Summary report

Class name : STAT 424
Instructor : Professor Pixu Shi
TEAM 23 : Jing Wen, Jungwon Woo, Hao Wang

I. Introduction:

Nowadays, we find smartphones to be the most essential component for modern-day society. As technology advances, they are becoming not only a means of verbal telecommunication, but also a blend of modern advanced technologies. However, at the same time, having too much functions, we are even unaware of what hidden applications or functions are in use of our battery. Thus, we are interested in finding out what factors affect on the battery consumption by designing and conducting an experiment on it. Moreover, we are also curious about whether or not the latest version of smartphone has a better energy efficiency compared to the older version. Therefore, our group decide to conduct 2^k design experiment with four different blocks so as to figure out which of chosen factors influence the pace of battery consumption and the differences among the battery consumption speed of each phone type. 2^kdesign with blocks is selected since some possible factors can only be either on or off, and we as above-mentioned also wanted to see the difference among the phone types. This report will include the process of collecting data, building the model, analyzing the design, conclusion of the experiment and strength and weakness of the experiment.

II. Factor choice and process of experiment execution:

For our experiment, among many candidates, we first choose *Background Application Refresh* (refreshing/updating applications automatically while not using. *BAR*, hereafter), *Brightness* (screen brightness), *Bluetooth* (wireless short-range communication technology), and *Auto Lock-out Time* (Time taken to automatically lock the screen). Four different types of *Iphone, (7 Plus, 8, XS M, X)* are used to testify the effects of the factors on the battery consumption. The reasoning behind the factor choice is that these four factors are not widely known but allegedly still significant factors in the battery consumption level.

Our data collection is done with each group member measuring the battery consumption (in percentage) and *screen-on* time (in minute) with different combinations of the levels of four binary factors. The levels of the factors are all binary, ON/OFF for *Background Application Refresh*, MAX/MIN for *Brightness*, ON/OFF *bluetooth*, and 30 seconds/300 seconds *Auto Lock-out Time.* All the data was obtained from statistics given in *Setting* tap of each smartphone. And the factor level was also controlled and strictly kept. While one person took in charge of 32 observations, the rest of group members generated 16 observations with minimum battery consumption of at least 5 percent and screen on time of at least 15 minutes to testify the impact of factors.

III. Choice of design model and reason:

Our group decide to use unreplicated 2^4factorial design with four blockings. Since we have four different types of phones and four different factors, with one replicate, there will be 64 observations. We choose to use 2^4factorial design as every factor can be placed into two levels. Time limitation is one reason we decided to use an unreplicated design. Each observation on average takes approximately 50 minutes, it was hard for us to do more replicates in the same procedure in a given time. With this dataset, our main goal is to explore the main effect of all four factors and the blocking factor, as well as interaction effects between these factors. The response variable of the model is the battery consumption percentage per minute, or the battery consumption percentage divided by the *screen-on* time. The predictor variables are the binary (two-leveled) factors of BAR, *Brightness, Bluetooth* and *Auto-lock Time* as stated above

IV. Execution of the experiment and Statistical analysis:

For the experiment, each of the group member measures the battery consumption at each combination of the levels. We used the following methods to execute the experiment. First, only *Youtube* application is used only while recording the consumption percentage. Thereby we eradicate the nuisance effects from using different applications. *Screen-on* time only accounts for time of the screen being turned on, *screen-off* time is excluded. *BAR* is checked by stopping to refresh not-in-use applications and vice versa. Lastly, *Bluetooth's* effect is measured by connecting the smartphone with another wireless devices such as a speaker or wireless headset. *Auto Lock-out time* is the duration before the screen lock out automatically.

First, we construct our 2^4factorial design with 4 blocks as planned. For a better visualization and comprehension, we decide to rename *BAR, Brightness, Bluetooth, Lock-out Time, Phone Type* as A, B, C, D, E respectively. The normal probability plot (Figure 1) and Lenth's plot (Figure 2) of the model indicate significant effects are main effects of A, B and C. Main effect of D is not significant.

For the next step, since factor D is not a significant factor, we decide to construct a reduced model without factor D first. Even after the exclusion of D, the other main factors A, B, C still remain significant, whereas factor E is still a significant factor. Moreover, the effects of all the interactions are not significant. Although the Lenth's plot (Figure 4) and qq plot (Figure 3) also show that blocking effects are insignificant, to see whether each phone model does not differentiate themselves from other models more clearly, we decided to use Tukey's multiple comparison test under the assumption that there is no interaction among the main factors. As a result, we found that there is no difference between the phone type in our experiment as every comparison has 0 within its confidence interval. We suspect this insignificance of the factor E is due to the similarity of battery capacity factor that is not considered in the model. But we decided to keep the phone model blocks although they are not significant since it is a blocking factor. After excluding main effect of factor D and all the insignificant interaction terms, in the end, we now obtain our reduced model.

