**MANM317 – Introduction to Marketing Analytics**

**Individual Coursework Assignment**

**Cem Ustundag**

**6530650**

# Project 1

## Task 1 (10 – 31)

Variable ‘respondent\_id’ is an identifier and has a unique value for each respondent.

Chart, histogram

Description automatically generated‘variety\_of\_choice’ is an attitudinal variable that indicates the respondent’s opinion on the variety of choice when shopping for office equipment. The variable has a minimum value of 4, a maximum value of 10, with a mean of 7.565. This indicates that this group of respondents value variety of choice, as this attitudinal variable has the highest variable mean.

Figure 1: Histogram of variable ‘variety\_of\_choice’.

Chart, histogram

Description automatically generated‘electronics’ is an attitudinal variable that indicates the respondent’s opinion on electronics availability when shopping for office equipment. The variable has a minimum value of 1, a maximum value of 10, with a mean of 4.45.

Figure 2: Histogram of variable ‘electronics’.

Chart, histogram

Description automatically generated‘furniture’ is an attitudinal variable that indicates the respondent’s opinion on furniture availability when shopping for office equipment. The variable has a minimum value of 0, a maximum value of 9, with a mean of 3.27. This indicates that this group of respondents do not value furniture availability, as this attitudinal variable has the lowest variable mean.

Figure 3: Histogram of variable ‘furniture’.

Chart, histogram

Description automatically generated‘quality\_of\_service’ is an attitudinal variable that indicates the respondent’s opinion on service quality when shopping for office equipment. The variable has a minimum value of 1, a maximum value of 9, with a mean of 3.53. This variable has a 3rd quartile value of 4, indicating that a small group of customers find service quality very important.

Figure 4: Histogram of variable ‘quality\_of\_service’.

Chart, histogram

Description automatically generated‘low\_prices’ is an attitudinal variable that indicates the respondent’s opinion on prices when shopping for office equipment. The variable has a minimum value of 1, a maximum of 10 and a mean of 4.795.

Figure 5: Histogram of variable ‘low\_prices’.

Chart, histogram

Description automatically generated‘return\_policy’ is an attitudinal variable that indicates the respondent’s opinion on the presence of a return policy when shopping for office equipment. The variable has a minimum of 1, a maximum of 10, with a mean of 4.25.

Figure 6: Histogram of variable ‘return\_policy’.

‘professional’ variable describes whether the respondent is a professional or not. Only 68 out of 200 respondents are professionals (34%).

Chart, histogram

Description automatically generated‘income’ variable indicates how much the respondent earns in thousands per year, in pound sterling. While the mean for ‘income’ is 32.17, the median is 19.5, indicating that most respondents earn very little, and a few respondents earn substantially more, with a maximum of 95.

Figure 7: Histogram of variable ‘income’.

Chart, histogram

Description automatically generated‘age’ variable indicates the respondent’s age. While the mean for ‘age’ is 32.52, the median is 27, indicating that respondents are concentrated below the age of 30 with the other half of respondents spread between the ages of 30 and 68.

Figure 8: Histogram of variable ‘age’.

## Task 2 (32 – 42)

A new dataframe ‘data\_att’ was created, where the attitudinal variables of the original dataset were isolated. Attitudinal variables were considered to be the six variables ‘variety\_of\_choice’, ‘electronics’, ‘furniture’, ‘quality\_of\_service’, ‘low\_prices’, and ‘return\_policy’.

These variables were then normalised to create a new dataframe, ‘data\_att\_norm’, to contain the normalised versions of these values. Z-score standardisation was used as the method of normalisation for all variables.

The ‘electronics’ variable had both the smallest minimum value and the largest maximum value across all six normalized variables, at -1.77534 and 2.85598 respectively.

## Task 3 (43 – 56)

To perform hierarchical clustering on the normalised attitudinal variables, the Euclidean distances between observations were calculated.

Chart

Description automatically generated with medium confidenceUsing these distances, hierarchical clustering with the appropriate library and the method “ward.D2” was performed. The dendogram of the algorithm’s resulting clusters can be seen in Figure 9.

Figure 9: Dendogram for hierarchical clustering algorithm.

