always_allow_html: yes

title: “Final Assignment” output: word_document: default html_notebook: default pdf_document: default html_document: default — # Experimental Design and Data Analysis - How does marital status affect hotel choices. # how does martial status effect hotels choices

Introduction

Importing data from original databse consumer class variable is created from the variablessrchadultscountand srchchildrencount. Consumers with asrchadultcountof 1 and 2 would be transformed to “sin-gle person” and “couples” respectively. Consumers with a srchchildrencount greater than 1 wouldbe called “parents”. All other consumers are called “others

Research question

The present work aims at discovering what influences clients to book properties in the Expedia website. Many explanatory variables are present, such as the user ID, the property ID, the mean star rating of hotels, and whether the user clicked and/or booked a property, among others.

Importing data from original databse

An initial shortening of the dataset was made necessary, since the original dataset had almost 4 million entries and 54 columns. The original database is the expedia dataset for kaggel competition which was provided in VU Data Minging class of 2017.

Consumer feature was created from the combination of srch number of adults and number of children single: one person : search adult == 1 couple: two people (real couple or friends) : search adult > 1 parents: anyone traveling with children search children > 0 other: more than 2 people in the room and no children : search adult > 2 & search shildren == 0

The original data set had a large amount of missing values which were excluded or replaced before importing the data to R.

loading and saving

due to the large dataset the original data set was saved in a RData object for faster loading and access

```
load(file = "../Data/mydata.RData")
# save(mydata,file = "../Data/mydata.RData")
mydata <- data
remove(data)
```

Trim database

uneccesery features were removed to make graphs more meaningful

```
# mydata <- subset(mydata, select = -c(prop_brand_bool,position,srch_saturday_night_bool,random_bool,pr
length(((mydata$srch_id)))
```

```
## [1] 221879
```

```
length((unique(mydata$srch_id)))
```

```
## [1] 199795
```

Data set contains 221879 search ids and 199795 uniqe search ids srch_id coresponds to a user searching search session ### Subsetting The data set is still too large for the purposes of this research, therefore only properties were the user showed interet by clicking are subset and prop_review_score of 0 which means the property has no ranking are also removed. To create a smaller sample size only the first 4000 srch_id are selected.

```
mydata <- mydata[which(mydata$click_bool ==  1),]
mydata <- subset(mydata, select = -c(click_bool))
mydata <- mydata[which(mydata$prop_review_score !=  0),]
mydata <- mydata[which(mydata$srch_id < 4000),]
# mydata <- head(mydata,1000)
length(((mydata$srch_id)))
```

```
## [1] 2611
```

```
length((unique(mydata$srch_id)))
```

```
## [1] 2360
```

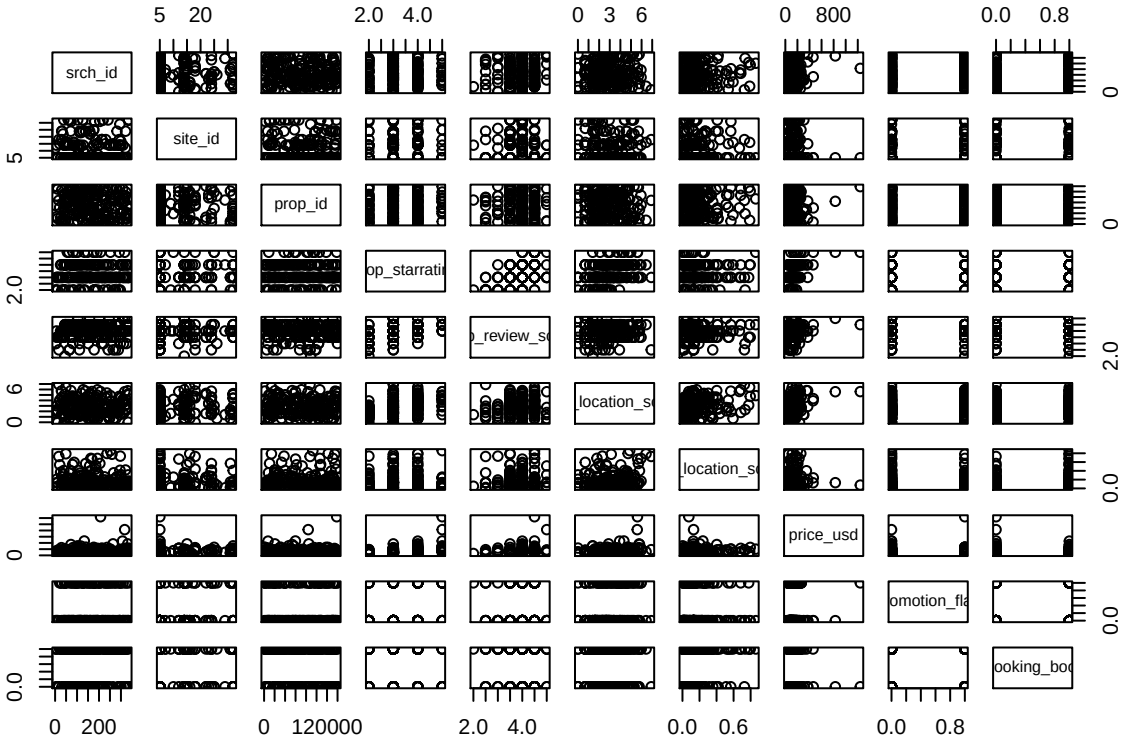
```
summary(mydata)
```

```
##     srch_id        site_id         prop_id       prop_starrating
##  Min.   :   1   Min.   : 1.00   Min.   :     4   Min.   :1.00
##  1st Qu.:1030   1st Qu.: 5.00   1st Qu.: 35474   1st Qu.:3.00
##  Median :2001   Median : 5.00   Median : 70789   Median :3.00
##  Mean   :2002   Mean   :10.14   Mean   : 71219   Mean   :3.46
##  3rd Qu.:2980   3rd Qu.:14.00   3rd Qu.:106868   3rd Qu.:4.00
##  Max.   :3999   Max.   :34.00   Max.   :140816   Max.   :5.00
##  prop_review_score prop_location_score1 prop_location_score2
##  Min.   :1.000     Min.   :0.000        Min.   :0.0000
##  1st Qu.:4.000     1st Qu.:1.790        1st Qu.:0.0499
##  Median :4.000     Median :2.830        Median :0.1304
##  Mean   :4.034     Mean   :2.969        Mean   :0.1735
##  3rd Qu.:4.500     3rd Qu.:4.110        3rd Qu.:0.2288
##  Max.   :5.000     Max.   :6.930        Max.   :0.9992
##    price_usd       promotion_flag    booking_bool      consumer
##  Min.   :  12.80   Min.   :0.0000   Min.   :0.0000   Length:2611
##  1st Qu.:  88.47   1st Qu.:0.0000   1st Qu.:0.0000   Class :character
##  Median : 120.00   Median :0.0000   Median :1.0000   Mode  :character
##  Mean   : 148.10   Mean   :0.2957   Mean   :0.6289
##  3rd Qu.: 179.00   3rd Qu.:1.0000   3rd Qu.:1.0000
##  Max.   :1242.00   Max.   :1.0000   Max.   :1.0000
```