V. Diagnostic (*plots attached below*)

To check whether the model satisfies the basic assumptions, we first checked the homoskedasticity and linearity assumption by visualizing a residual plot (Figure 6). In this plot, we can detect that the residuals of observations are shaping a funneling trend, which seems to be a violation of homoscedasticity assumption, whereas the linearity assumption is still satisfied. The normality assumption is examined afterward and results that not many observations are significantly located away from the normal probability line (Figure 5), thus it is also satisfied. To satisfy the homoscedasticity assumption, we next use a Box-Cox procedure to transform the response variable into the power of lambda of the response variable. With visualized Box-Cox plot (Figure 7), we estimate the optimal lambda that maximizes the log-likelihood to be approximately 0.75. With the estimated lambda of 0.75, we get the final model of our experimental design. The ${R_{adj}}^2$ as large as 0.94 and p-value of the total model is also extremely small, thus significant. The final model also satisfies the three essential assumptions, linearity, normality and homoscedasticity. The plots attached below (Figure 8 and Figure 9) show that the assumptions are indeed satisfied.

VI. Conclusion:

From our experiment, we find that the brightness level is the most significant factor on the battery consumption and BAR and Bluetooth are of also the significance. Lock-out time turns out to be an insignificant factor. According to the result, a clear explanation of the model is as follows. If one wants to save the battery, s/he should lower the brightness first and turn off background auto-refresh option and bluetooth if in use. Shortening auto lock-in time does not help you save the battery.

The biggest strength of our experiment is its high reliability. Since the data were directly collected from the smartphone statistic window, human biases or errors in the observation were minimized. This also indicates that the experiment can be easily duplicated by others as the experiment was designed as accurate and simple as possible.

There are some weaknesses as well. One major issue is that the initial model failed to satisfy the homoskedasticity assumption, hence the model itself based on ANOVA results can be invalid. Thus, we replace our model into the transformed model.

We do not take other hidden or unknown functions that might affect the battery consumption into account. Also, allegedly the battery consumption and the battery health (the remaining battery capacity in percentage) is significantly correlated, yet we were not able to consider the battery health as only four of the specimens were available. If we were given more experiment time and more phones of those four phone types, more replicate can be done and the result should be more accurate.

VII. Plots:

Full model: Ratio~E+ A*B*C*D

Figure 1: normal q-q plot of full model

This plot shows that main effects of A, B, and C are significant.

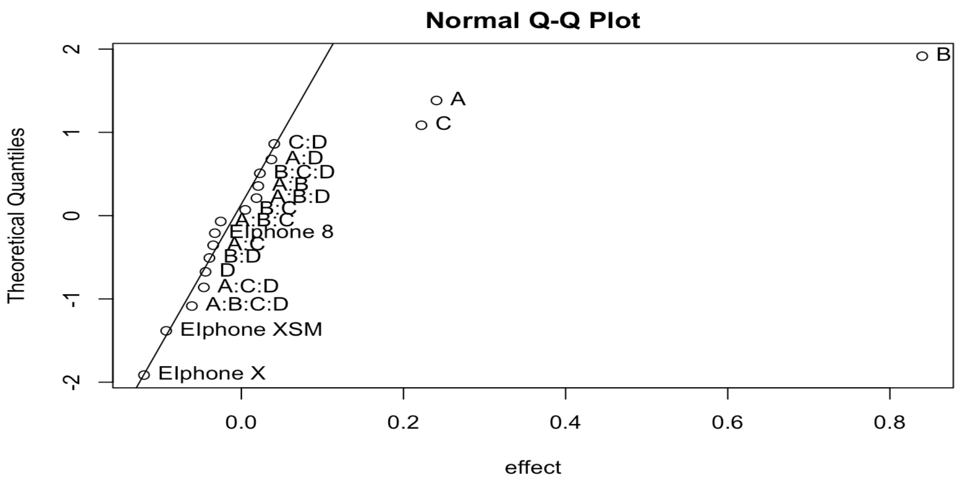
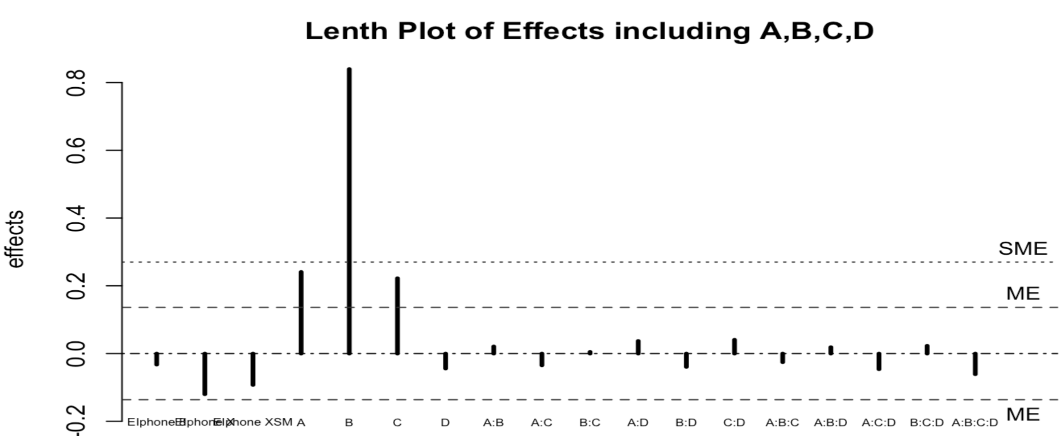