## Task 4 (57 – 67)

Observation numbers for each cluster of a six-cluster solution can be seen in Table 1. 59 observations were assigned to the largest cluster, 1, and only 8 observations were assigned to the smallest cluster, 2.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 | Cluster 6 |
| 59 | 8 | 52 | 17 | 35 | 29 |

Table 1: Number of observations assigned to each cluster for a six-cluster solution.

## Task 5 (68 – 86)

Chart, bar chart

Description automatically generatedThe segment profile plot, for a six-cluster solution, generated by the ‘flexclust’ package can be observed in Figure 10.

Figure 10: Segment profile plots for each cluster in a six-cluster solution.

The table of cluster memberships can be observed in Table X. The results indicate that ‘hclust’ and ‘as.kcca’ procedures are almost in full agreement, as only 2 observation clusters were reassigned as a result of the procedures. The reassigned observations can be found in Table 2.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 1 | 2 | 3 | 4 | 5 | 6 |
| 1 | 0 | 59 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 8 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 52 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 17 |
| 5 | 33 | 2 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 29 | 0 |

Table 2: Cluster assignments for ‘hclust’ (vertical) and ‘as.kcca’ (horizontal) procedures.

## Task 6

Cluster 1 was assigned 59 observations in total. Customers of this cluster value variety of choice and furniture more than the average customer, but do not care for return policies, low prices, or quality of service as much as the average customer.

Cluster 2 was assigned 8 observations in total. Customers of this cluster value low prices a lot more than the average customer, and they did not find it important whether an office supply store had furniture, compared to the average customer. They also did not find return policies important.

Cluster 3 was assigned 52 observations in total. Customers of this cluster value return policies and low prices significantly more than average. These customers, when compared to the average, cared less about all other aspects of the store.

Cluster 4 was assigned 17 observations. These customers find it important that their office supplies store carries electronics, and they find return policies to be even more important. However, customers of this cluster do not care for variety of choice and are not looking for low prices.

Cluster 5 was assigned 35 observations. These customers find electronics, variety of choice and furniture to be important aspects of an office supplies store. They do not care as much about quality of service and found return policies to be less important when compared to the average.

Cluster 6 was assigned 29 observations. Customers of this cluster found everything to be of little importance when compared to quality of service. This cluster’s customers rated quality of service importance to be the highest out of any other cluster.

## Task 7

Cluster 2 only contains eight observations, which makes it a significantly smaller cluster when compared to all other clusters. This indicates that the cluster membership is very specific, which are less useful when observing customer behaviour as we are attempting to generate a generalised solution. Hence, it would be wiser to observe the results of a five or less cluster solution, where the cluster’s observations could be absorbed by other clusters.

## Task 8 (91 – 101)

Observation numbers for each cluster of a five-cluster solution can be seen in Table 3. 60 observations were assigned to the largest cluster, 2, and 17 observations were assigned to the smallest cluster, 3.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 |
| 59 | 60 | 17 | 35 | 29 |

Table 3: Number of observations assigned to each cluster for a five-cluster solution.

## Task 9 (102 – 120)

Chart, bar chart

Description automatically generatedThe segment profile plot for a five-cluster solution, generated by the ‘flexclust’ package, can be observed in Figure 11.

Figure 11: Segment profile plots for each cluster in a five-cluster solution.

Cluster 1 was assigned 59 observations. This cluster could be named ‘Interior Designers’, as they value variety of choice and furniture in an office supply store, indicating that they enjoy decorating with a wealth of choice.

Cluster 2 was assigned 60 observations. This cluster could be named ‘Serial Shoppers’ as they value low prices and return policies, indicating that they buy and return products frequently.

Cluster 3 was assigned 17 observations. This cluster could be named ‘Tech Reviewers’, as they value electronics and return policies, indicating that they enjoy trying electronics and returning them

Cluster 4 was assigned 35 observations. This cluster could be named ‘Amazon Shoppers’, as they value electronics, variety of choice and furniture, indicating that they enjoy shopping various categories of products but do not care for quality of service.

Cluster 5 was assigned 29 observations. This cluster could be named ‘Luxury Seekers’, as they value quality of service significantly and do not care for other aspects of the store, indicating that they are happy with their store experience if they are treated well by the store.