The data set now has 2611 search ids in which 2360 are uniqe. Prop_starrating ranges from 1 to 5 with step of 0.5 representing the star rating of the property. Prop_review_score ranges from 1 to 5 representing the user's review score of the property. Prop_location_score1 and prop_location_score2 are the internal location scoring of the property from Expedia. Price_usd coresponds to the price of the property. Promotion_flag is a binary 0 or 1 value on whether the property was promoted or not. Booking_bool is also a binary 0 or 1 determining if the user has booked the property. Consumer is a catagorical variable with classes Single, Couple, Parents and Other.

pairs plot

```
df <- subset(head(mydata,200), select = -c(consumer))
# df <- subset(head(mydata,100), select = c(price_usd,prop_starrating,prop_review_score))
pairs(df)
```




```
# library(plotly)
# library(ggplot2)
# pm <- GGally::ggpairs(df)
# p <- ggplotly(pm)
# tmpFile <- tempfile(fileext = ".png")
# export(p, file = tmpFile)
```

```
shapiro.test(mydata$price_usd)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  mydata$price_usd
## W = 0.76229, p-value < 2.2e-16
```

```
# quickplot(sample = price_usd, data = mydata, color=consumer)
```

disterbution test for price is proven to be not normally disterbuted

```
library(outliers)
chisq.out.test(mydata$price_usd, variance = var(mydata$price_usd),opposite = TRUE)
```

```
##
##  chi-squared test for outlier
##
## data:  mydata$price_usd
## X-squared = 1.8554, p-value = 0.1732
## alternative hypothesis: lowest value 12.8 is an outlier
```

```
chisq.out.test(mydata$price_usd, variance = var(mydata$price_usd),opposite = FALSE)
```

```
##
##  chi-squared test for outlier
```

```
##
## data:  mydata$price_usd
## X-squared = 121.28, p-value < 2.2e-16
## alternative hypothesis: highest value 1242 is an outlier
```

removing outliers

```
mydata <- mydata[which(mydata$price_usd < 1242 ),]
chisq.out.test(mydata$price_usd, variance = var(mydata$price_usd),opposite = TRUE)
```

```
##
##  chi-squared test for outlier
##
## data:  mydata$price_usd
## X-squared = 1.9331, p-value = 0.1644
## alternative hypothesis: lowest value 12.8 is an outlier
```

```
chisq.out.test(mydata$price_usd, variance = var(mydata$price_usd),opposite = FALSE)
```

```
##
##  chi-squared test for outlier
##
## data:  mydata$price_usd
## X-squared = 77.699, p-value < 2.2e-16
## alternative hypothesis: highest value 1002.82 is an outlier
```

```
library(plotly)
```

```
## Loading required package: ggplot2
```

