Special Work Performance 3

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Summary

The purpose of this document is to describe the survey data gathered from 593 people regarding different Bluetooth speakers. The main interest of this survey is to assess people`s overall awareness of the main players on the market, whether respondents own or intent to buy a new speaker and which attributes play key role during the process of decision making. 5 item Subjective Knowledge Scale was used for analyzing *consumer's perception of the amount of information they have stored in their memory*. The first part of this document provides an overview of the survey and reports about interesting findings, while the second part tries to create homogenous segments by using different clustering techniques.

Demographics

Out of 593 participants 44% were female, 53% male and 3% did not provide their gender. 28 nationality were represented in the sample. The majority of people, 56%, were residents of Germany, followed by Turkey - 7%, Belgium – 4%, France – 3%, US - 3%. Others were less than 3%. Most of the people were “Students” with 56%, followed by “Employed” - 34%. “Self-employed”, “Unemployed” and “Retired” totaled 10%. The larger part of respondents – 82% were between 18 and 29 years old. The income distribution by occupation was following:

OccupationLabel	<500	501-1000	1001-1500	1501-2000	2001-2500	2501-3000	>=3001	rather not say
Employed	4%	14%	16%	14%	14%	3%	16%	18%
Retired	0%	0%	50%	0%	0%	50%	0%	0%
Self-employed	8%	11%	14%	14%	5%	3%	30%	16%
Student	28%	47%	12%	2%	0%	0%	1%	9%
Unemployed	27%	23%	14%	0%	5%	0%	18%	14%

Own and intention to buy

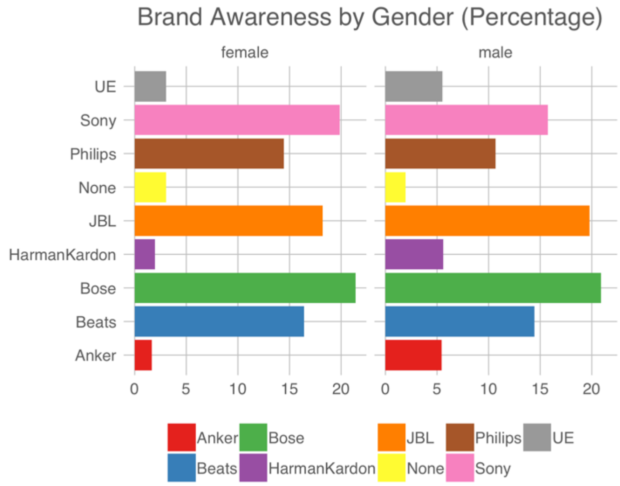
When it comes to owning a speaker, most people 55% did not own one, while 45% did. It is interesting to note that this proportion still exists if we spread participants by Occupation. But when it comes to gender, 51% of males own a speaker, while for the females the number is only 39%. It could indicate that interest for the speakers does not differ by age or occupation. We cannot say that Students are more likely to buy them than Employed people. But its clear that males are more interested in owning one than females.

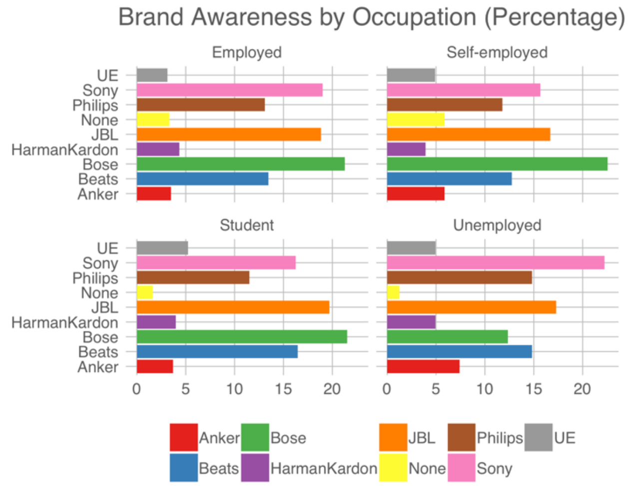
67% of participants are not planning to purchase a new speaker, while 33% do. This proportion is maintained within the gender and occupation status. Only self-employed people tend to be lower on scale to purchasing new one - 24%. Income wise the lowest proportion goes to the people who earn most. Only 26% plan to buy one.