## Task 10

The five-cluster solution is better because the smallest cluster in the six-cluster solution was absorbed by another larger cluster, providing for more generalised insights over the data.

## Task 11 (123 – 161)

Cluster 1 contains respondents that are younger on average at 29.51 years. This cluster has the second lowest average income at 26 thousand pounds per year. 18.64% of respondents were reported to be ‘professional’, second lowest out of all clusters. This cluster valued ‘variety\_of\_choice’ and ‘furniture’ most out of all other clusters. To target this cluster, more stock could be developed, especially in furniture and electronics, to provide for more variety in choice.

Cluster 2 contains respondents that are the youngest on average at 25.53 years. This cluster also has the lowest average income at 19.05 thousand pounds per year, which explains why this cluster found ‘low\_prices’ and ‘return\_policy’ to be important. Only 5% of respondents were reported to be ‘professional’, lowest out of all other clusters. To target this cluster, discounts and deals could be prioritised, and online advertising through social media should be employed. Return policies could be revised to be more lenient.

Cluster 3 contains respondents that are older on average at 38.59 years. This cluster has the second highest average income at 45.59 thousand pounds per year. 70.59% of respondents were reported to be ‘professional’, second highest out of all other clusters. This cluster valued ‘electronics’ and ‘return\_policy’ most but valued ‘variety\_of\_choice’ very little. To target this cluster, investment in electronics can be made, and return policies could be revised to be more lenient.

Cluster 4 contains respondents that are on average 35.26 years old. This cluster has an average income of 39.83 thousand pounds per year. 51.43% of respondents were reported to be ‘professional’. This cluster sits in the middle of all metrics when compared to other clusters, and their figures are all around or above average. This cluster valued ‘electronics’, ‘variety\_of\_choice’ and ‘furniture’ more than the average customer. To target this cluster, a web store could be established, where variety of choice for electronics and furniture can be utilised better than a physical location.

Cluster 5 contains respondents that are the oldest on average at 46.21 years, which lines up with the increased service quality importance of this cluster. This cluster also has the highest average income at 54.76 thousand pounds per year, which explains why this cluster did not find ‘low\_prices’ important. 82.76% of respondents in this cluster were reported to be ‘professional’, highest out of all other clusters. To target this cluster, employee training could be improved, and commercials could be run through more traditional channels, such as television and newspaper.

## Task 12 (162 – 177)

Observation numbers for each k-means cluster of a five-cluster solution can be seen in Table 4. 61 observations were assigned to the largest cluster, 5, and 17 observations were assigned to the smallest cluster, 2.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 |
| 60 | 17 | 33 | 29 | 61 |

Table 4: Number of observations assigned to each cluster for a k-means five-cluster solution.

## Task 13 (178 – 222)

The hit rate between the two procedures is 99%. Only two observations were assigned different clusters, which is a behaviour that was also apparent in ‘as.kcca’ method, where two observations were assigned to a cluster different than the hierarchical cluster assignments.

# Project 2

## Task 1 (233 – 254)

‘discount’ variable is a categorical variable that indicates whether the user was offered a 10% discount on their first order or not. 6036 users out of 25046 total users were offered this discount which is 24.10% of users.

Chart, bar chart

Description automatically generated

Figure 12: Histogram of variable ‘discount’.

A screenshot of a computer

Description automatically generated with medium confidence‘conversion’ variable is a categorical variable that indicates whether the user made a purchase on the ecommerce website. 4406 users out of 25046 total users made a purchase, which is only 17.59% of users.

Figure 13: Histogram of variable ‘conversion’.

‘source’ variable is a categorical variable that indicates how the user accessed the ecommerce website. There are three possible values for this variable: through advertisements (‘ads’), directly through what can be assumed the ecommerce website’s URL (‘direct’), and through a search which can be assumed as a search engine result (‘search’). Most users accessed the ecommerce website through a search engine result, at 82.84%. Following ‘search’ is ‘direct’ at 10.4%, and ‘ads’ at 6.76%.

Chart

Description automatically generated

Figure 14: Histogram of variable ‘source’.

Chart, histogram

Description automatically generated‘total\_pages\_visited’ is a numerical variable that indicates how many pages of the ecommerce website the user visited. This variable has a mean of 4.344 and a median of 4. The third quartile value for this variable is 6, indicating 75% of users visit 6 pages or less.