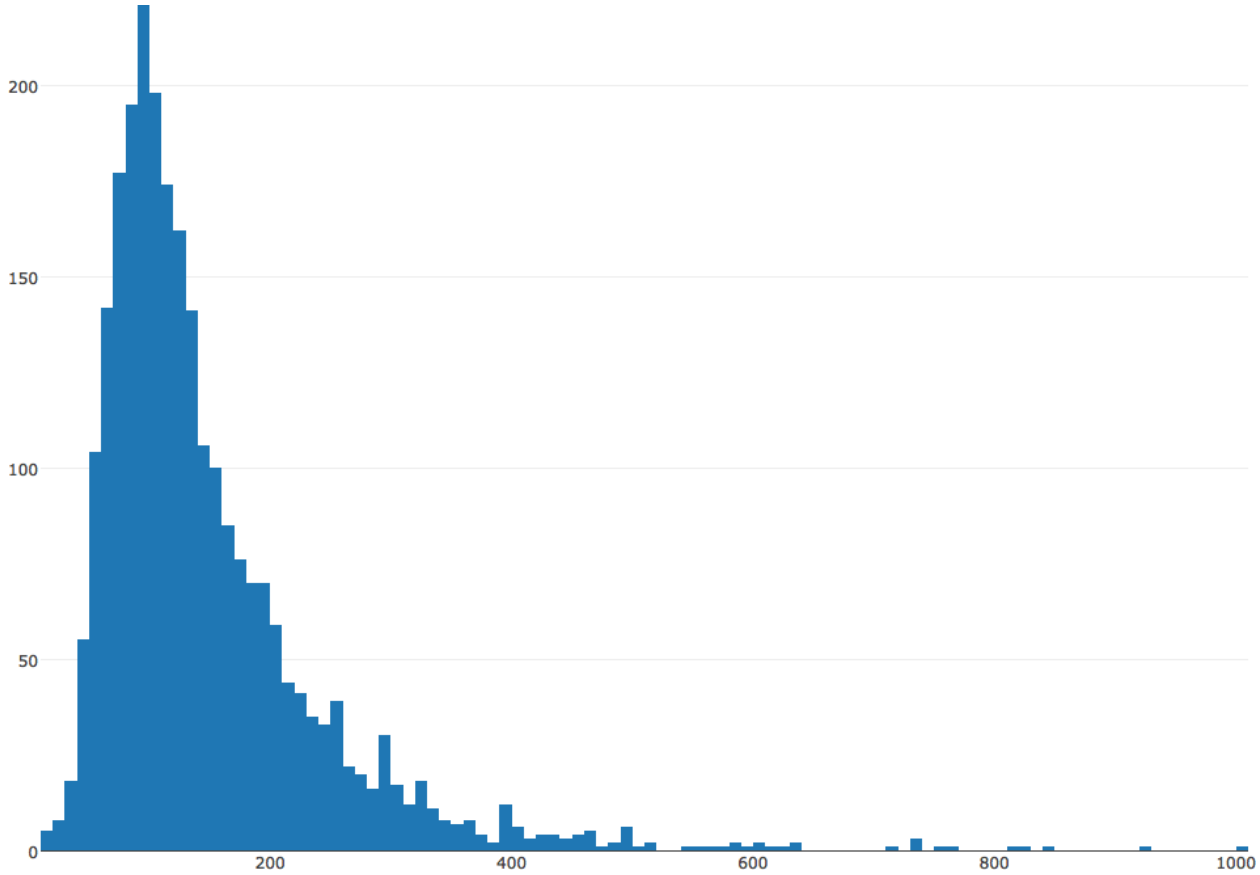
```
##
## Attaching package: 'plotly'
```

```
## The following object is masked from 'package:ggplot2':
##
##     last_plot
```

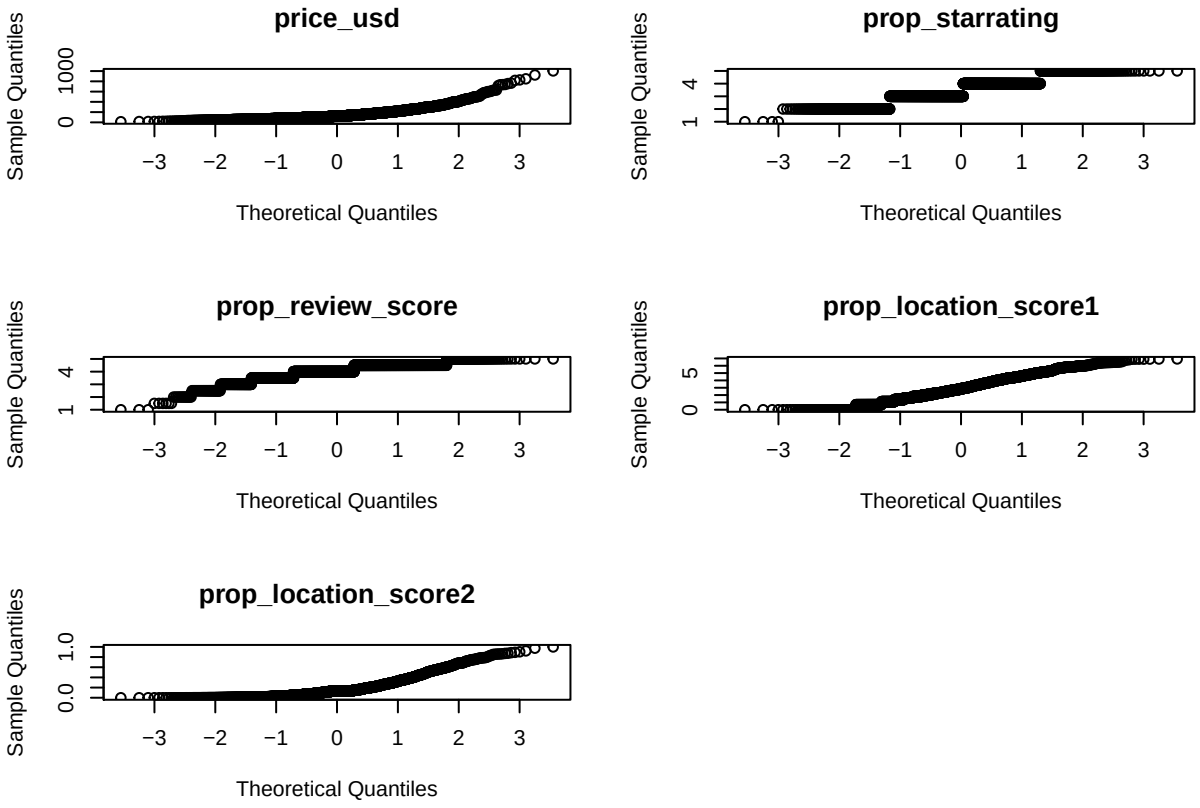
```
## The following object is masked from 'package:stats':
##
##     filter
```

```
## The following object is masked from 'package:graphics':
##
##     layout
```