Figure 2: Lenth's plot of full model

This plot shows that main effect of factor B is significant and main effects of A and C may also be considered as significant.



Reduced model: Ratio~E+A*B*C

Figure 3: normal q-q plot of reduced model

Normally q-q plot of reduced model shows that the main effects of A, B, and C are still significant.

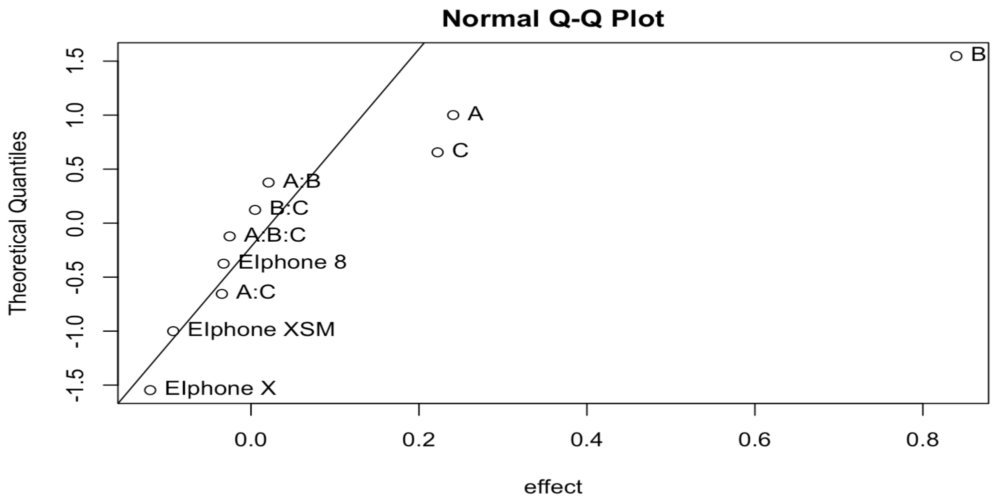
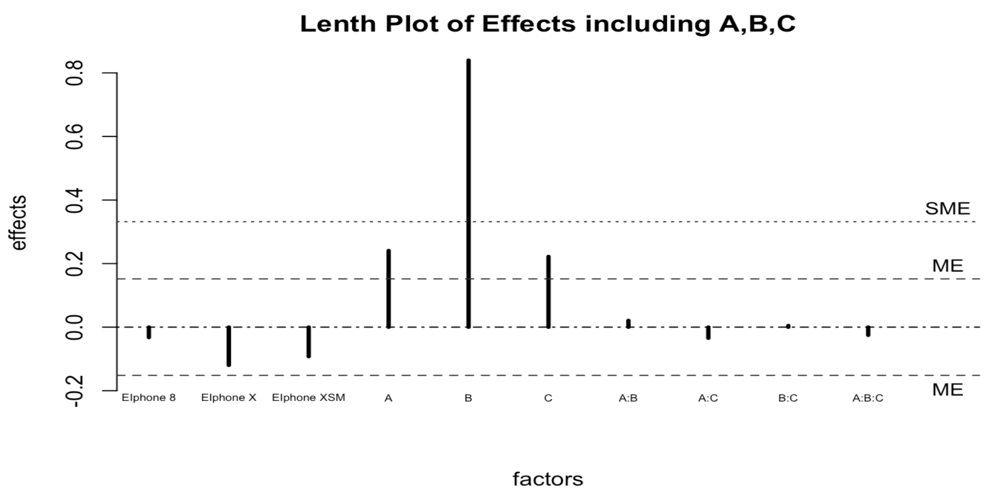


Figure 4: Lenth's plot of reduced model

Lenth's plot of reduced model shows that the main effect of B is significant and the main effects of A and C may also be considered as significant.