Brand Awareness

The most well-known brand among participants is Bose. Out of 593 people, 391 know about it.

Close competitors are: JBL – 354 and Sony – 327. Least popular brands are – UE – 84 HarmanKardon – 78 and Anker with 74 votes. There is a difference between proportion for gender as well as occupation.





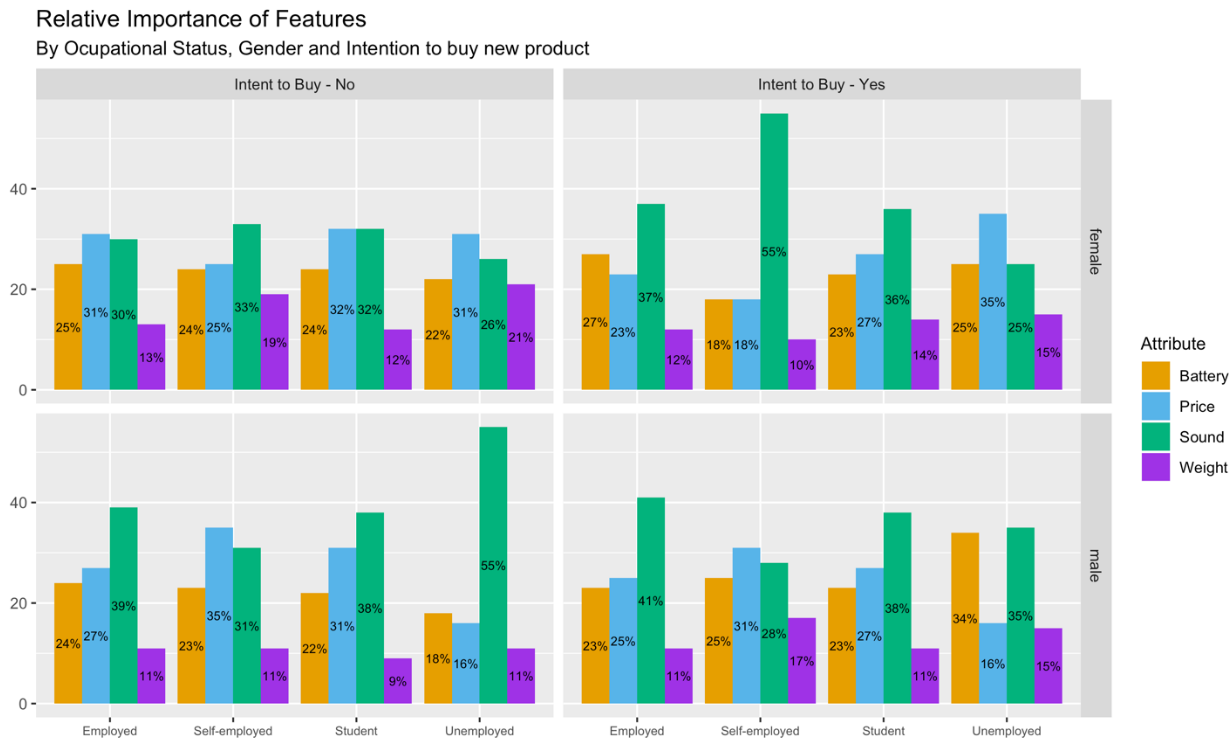
It is worth noting that for people who are willing to purchase new speakers, Bose is still number one with 138 votes out of 198 with closest to it JBL – 133. Anker, UE and HarmanKardon still remain on the bottom with 27, 26 and 29 votes.