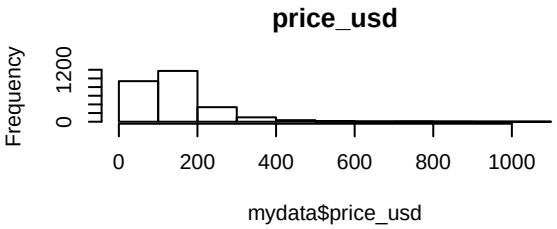
```
# library(ggplot2)
p <- plot_ly(x = mydata$price_usd, type = "histogram")
# ggplotly(p)
# ggplotly(p)


tmpFile <- tempfile(fileext = ".png")
export(p, file = tmpFile)
```

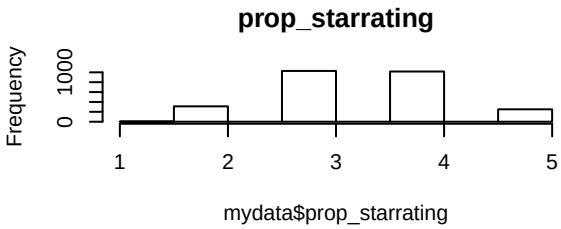


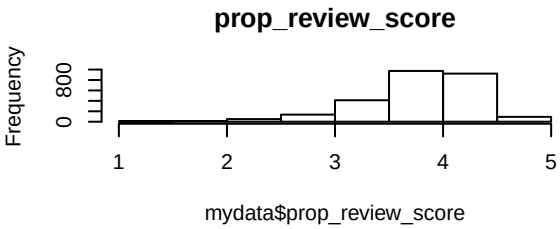

```
par(mfrow=c(3,2));
qqnorm(mydata$price_usd,main="price_usd")
qqnorm(mydata$prop_starrating,main="prop_starrating")
qqnorm(mydata$prop_review_score,main="prop_review_score")
qqnorm(mydata$prop_location_score1,main="prop_location_score1")
qqnorm(mydata$prop_location_score2,main="prop_location_score2")
```

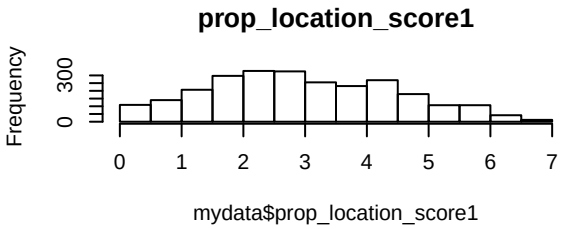


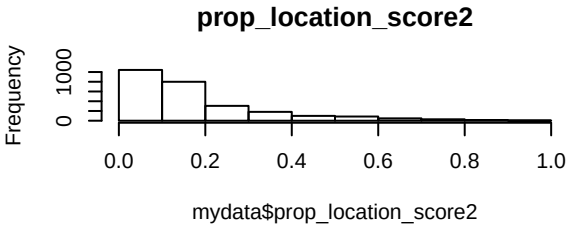

```
par(mfrow=c(3,2));
hist(mydata$price_usd,main="price_usd")
hist(mydata$prop_starrating,main="prop_starrating")
hist(mydata$prop_review_score,main="prop_review_score")
hist(mydata$prop_location_score1,main="prop_location_score1")
hist(mydata$prop_location_score2,main="prop_location_score2")
```












```
options(warn=-1)
df <- subset(mydata, select = -c(consumer,srch_id,booking_bool))
# round(cor(df),3)
library(Hmisc)
res<-rcorr(as.matrix(df))
signif(res$r, 2)
```

