Question 2: Choice-Based Conjoint Analysis

1. **Explore the data**

As you can see it on our code in the appendix, first we explored the data sets to learn more about their structure.

We began working on the data set “alt_data” and divided it into different renamed columns for each attribute of the watch (product, color, brand, price and battery life in hour). We also checked for missing values, and there were none. We checked the length and class of each variable. Every attribute was in characters, and it was not the best in our opinion. Therefore, we converted the attributes “color” and “brand” into factors and the attributes “price”, “battery life” and “product” into numerical. We used the summary function to get a good overview of the data set. We checked the distribution and proportion for all variables and used the describe function to obtain many descriptive statistics.

We then operated in the same way for the data sets “sets_data” and “response_data”.

2. **Investigate the respondents’ preference for smart watches**

2.a. Select your DV and IVs

Our independent variables are all the attributes taken into account in the choice sets of smart watches:

- Color,
- Brand,
- Price,
- Battery life.

Our dependent variable is the best smart watch chosen by the respondent among the three alternatives proposed in each choice set.

2.b. Choose (an) appropriate method(s) and build your model(s)

We want to run a choice-based conjoint analysis to predict the preference of watch of a customer. The attributes of the watches and the preference (choice) of the customer are stored in different data sets, respectively “alt_data” and “response_data”. We namely need to first merge these two data sets into the new data frame called “response_wide” for each alternative watch (“prodID1”, “prodID2” and “prodID3”). To do so, we also rename the 11th to 14th columns, then the 15th to 18th and then the 19th to 22nd columns.

We are going to build a multinomial logit model and therefore use the “mlogit” function. Before that, we convert our new data frame “response_wide” to a format that “mlogit” can handle, using the “mlogit.data” function for estimation and validation.

For our **first model**, we use the part-worth function (with the “as.factor” function) on the effect of color and brand and the linear effect function on the effect of price and battery life of the watch. We also include some of the personal variable in our model: the age and gender of the respondent (we think that the region where the respondent comes from does not really matter). For comparison, we decide to create five other alternative models:

- **Model 2**: a new mlogit model, using the part-worth function on every watch attributes (as.factors) and the age and gender of the respondent.
- **Model 3**: a new mlogit model similar to the first one but with the region variable added.
- **Model 4**: a new mlogit model like the first one but with a non-linear term for the attribute battery life included, to check if the effect of the battery life on the utility is in a quadratic form. We wanted also to try this method with the price attribute, but we received an error message.
- **Model 5**: a restricted model with the same arguments as the model 1 but without the variable age.
- **Model 6**: a restricted model, with the same arguments as the model 1 but without the age and gender variables.

2.c. Model validation and comparisons

We previously split the original sample of "response_wide" into estimation and validation samples with the functions "training" and "testing".

To compare our models, we mostly focus on their accuracy rate. We also compute their Akaike information criterion (the lower, the better the model is) and we make a likelihood ratio test:

- **Model 1**: accuracy rate = 48.53% (>1/3 which is the probability of one of the three watches to be chosen randomly by the respondent); AIC = 9466.892; Likelihood ratio test: chisq = 78.839 (p.value = 8.4745e-13).
- **Model 2**: accuracy rate = 48% (no real increase compared to the first model); AIC = 9467.542; Likelihood ratio test: chisq = 86.189 (p.value = 1.9807e-12).
- **Model 3**: accuracy rate = 23,74% (decrease of the accuracy rate by 0.2253333); AIC = 9483.175; Likelihood ratio test: chisq = 102.56 (p.value = 7.2984e-10).
- **Model 4**: accuracy rate = 23.73 % (decrease of the accuracy rate by 0.2253333); AIC = 9468.671; Likelihood ratio test: chisq = 79.061 (p.value = 2.2414e-12). We will use the model where we are assuming that the battery level affects the total utility in a linear way, because here the accuracy rate is too low.
- **Model 5**: accuracy rate = 46.533 %; AIC = 9463.187; Likelihood ratio test: chisq = 78.544 (p.value = 9.5963e-14).
- **Model 6**: accuracy rate = 32.933 %; AIC = 9838.861.