Figure 15: Histogram of variable ‘total\_pages\_visited’.

Chart, histogram

Description automatically generated‘visit\_duration’ is a numerical variable that indicates how long the user stayed on the ecommerce website, in seconds. This variable has a mean of 260 seconds and a median of 241.19 seconds, indicating most users spend less than 5 minutes on the website in total.

Figure 16: Histogram of variable ‘visit\_duration’.

Chart, bar chart

Description automatically generated‘country’ is a categorical variable that indicates where the users reside. There are four possible values for this variable: ‘france’, ‘germany’, ‘ireland’ and ‘uk’. Most users in this dataset visited the ecommerce website from the UK, at 36.02%.

Figure 17: Histogram of variable ‘country’.

## Task 2 (255 – 262)

The coefficient estimate of ‘discountyes’ for model ‘m1’ is 1.10090. The sign is positive. The coefficient is statistically significant to 10^-3 level.

## Task 3 (263 – 267)

The odds ratio for ‘discountyes’ is 3.006872. This means that when a user of the ecommerce website was offered a 10% discount on their first order, they were 3 times more likely to make a purchase, compared to users that were not offered this discount.

## Task 4 (268 – 272)

The 95% confidence interval for the odds ratio for ‘discountyes’ is between 2.8071755 and 3.2205543. This means that the middle 95% of users were 2.8 to 3.2 times more likely to make a purchase if they were offered a discount, compared to users that were not offered this discount.

## Task 5 (273 – 289)

Chart, bar chart

Description automatically generatedThe double decker mosaic plot featuring the impact of discount on conversion, for each ‘source’ type, can be observed in Figure 18.

Figure 18: Double decker mosaic plot for effect of discount over conversion, by source type.

Discounts appear to have the most effect on conversion when the user source type is ‘search’. Assuming type ‘search’ means that the user arrived on the ecommerce site through a search engine query, this finding can be used to target users who arrive on the ecommerce site through this channel, and to offer discounts specifically for them.

For user source type ‘ads’, the discount offer appears to have had little impact at best, indicating the store users do not care for discounts when they arrive on the ecommerce site through an advertisement.

Finally, for user source type ‘direct’, the discount offer appears to have had some impact, but less than the impact discounts had on ‘search’.

## Task 6 (290 – 297)

The coefficient estimate of ‘sourcedirect’ for model ‘m2’ is 0.69434. The sign is positive. The coefficient is statistically significant at 99.999% level.

The coefficient estimate of ‘sourcesearch’ for model ‘m2’ is 0.73645. The sign is positive. The coefficient is statistically significant at 99.999% level.

## Task 7 (298 – 302)

The odds ratio for ‘sourcedirect’ is 2.00238016. This means that if the ecommerce user accessed the ecommerce website directly, they were 2 times more likely to make a purchase, compared to users that accessed the ecommerce website through another source.

The odds ratio for ‘sourcesearch’ is 2.08849965. This means that if the ecommerce user accessed the ecommerce website through a search, they were 2 times more likely to make a purchase, compared to users that accessed the ecommerce website through another source.

## Task 8 (303 – 310)

The coefficient estimate of ‘discountyes:sourcedirect’ for model ‘m3’ is 0.30445. The sign is positive. The coefficient is statistically significant at 90% level.

The coefficient estimate of ‘discountyes:sourcesearch’ for model ‘m3’ is 1.30923. The sign is positive. The coefficient is statistically significant at 99.999% level.

## Task 9 (311 – 315)

The 95% confidence interval for the odds ratio for ‘discountyes:sourcedirect’ is between 0.9561778 and 1.9205866. This means that the middle 95% of users were 0.95 to 1.92 times more likely to make a purchase if they were offered a discount and if they accessed the ecommerce website directly, compared to users that were not offered this discount and/or accessed the ecommerce website through other channels.

The 95% confidence interval for the odds ratio for ‘discountyes:sourcesearch’ is between 2.7653813 and 4.9569491. This means that the middle 95% of users were 2.76 to 4.95 times more likely to make a purchase if they were offered a discount and if they accessed the ecommerce website through a search, compared to users that were not offered this discount and/or accessed the ecommerce website through other channels.