Subject Knowledge

The survey contained 5 item Subject Knowledge Scale to determine the participants perception regarding the information they think they know about speakers. Using factor analysis, two factors were enough to explain 74% of the variation. Third item – "*Among my circle of friends, I'm one of the "experts" on portable Bluetooth speakers* "seem to be most different of other items and respondents tend to have twice the lower points for this item, than on average. When it came to gender, females put lower points on average than men, meaning females do not believe they are experts on Bluetooth speakers. It is important to mention, that people who answered that and were going to buy a product also tend to give themselves higher scores. It can indicate that buying Bluetooth speaker is less of an impulsive decision and before actual purchase people do their research. There is a difference also by occupation. Self-employed people tend to score themselves highest, followed by students and employed people.

Relative Importance of Features

Survey provides the data about relative importance of features. People were asked to assign 100% of weights to the four features: Battery, Price, Sound and Weight. Taking overall average: The sound is most important feature – 36%, followed by price – 29%, battery – 23% and weight – 12%. This pattern continues within the more relevant group, people with intention to buy a new product, especially in two largest groups employed and students. For employed females Battery life is more important than price. The graph below provides full detailed information.



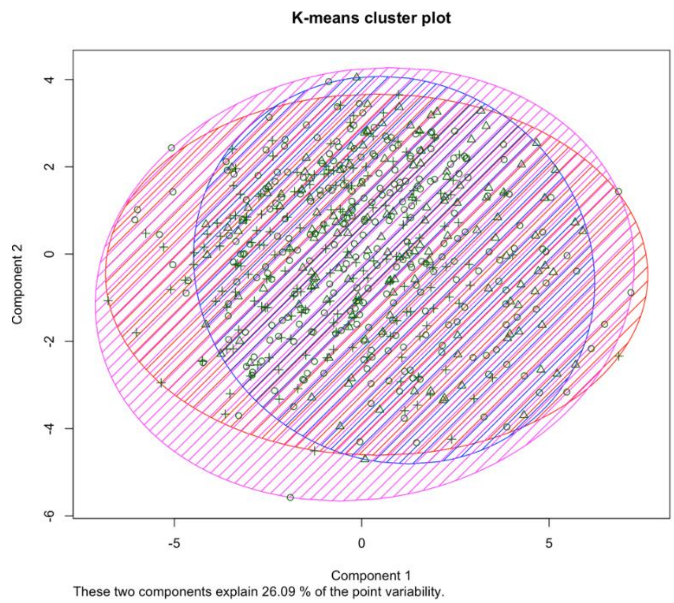
Clustering

After general overview of the survey data and investing some patterns in it, clustering techniques are used to discover new customer segments. The main goal of this process is to create segments that are similar within the group and different from other groups, so it will be easy for marketers to create specific marketing campaigns for each of them and target them better.

As first step specific variables from the data are chosen, that to our belief can have the biggest impact in the clustering process. Variables are chosen based on the exploratory data analysis done in the first part. The variables are: Own, Intent to Buy, all of Subject Knowledge, PII and Relative importance, Gender, Age, Residence, Occupation and Income. Also new variable – Brand Knowledge is created – which is sum of all brand awareness questions. It can help to adjust Subject Knowledge. During the process, several pairs of variables were selected, so we could find best selection of variables, that could give best segments.

The first clustering technique we will be using is K-means, even though it rises a problem. K-means relies on Euclidean distance, while our data contains some binary data, like Own and Intent to buy, as well as non-metric data, like Gender, Age, Residence and so on. The good thing is that binary factors can be coerced to numeric with no alteration of meaning. And non-metric data can be converted to binary variables by dummying them. The mlr package's create Dummy Features were used for this purpose. As goal, we chose 3 clusters, which could be extended maximum to five, as we believe that this is the maximum number of segments, marketers can use to target and create special campaigns for.

Using K-means did not show much success, as it created groups that were very similar to each other, making it impossible to interpret them and not allowing business decision making. The main difference occurred in the relative importance of features, but the features, like income level, gender, occupation were very similar. This result was expected, as it is not optimal to cluster binary values with k-means, but as it was mix of binary and non-binary data it is always worth to try, especially if we take *no free lunch theorem* into consideration.