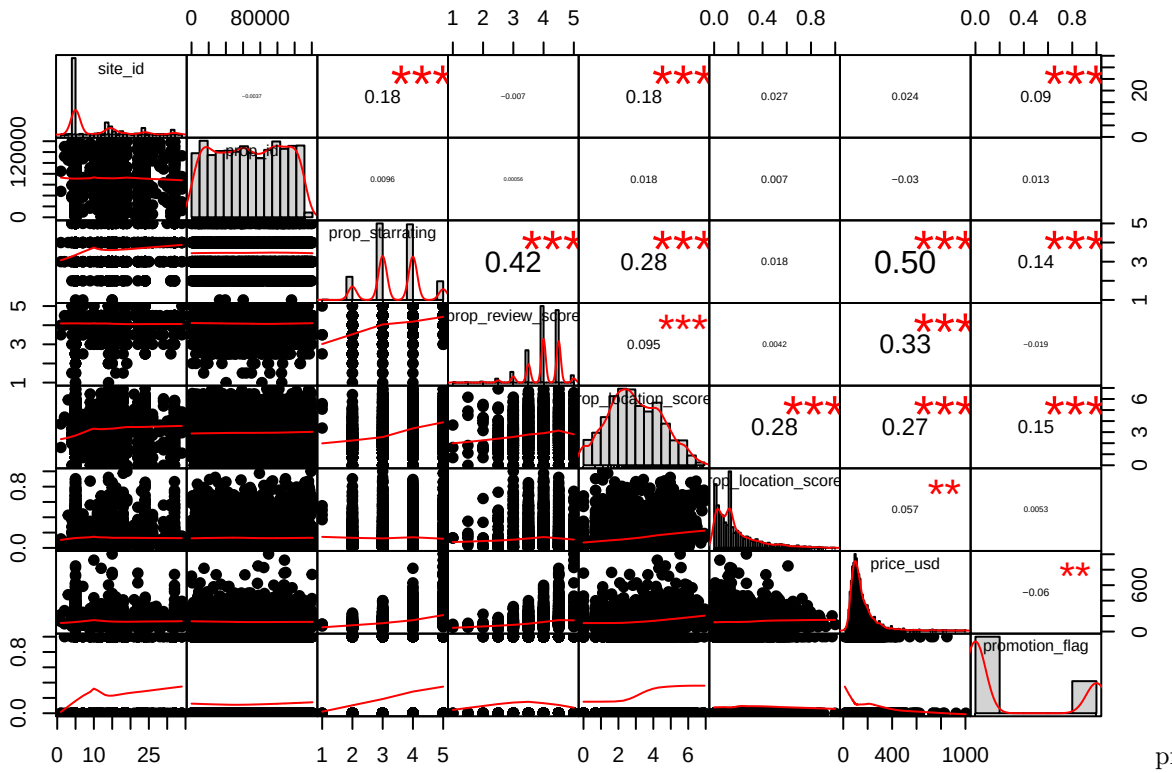
```
##                     site_id  prop_id prop_starrating prop_review_score
## site_id              1.0000 -0.00370          0.1800          -0.00700
## prop_id             -0.0037  1.00000          0.0096           0.00056
## prop_starrating      0.1800  0.00960          1.0000           0.42000
## prop_review_score   -0.0070  0.00056          0.4200           1.00000
## prop_location_score1 0.1800  0.01800          0.2800           0.09500
## prop_location_score2 0.0270  0.00700          0.0180           0.00420
## price_usd            0.0240 -0.03000          0.5000           0.33000
## promotion_flag       0.0900  0.01300          0.1400          -0.01900
##                     prop_location_score1 prop_location_score2 price_usd
## site_id                            0.180               0.0270     0.024
## prop_id                            0.018               0.0070    -0.030
## prop_starrating                    0.280               0.0180     0.500
## prop_review_score                  0.095               0.0042     0.330
## prop_location_score1               1.000               0.2800     0.270
## prop_location_score2               0.280               1.0000     0.057
## price_usd                          0.270               0.0570     1.000
## promotion_flag                     0.150               0.0053    -0.060
##                     promotion_flag
## site_id                     0.0900
## prop_id                     0.0130
```

```
## prop_starrating              0.1400
## prop_review_score           -0.0190
## prop_location_score1         0.1500
## prop_location_score2         0.0053
## price_usd                   -0.0600
## promotion_flag               1.0000
```

```
signif(res$P,2)
```

```
##                      site_id prop_id prop_starrating prop_review_score
## site_id                   NA    0.85         0.0e+00           7.2e-01
## prop_id                8.5e-01      NA         6.2e-01           9.8e-01
## prop_starrating        0.0e+00    0.62              NA           0.0e+00
## prop_review_score      7.2e-01    0.98         0.0e+00                NA
## prop_location_score1   0.0e+00    0.35         0.0e+00           1.2e-06
## prop_location_score2   1.6e-01    0.72         3.6e-01           8.3e-01
## price_usd              2.2e-01    0.13         0.0e+00           0.0e+00
## promotion_flag         4.2e-06    0.49         1.7e-13           3.4e-01
##                      prop_location_score1 prop_location_score2 price_usd
## site_id                           0.0e+00               0.1600    0.2200
## prop_id                           3.5e-01               0.7200    0.1300
## prop_starrating                   0.0e+00               0.3600    0.0000
## prop_review_score                 1.2e-06               0.8300    0.0000
## prop_location_score1                   NA               0.0000    0.0000
## prop_location_score2              0.0e+00                   NA    0.0035
## price_usd                         0.0e+00               0.0035        NA
## promotion_flag                    5.8e-15               0.7900    0.0021
##                      promotion_flag
## site_id                     4.2e-06
## prop_id                     4.9e-01
## prop_starrating             1.7e-13
## prop_review_score           3.4e-01
## prop_location_score1        5.8e-15
## prop_location_score2        7.9e-01
## price_usd                   2.1e-03
## promotion_flag                   NA
```

```
library(PerformanceAnalytics)
chart.Correlation(df, histogram=TRUE, pch=19)
```



prop_review_score prop_location_score1 prop_location_score2 price_usd promotion_flag booking_bool
prop_starrating 1.00 0.31 0.30 0.05 0.47 0.19 0.00 prop_review_score 0.31 1.00 0.15 0.04 0.22 0.06 0.12
prop_location_score1 0.30 0.15 1.00 0.29 0.27 0.16 0.00 prop_location_score2 0.05 0.04 0.29 1.00 0.02
0.03 0.11 price_usd 0.47 0.22 0.27 0.02 1.00 -0.01 -0.11 promotion_flag 0.19 0.06 0.16 0.03 -0.01 1.00 0.11
booking_bool 0.00 0.12 0.00 0.11 -0.11 0.11 1.00

with 0.47 prop_starrating has the highest colinearity with price_usd followed by 0.31 for prop_starrating and prop_review_score

randomized block design

```
xtabs(price_usd ~ prop_starrating + consumer ,data=mydata)
```