It appears that the best models here are the models 1, 2 and 5.

So, the model 1 has also one of the best accuracy rates and an acceptable AIC (really close to the other ones). Futhermore, in the model 1, we decided that the effects of the attributes "color" and "price" should be nominal, and the effects of the attributes "price" and "battery level" should be linear/numeric. The model 1 is namely less complex, compared to the model 2: less attributes (2 versus 4) are treated as factors (nominal variable). Another important point is that the model 1 is also a full/complete model, compared to the model 5. That is why our model is better than another alternative model.

2.d. Estimate your selected model using the whole data set and discuss model fit statistics

We just previously chose the best model according to us: the model 1. Using now the whole data set, we are going to re-estimate this model. To do so, we first convert the "response_wide" data frame to a format which mlogit understands. This new data frame is called "estimation_data". We then compute the odds ratio.

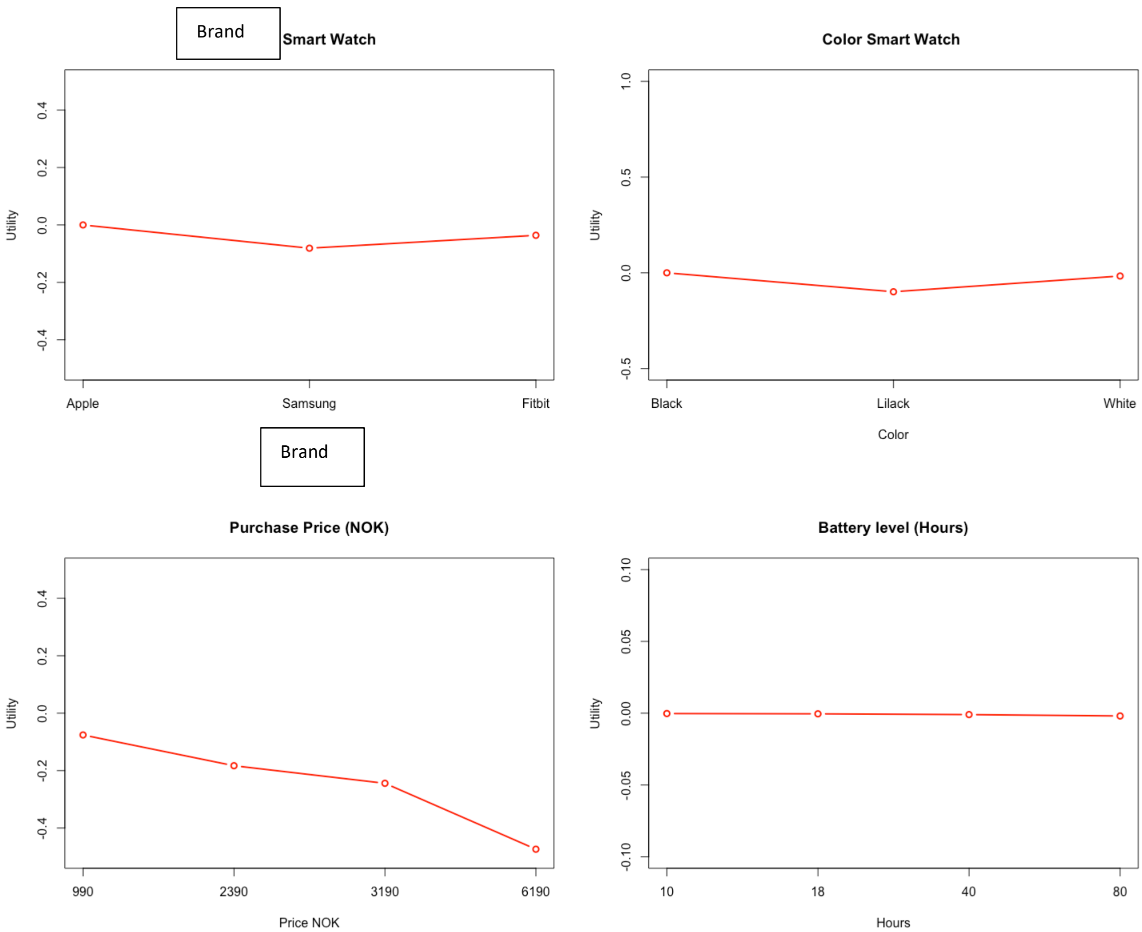
We obtain a model with an Akaike information criterion equal to 12592.56 and a likelihood ratio test: chisq = 86.764 (p.value = 2.341e-14).