Second-reduced model: ratio~ E+A+B+C

Diagnostic of model:

Figure 5: qq plot of Second-reduced model

The normality assumption of reduced model can be held

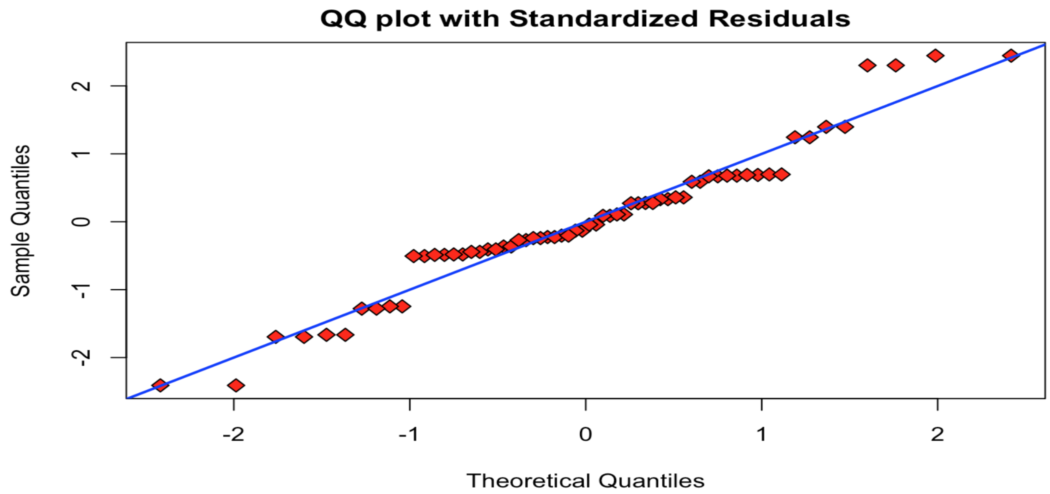


Figure 6: residual plot of Second-reduced model

The homoscedasticity assumption of reduced model is violated, but the linearity assumption is held

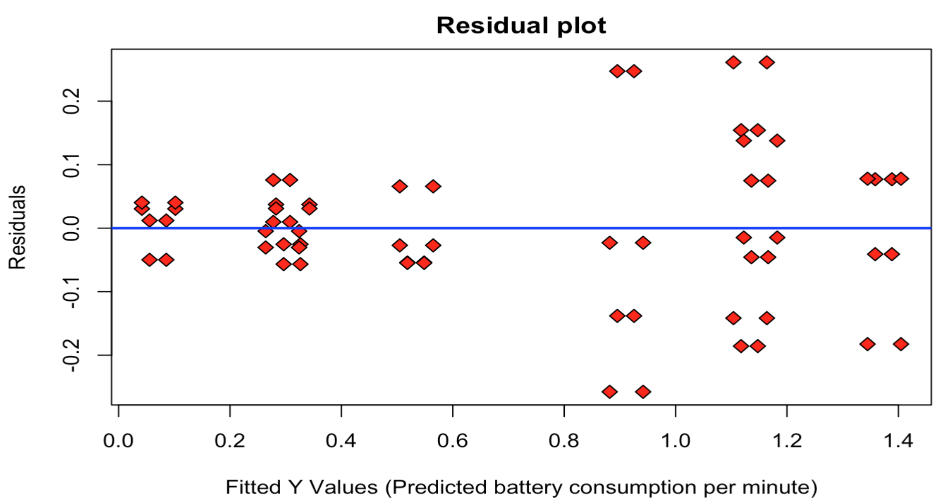
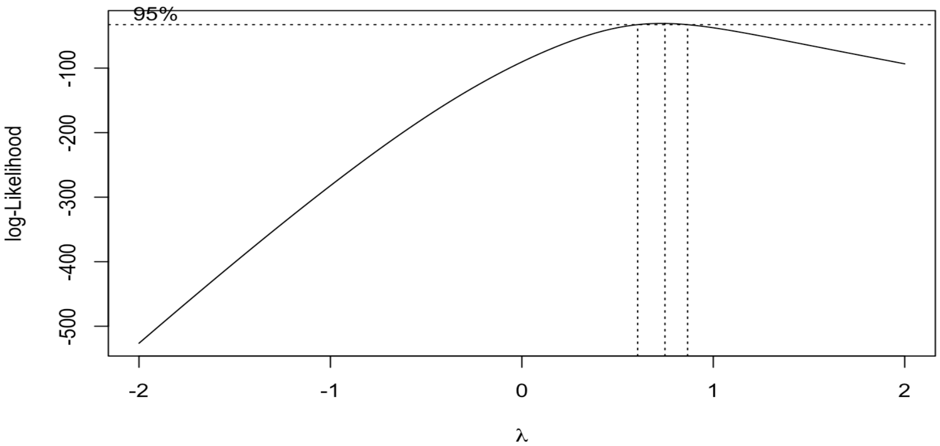