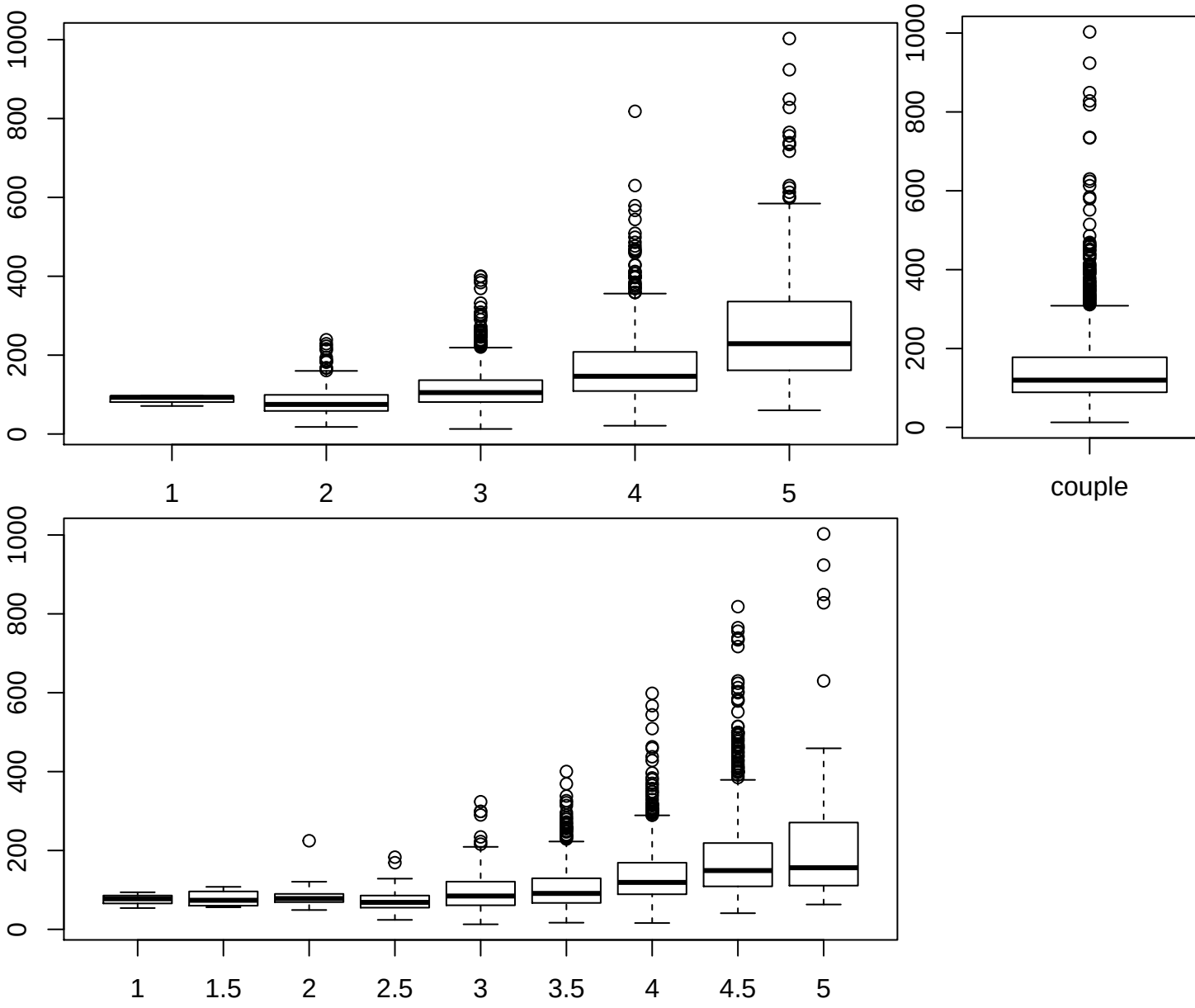
```
##                consumer
## prop_starrating   couple    other  Parents   single
##               1   283.27     0.00     0.00    71.00
##               2 14137.50  3322.21  2472.32  6026.93
##               3 70900.22 14139.67  7777.78 26433.55
##               4 97350.56 21189.41 12108.00 39897.67
##               5 41575.44  8771.48  5074.91 13921.75
```

```
xtabs(price_usd ~ prop_starrating + prop_review_score ,data=mydata)
```

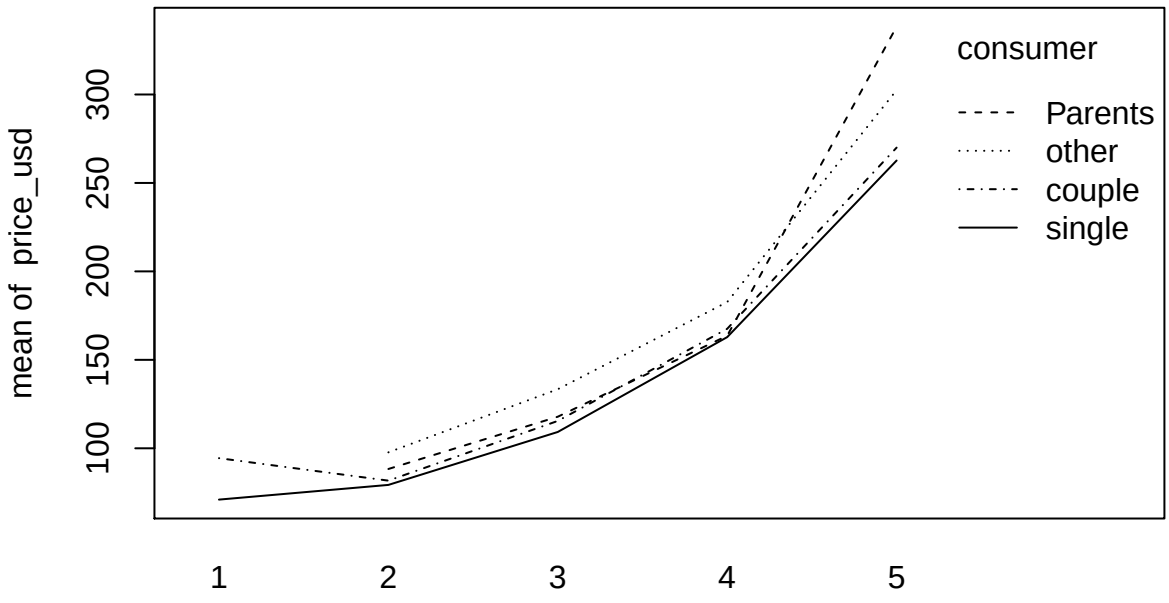
```
##                prop_review_score
## prop_starrating         1       1.5         2       2.5         3       3.5
##               1      0.00      0.00      0.00     71.00      0.00   187.94
##               2     94.00    130.00    602.96   2557.00   4836.28  7592.06
##               3     54.00    241.20    258.23    842.83   6289.98 20924.98
##               4     77.46     96.14    302.71    253.01   2007.35 14835.05
##               5      0.00      0.00      0.00      0.00    290.75  1369.09
##                prop_review_score
## prop_starrating         4       4.5         5
```