## Task 10 (316 – 326)

The variables ‘visit\_duration’, ‘sourcedirect’, and ‘discountyes:sourcedirect’ were the only coefficients significant at a 95% level.

## Task 11 (327 – 331)

The correlation between ‘total\_pages\_visited’ and ‘visit\_duration’ is 0.9993129, which means that the two variables are almost entirely positively correlated. These two models are understandably correlated; logically if a user visits more pages, their visit duration will also be longer.

However, this may result in multicollinearity in our model, where the independent variables of our model are not independent from each other. Multicollinearity can impact the accuracy of coefficient estimates.

## Task 12 (332 – 345)

For model ‘m5’, ‘total\_pages\_visited’ has a coefficient estimate of 0.416732. This coefficient estimate is also statistically significant at a 99.999% level.

For comparison, ‘total\_pages\_visited’ had a coefficient estimate of -0.054773 in model ‘m4’, which was not statistically significant.

The changes made in model ‘m5’ can overall be deemed positive, as the impact of ‘total\_pages\_visited’ is modelled more accurately.

## Task 13 (346 – 368)

Chart, box and whisker chart

Description automatically generatedThe visualisation of odds ratios and confidence intervals for the independent variables of model ‘m5’ can be observed in Figure 19.

Figure 19: Odds ratios (points) and confidence intervals (error bars) of each variable of model ‘m5’.

## Task 14 (369 – 382)

The mean value of ‘base\_probs’ is 0.1759163.

## Task 15 (383 – 394)

Using a threshold value of 0.5 for the indicator variable ‘pred\_conversion’, 1358 users were predicted to convert.

## Task 16 (395 – 408)

‘pred\_conversion’ has an accuracy of 84.237% over ‘conversion’.

## Task 17 (409 – 414)

AUC metric for predictions made with model ‘m5’ is 0.774793.

## Task 18 (415 – 438)

Upon increasing all users’ ‘total\_pages\_visited’ metric by one unit, i.e., one more page visited by all users, and adding the new probabilities generated by the model to the dataset, the mean of the probabilities is 0.1759163, which is identical to the figure calculated in Task 14.

## Task 19 (439 – 443)

Lift calculation for the difference between model ‘m5’ and the hypothetical scenario where all users visited an additional page yields the value 2.00377e-13, as probability calculations for the two models do not change much. The value is very close to zero because a change that impacts all values of a variable equivalently should not change the probability calculations from the previous model.

# Project 3

## Task 1 (451 – 472)

‘respondent\_id’ is first of the four identifier variables of this dataset. This variable indicates the respondent that made the choice, which can be one of 200 total respondents.

‘choiseset\_id’ is an identifier variable that indicates the count of the choice sets that were offered to each respondent. Each respondent should have 15 choice sets in total.

‘alternative\_id’ is an identifier variable that refers to the alternative number within each choice set. Each choice set should have 3 alternatives.

‘choice\_id’ is an identifier variable that indicates the choice set an entry belongs to, within the greater scale of the dataset. There should be 3000 unique values, and 3 entries should share the same ‘choice\_id’ value with each other.

‘cloud\_storage’ is a categorical variable that indicates the cloud storage size in gigabytes. There are 3 possible values for this variable: ‘30gb’, ‘2000gb’ and ‘5000gb’.

‘customer\_support’ is a categorical variable that indicates whether customer support is included within the alternative.

‘cloud\_services’ is a categorical variable that indicates the features that are included within the alternative. There are 3 possible values for this variable: ‘email’, ‘email + video’, and ‘email + video + productivity’.

‘price’ is a categorical variable that indicates the price of the alternative. There are 3 possible values for this variable: ‘p6’, ‘p12’, ‘p18’.

Each non-identifier variable mentioned up to this point have evenly distributed levels.

‘choice’ is a numerical variable that indicates whether an alternative was chosen by the respondent or not.

## Task 2 (473 – 479)

A relevel is required for the variables ‘cloud\_storage’ and ‘price’. This is because when dummy variables are added to variables of type factor such as the aforementioned variables, the dataset splits factors into dummy variables for each level except for the base level. Defining a base level allows the model to display coefficients for levels other than the base level, thus making coefficients, or in this case the upgrades to features, easier to interpret.

