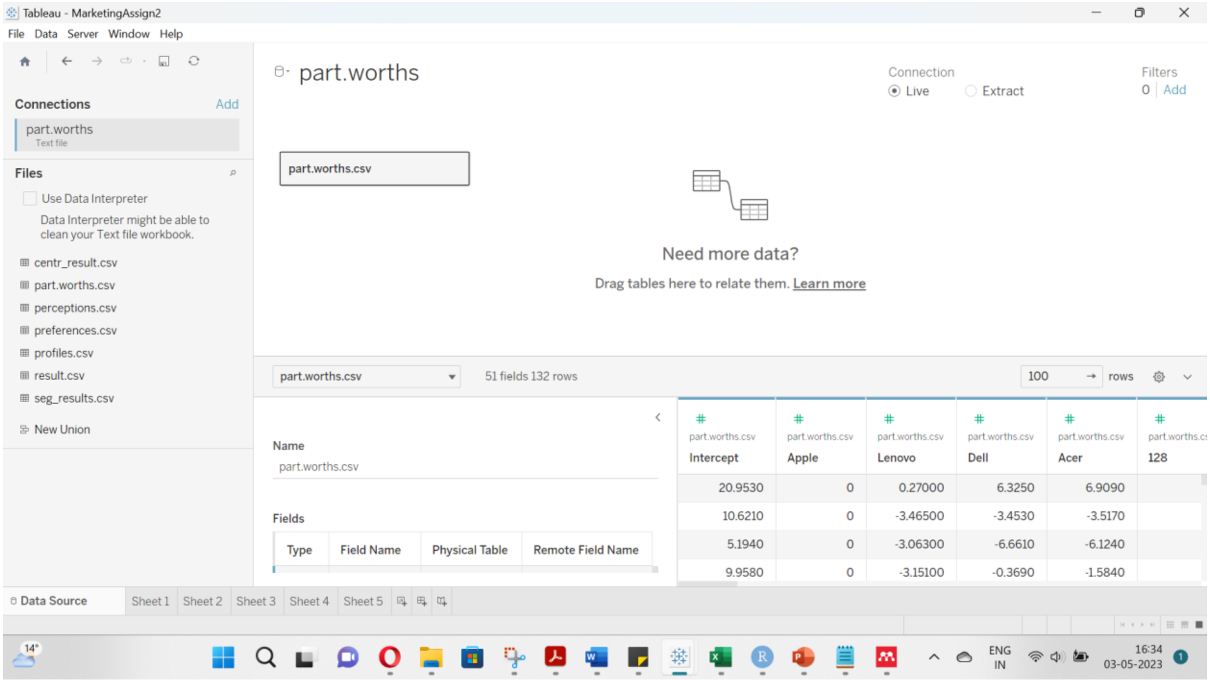
##Proportion of variance explained (PVE)

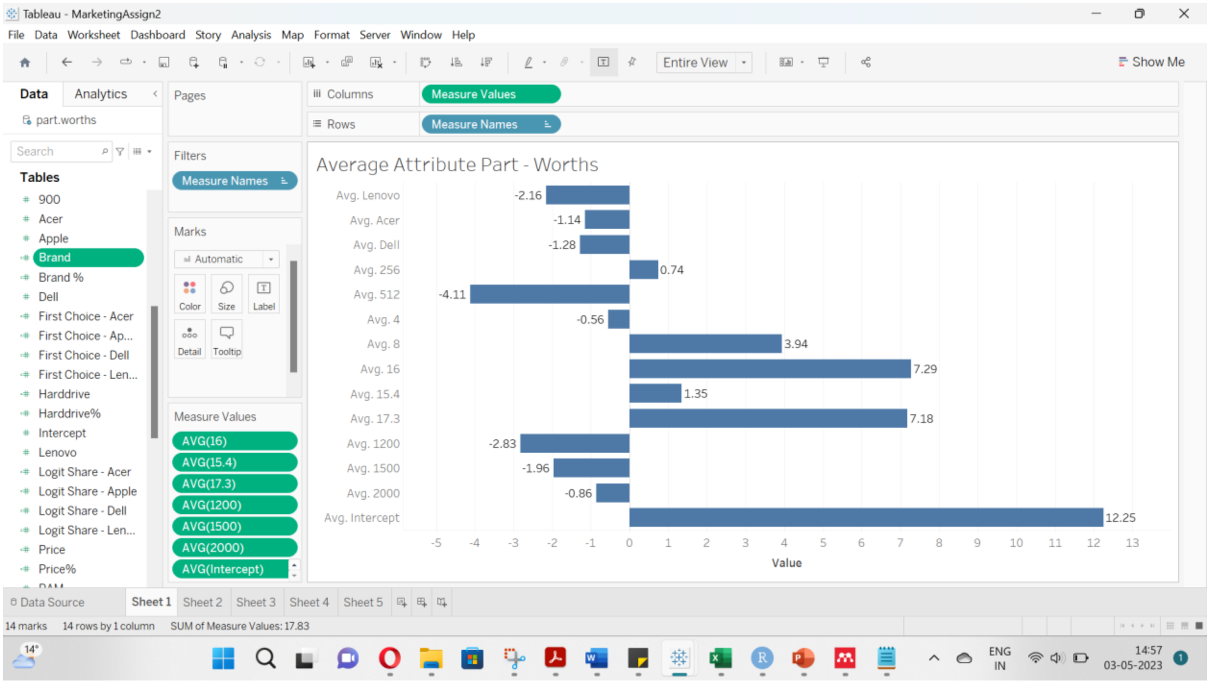
PVE <- data_centered_eigen$values / sum(data_centered_eigen$values)