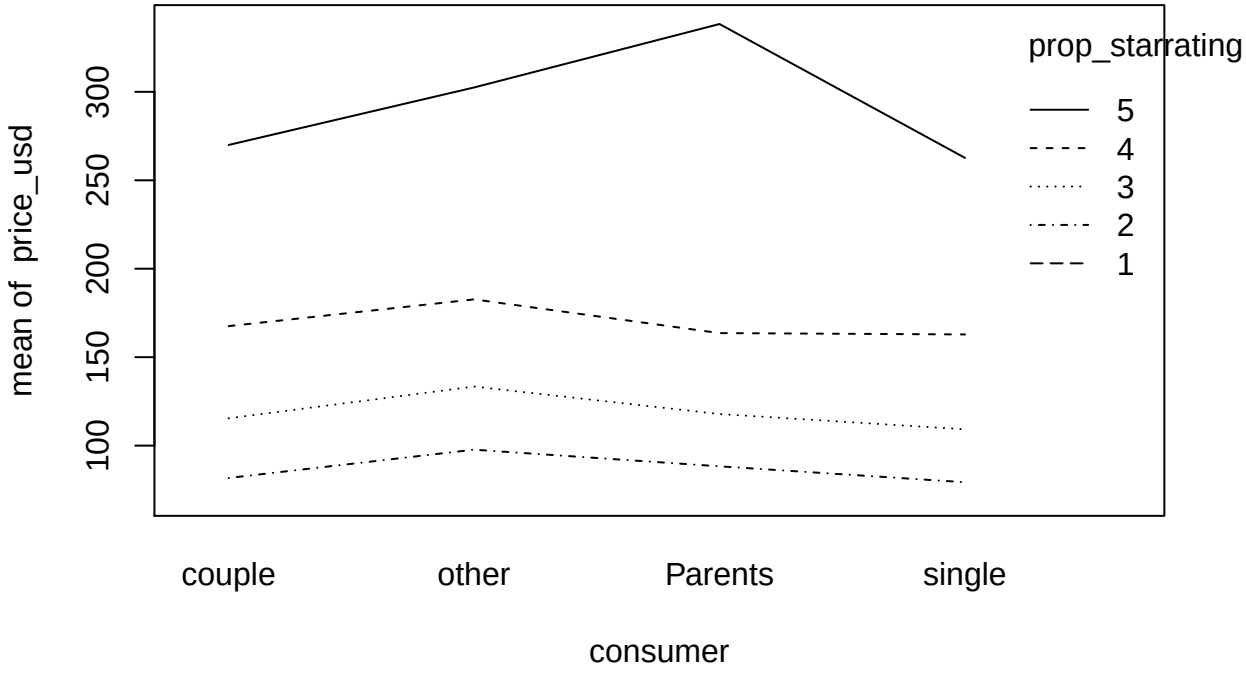
```
##               1     0.00     0.00    95.33
##               2  7519.50  2366.98   260.18
##               3 48109.98 38167.51  4362.51
##               4 67381.06 79444.55  6148.31
##               5 10287.25 47696.34  9700.15
```

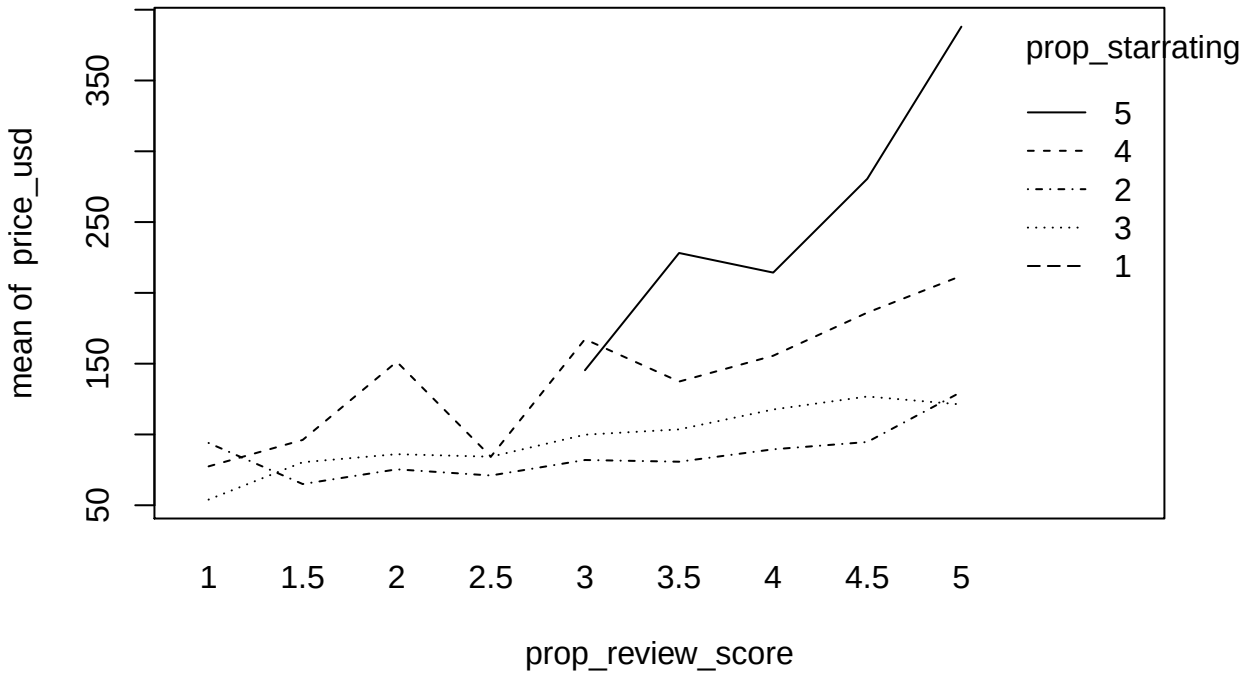
```
attach(mydata)
# par(mfrow=c(3,3))
boxplot(price_usd~prop_starrating); boxplot(price_usd~consumer) ; boxplot(price_usd~prop_review_score)
```




```
interaction.plot(prop_starrating,consumer,price_usd); interaction.plot(consumer,prop_starrating,price_us
```