Figure 7: Box-Cox plot

This plot shows the best transformation of response variable that will fit the model.



Diagnostic of final model: (Ratio^0.75) ~E+A+B+C

Figure 8 residual plot of final model

The homoscedasticity and linearity assumptions of final model are held after transformation on response variable.

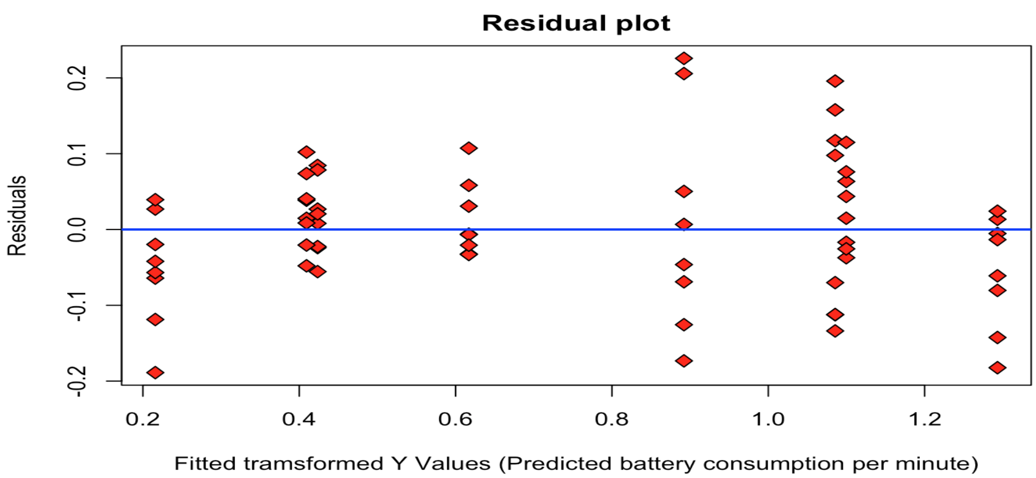
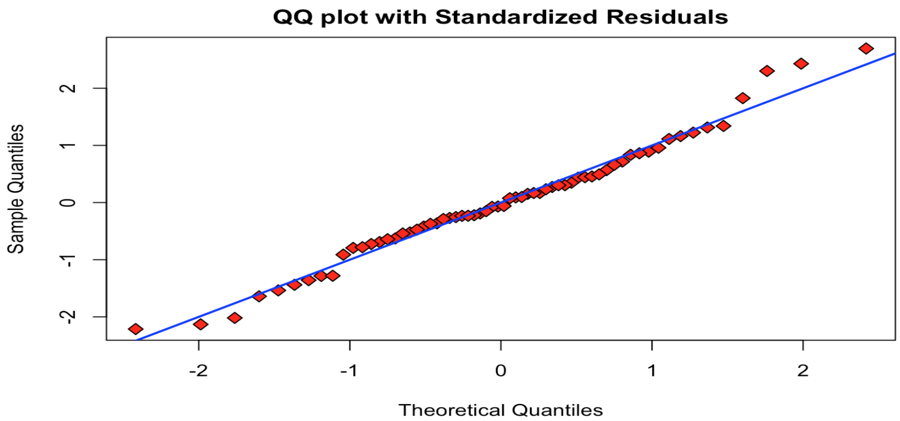


Figure 9: qq plot of final model

The normality assumption of final model is still held.



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