## Task 3 (480 – 499)

The mean of the newly created ‘price\_n’ variable is 12.01533.

## Task 4 (500 – 512)

Respondents within the dataset chose the ‘30gb’ option 830 times out of the 3000 total choices.

20.8% of the respondents’ choices had ‘email’ for their ‘cloud\_services’ variable.

## Task 5 (513 – 523)

Dataset ‘m\_data’ contains 8 columns.

## Task 6 (524 – 534)

The coefficient estimate of ‘cloud\_storage5000gb’ for model ‘model1’ is 0.894883. The estimate is statistically significant at a 99.999% level.

The coefficient estimate of ‘pricep12’ for model ‘model1’ is -0.836795. The estimate is statistically significant at a 99.999% level.

## Task 7 (535 – 545)

The coefficient estimate of ‘price\_n’ for model ‘model2’ is -0.133936. The estimate is statistically significant at a 99.999% level. Since this coefficient estimate is continuous, the coefficient estimate indicates that if all other variables stayed constant, and price was increased by one unit, the target variable would decrease by 0.133936. This is different from the ‘price’ variable coefficients in model ‘model1’, as those coefficients could only measure the effect of ‘price = p12’ and ‘price = p18’ on the target variable.

## Task 8 (546 – 550)

The models ‘model1’ and ‘model2’ are not very different from each other, as their log likelihood is only apart by 0.2. However, model ‘model1’ has the slight edge over model ‘model2’ in log likelihood, and thus is the better choice.

## Task 9 (551 – 559)

Upon predicting the choice probabilities of different alternatives, the predicted probability of choosing the third alternative in the first choice set is 0.0284, or 2.84%.

## Task 10 (560 – 573)

Upon computing the predicted alternatives for each choice using the maximum choice probabilities, the predicted alternative in the third choice set is 2.

## Task 11 (574 – 583)

Upon extracting the selected alternatives for each choice set, the selected alternative in the fifteenth choice set is 2.

## Task 12 (584 – 592)

The confusion matrix for model ‘model2’ can be observed in Table 5.

|  |  |  |  |
| --- | --- | --- | --- |
|  | 1 | 2 | 3 |
| 1 | 579 | 211 | 197 |
| 2 | 190 | 624 | 200 |
| 3 | 185 | 200 | 614 |

Table 5: Confusion matrix for model ‘model2’.

The accuracy of model ‘model2’ is 0.6056667, or 60.57%. Compared to the expected baseline random prediction accuracy of 33%, model ‘model2’ is almost twice as good at making correct predictions.

## Task 13 (593 – 603)

Coding task.

## Task 14 (604 – 611)

Coding task.

## Task 15 (612 – 618)

The predicted market share for alternative four of the hypothetical market is 0.1445737, or 14.46%.

## Task 16 (619 – 632)

Upon modifying the ‘cloud\_services’ attribute for the fifth alternative in the hypothetical market, the predicted market share for alternative four increased to 0.1867029, or 18.67%.

## Task 17 (633 – 637)

Changes in market share between the first hypothetical scenario and the new hypothetical scenario can be observed in Table 6.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Alternative 1 | Alternative 2 | Alternative 3 | Alternative 4 | Alternative 5 |
| 0.05245839 | 0.04419348 | 0.03846904 | 0.04212921 | -0.17725012 |

Table 6: Changes in market share for each alternative, from first hypothetical scenario to the new hypothetical scenario.

Alternative 5’s market share changed the most, as its market share decreased 17.72%. The change made in the new hypothetical scenario was essentially a downgrade for alternative 5 in terms of features without a change in price, and thus the market share figures accurately reflect the change as alternative 5 becomes less desirable for the price.

## Task 18 (638 – 642)

Using the model ‘model2’ coefficients, a consumer would be willing to pay £3.68 more per month for customer support.

## Task 19 (643 – 647)

Using the model ‘model2’ coefficients, a consumer would be willing to pay £1.23 more per month for an upgrade from 30GB to 2000GB cloud storage.

## Task 20 (648 – 652)

Using the model ‘model2’ coefficients, a consumer would be willing to pay £ 5.45 more per month for an upgrade from 2000GB to 5000GB cloud storage.

# Appendix

## script.R file (included within submission)