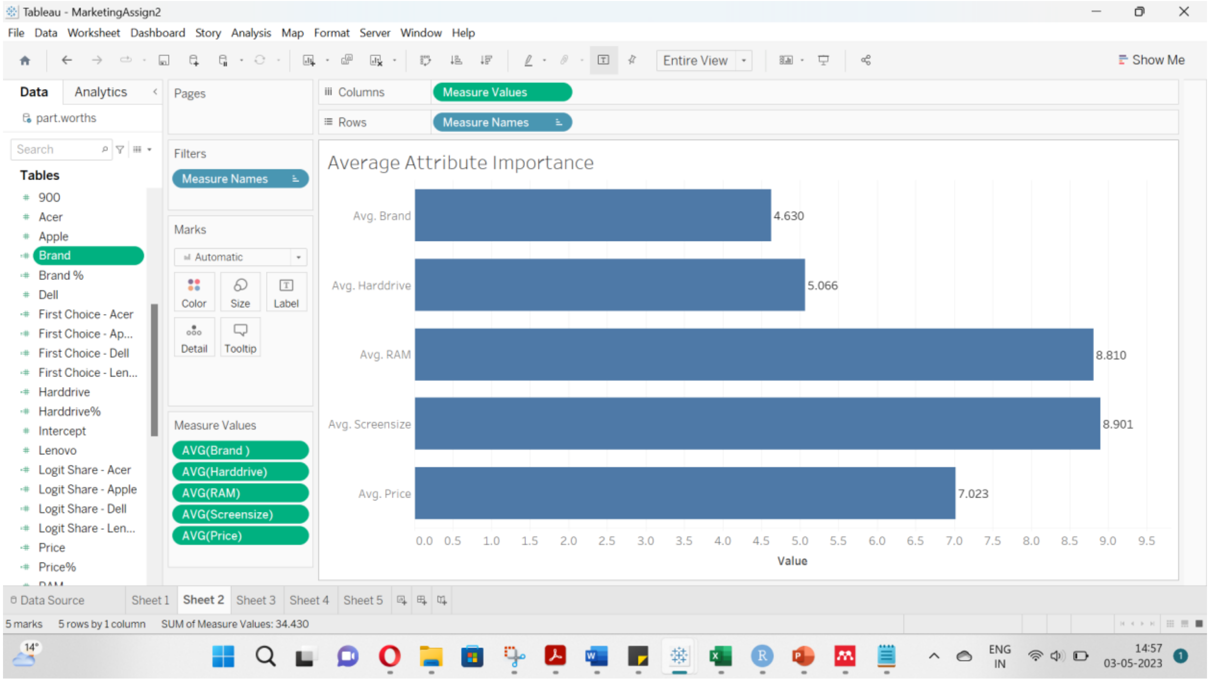
round(PVE, 2)