As the second approach into clustering survey data hierarchical clustering was used. Like K-means, hierarchical clustering also starts with proper selection of variables. Other than that, it has its own constraints that needs to be taken into considerations before moving forward. As it is distance-based algorithm, where primary information is the distance between observations, it only accepts numeric values. But most of the variables of survey data are factor variables. To convert them into Euclidean distance, daisy function from the “cluster” library was used. After getting distance matrix, hclust function was used for creating hierarchical cluster. For the first attempt complete linkage method was used. For checking goodness-of-fit cophenetic correlation coefficient was used which gave 0.38 for “complete” and 0.31 for “single” linkage. Meaning, its still highly ambiguous groups, but results are much better than K-means. The graph below represents the groups that were created after choosing four clusters from the dendrogram.

The main differentiator between groups were Occupation, Income Level and Gender. Also for this people different features of Bluetooth speakers played an important role.

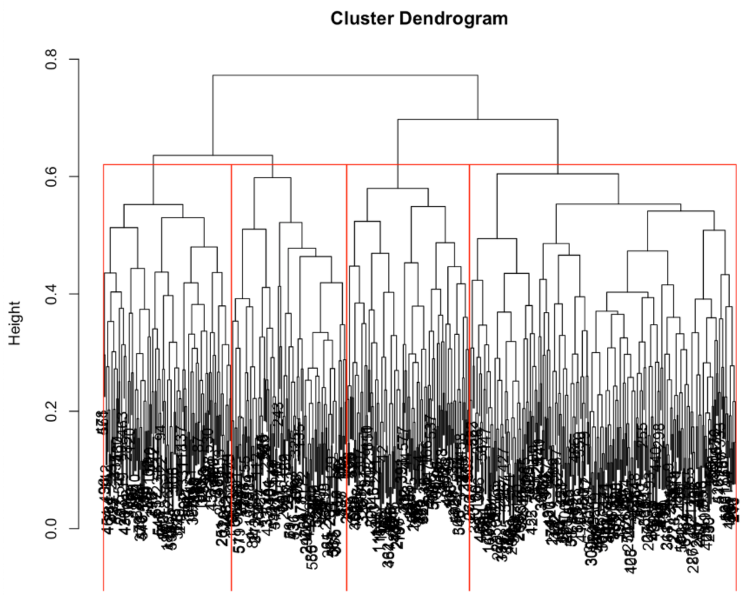
Four clusters were built. Interesting to observe is that two of the four clusters contain almost only males and the other two clusters are built with a majority of females. Trying to sum up the main relevant values from each of the groups, we could describe them like this:

-1st cluster: Mostly young females with occupational status "Student", low income level and low educational status (directly linked to the age and the occupational status).

-2nd cluster: Mostly young males with occupational status "Student", low income level and low educational status. It differs to the 1st cluster mainly by the gender characteristics.

-3rd cluster: Mostly older males with higher income and educational level, working as employees.

-4th cluster: Mostly older females with higher education, higher income level (the group with the highest income level), employed.



After building these 4 groups from the replicants, an evaluation on the quality preferences could be carried out. It could be observed that the 1st and 2nd cluster look more into the prices which could be logically linked to the lower income level of those groups. Interesting to note, is that the sound quality plays a much bigger role for the male groups (2nd and 3rd). The weight, on the other hand, is more important for females (1st and 4th). Battery life is of a greater importance for the groups with older participants (3rd and 4th), which could indicate they want a more secure and reliable product.

All of those statements could be explained with certain qualities of the different groups which makes the cluster analysis useful for targeting different groups with various marketing campaigns and even probably products. The division of customers into different groups pays off as different groups could be addressed with specific features to better match their preferences. Despite not being the best result statistically, this cluster analysis makes the most sense from a business decision making perspective.