We found out that all attributes have a high p-value except the price, with a p-value close to 0. The attribute "price" can therefore be considered as a promising predictor, which totally make sense in the preference-making-process of a customer.

2.e. Report findings, interpret the results, and formulate conclusions

<u>a) Effect of attribute level on utility</u>

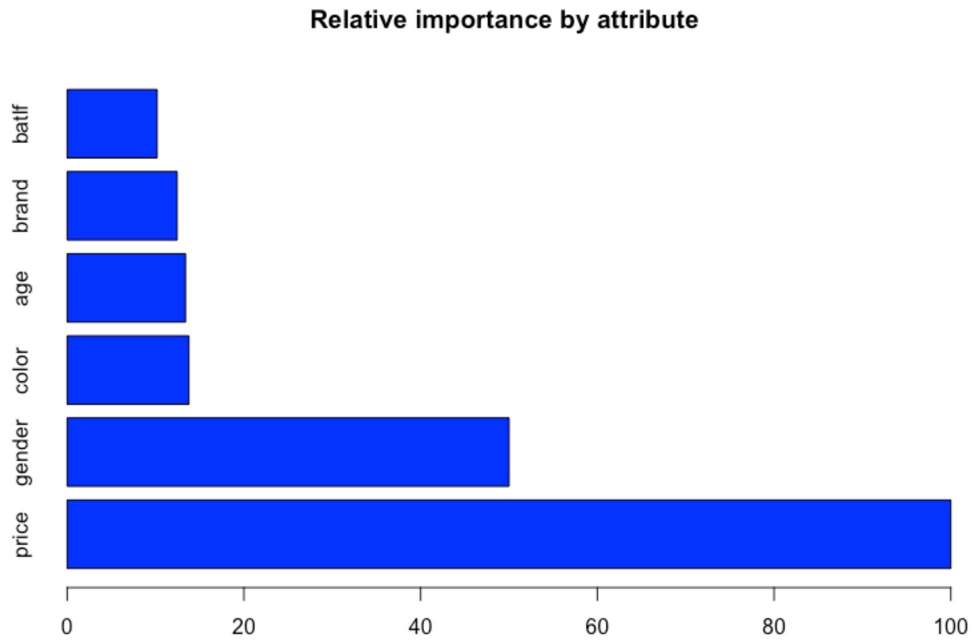
We first estimate all the parameters and then we make the utility plots for all the attributes of the watch: the variables color, brand, price and battery level:



As we anticipated it before with the p-values, the price attribute is the most determinant in the preference-making-process of the respondent. The higher the price will be, the less the respondent will be likely to choose the corresponding watch. For the other attributes, the difference in preference is less marked (it would be easier to state what alternative the respondent would not prefer). Indeed, the battery level does not seem to affect the choice of the respondent. For the color, the respondent will slightly prefer a black or white watch, compared to a Lilack one. For the brand, it does not matter if the watch is from Apple or Fitbit.

<u>b) Relative importance of attributes</u>

We finally plot the relative importance of each attribute of the watch and the gender and age of the respondent:



It seems once again clear that the most important factor is, on average, price. The least important factor is the battery life.

As a conclusion, based on our observations, the ideal smart watch would be either black or white and either from Apple or Fitbit. Concerning the price criteria, the less is the better for the customer. So, ideally the watch would cost NOK 990. We see that the battery life level is not a decisive criterion in the choice of the watch (no real difference of utility to the scale shown on this plot).

If we are realistic, buying a new apple watch for NOK 990 is quite impossible. The average price of an Apple watch is around NOK 4500. It would therefore be more credible to imagine that the ideal, and realistic, preferred watch for the customer is a black or white watch from the brand Fitbit, with the lowest possible price and a battery with a life of between 10 and 80 hours.