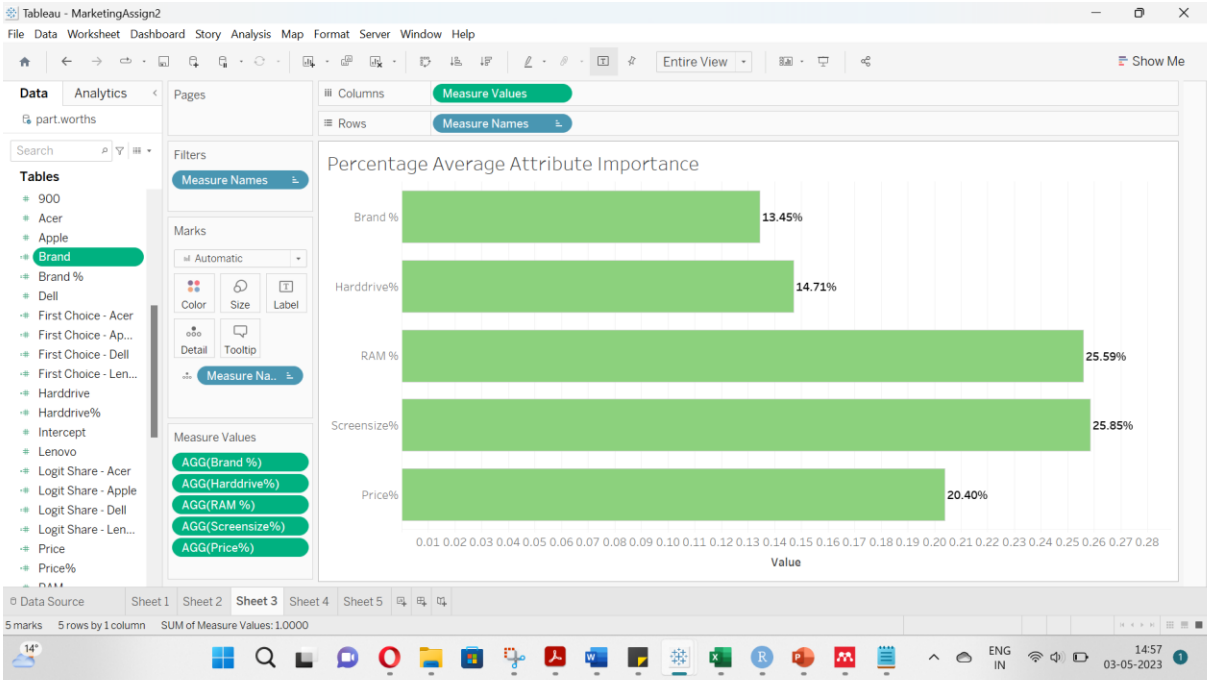


5.1 Appendix - Tableau






Average Attribute Importance
Avg. Brand
4.630
Avg. Harddrive
5.066
Avg. RAM
8.810
Avg. Screensize
8.901
Avg. Price
7.023
Value


Percentage Average Attribute Importance
Brand %
13.45%
Harddrive%
14.71%
RAM %
25.59%
Screensize%
25.85%
Price%
20.40%
Value

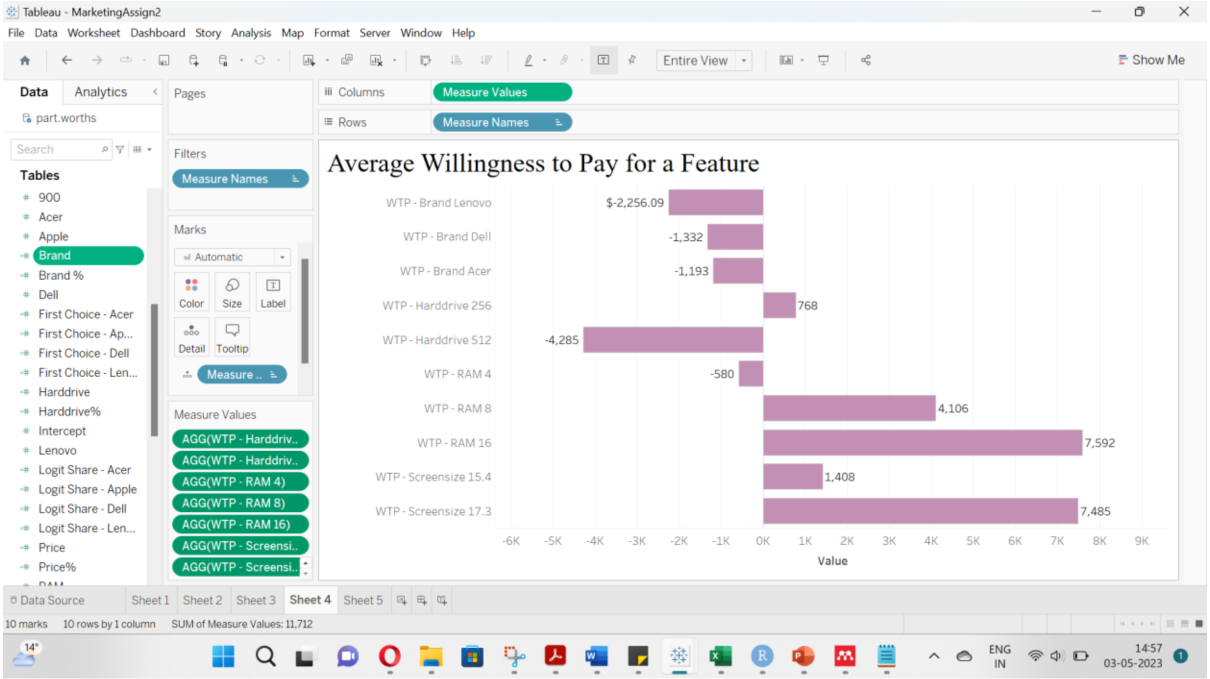


Tableau - MarketingAssign2
Average Willingness to Pay for a Feature
WTP - Brand Lenovo
$-2,256.09
WTP - Brand Dell
-1,332
WTP - Brand Acer
-1,193
WTP - Harddrive 256
768
WTP - Harddrive 512
-4,285
WTP - RAM 4
-580
WTP - RAM 8
4,106
WTP - RAM 16
7,592
WTP - Screensize 15.4
1,408
WTP - Screensize 17.3
7,485
-6K -5K -4K -3K -2K -1K 0K 1K 2K 3K 4K 5K 6K 7K 8K 9K
Value
10 marks 10 rows by 1 column SUM of Measure Values: 11,712

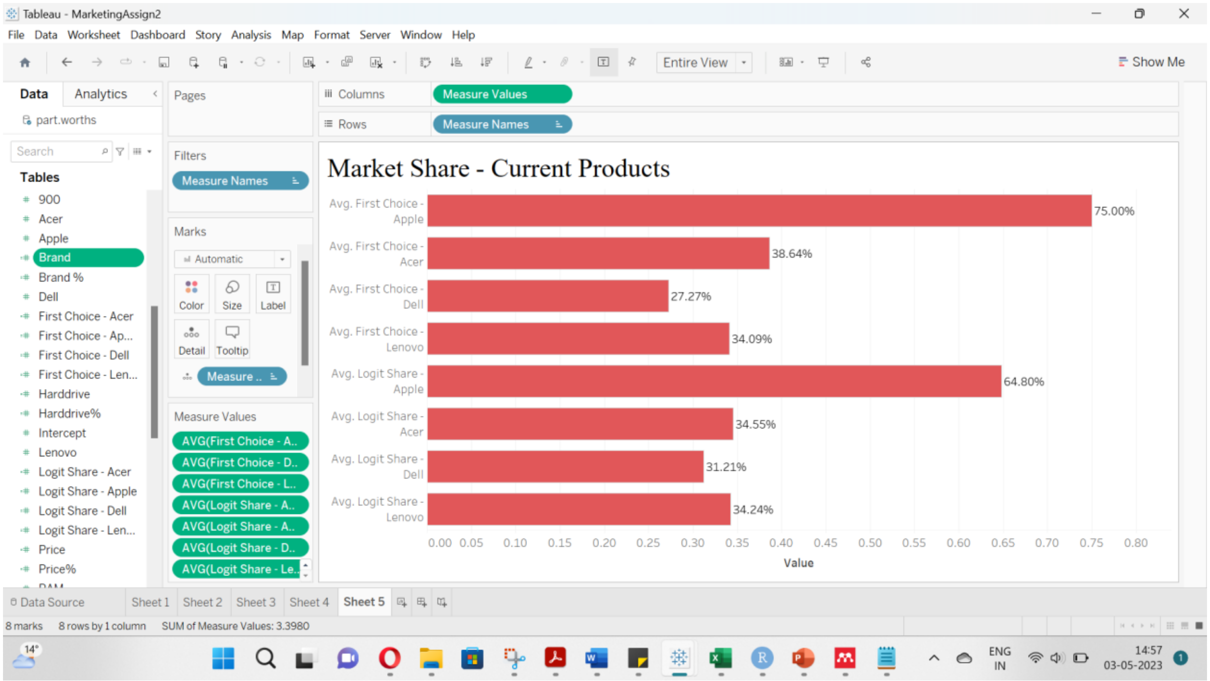


Tableau - MarketingAssign2
Market Share - Current Products
Avg. First Choice - Apple
75.00%
Avg. First Choice - Acer
38.64%
Avg. First Choice - Dell
27.27%
Avg. First Choice - Lenovo
34.09%
Avg. Logit Share - Apple
64.80%
Avg. Logit Share - Acer
34.55%
Avg. Logit Share - Dell
31.21%
Avg. Logit Share - Lenovo
34.24%
0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50 0.55 0.60 0.65 0.70 0.75 0.80
Value
8 marks 8 rows by 1 column SUM of Measure Values: 3.3980

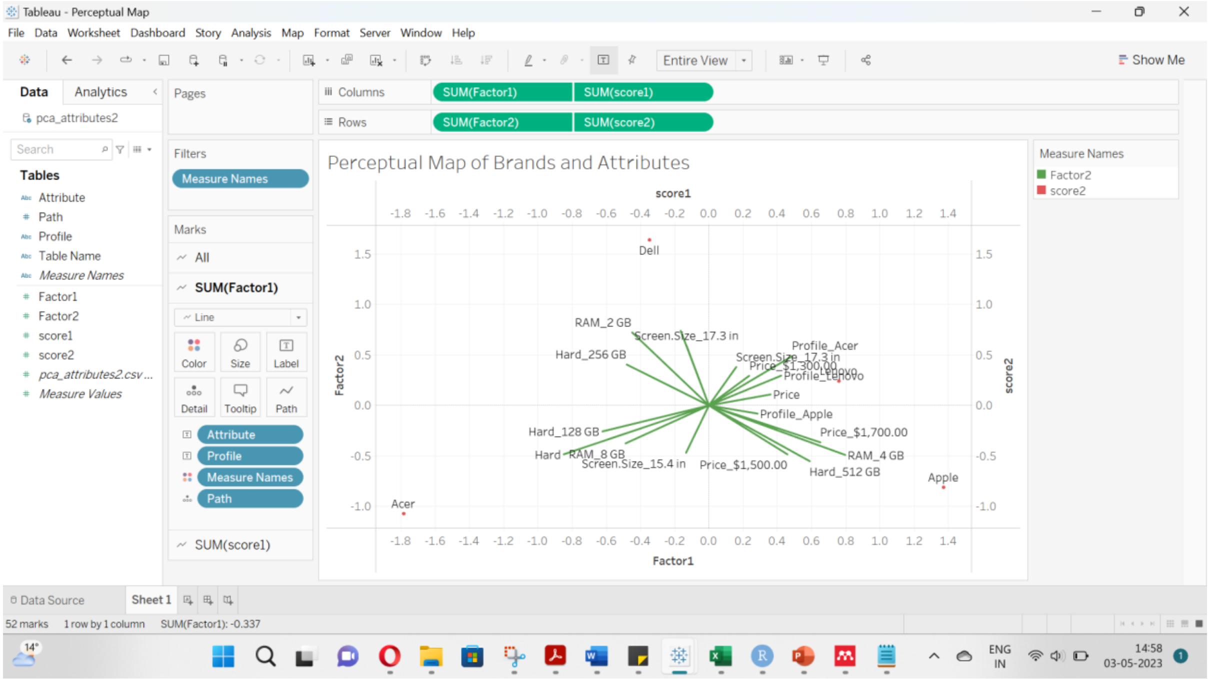


Tableau - Perceptual Map
Perceptual Map of Brands and Attributes
score1
Factor1
Factor2
score2
Measure Names
Dell
Acer
Apple
RAM_2 GB
Screen.Size_17.3 in
Hard_256 GB
Profile_Acer
Price
Profile_Apple
Price_$1,700.00
Hard_128 GB
RAM_4 GB
Hard_512 GB
Price_$1,500.00
Screen.Size_15.4 in