consumer
Parents
other
couple
single
mean of price_usd
100
150
200
250
300
1
2
3
4
5
prop_starrating


prop_starrating
5
4
3
2
1
mean of price_usd
100
150
200
250
300
couple
other
Parents
single
consumer




```
mydata$prop_starrating=factor(mydata$prop_starrating)
mydata$prop_review_score=factor(mydata$prop_review_score)

aovpen=lm(price_usd~prop_starrating+prop_review_score,data=mydata)

anova(aovpen)
```

```
## Analysis of Variance Table
##
## Response: price_usd
##                     Df   Sum Sq Mean Sq F value    Pr(>F)
## prop_starrating      4  6891830 1722958 263.075 < 2.2e-16 ***
## prop_review_score    8   654198   81775  12.486 < 2.2e-16 ***
## Residuals         2597 17008542    6549
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(aovpen)
```

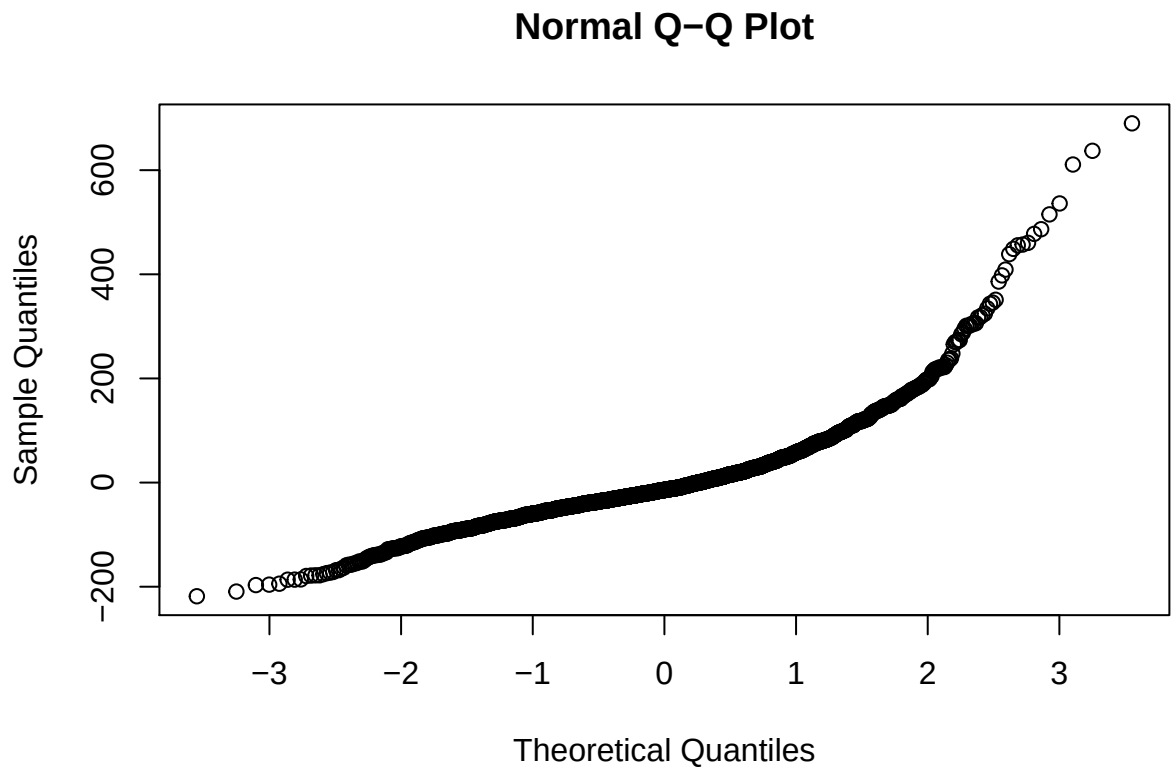
```
##
## Call:
## lm(formula = price_usd ~ prop_starrating + prop_review_score,
##     data = mydata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -218.34  -44.54  -14.29   27.88  689.93
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)            41.344     61.947   0.667   0.5046
## prop_starrating2        4.234     40.845   0.104   0.9174
## prop_starrating3       24.803     40.731   0.609   0.5426
```

```
## prop_starrating4       72.390     40.767   1.776   0.0759 .
## prop_starrating5      169.608     41.022   4.135 3.67e-05 ***
## prop_review_score1.5   10.668     57.228   0.186   0.8521
## prop_review_score2     28.720     51.858   0.554   0.5797
## prop_review_score2.5   20.780     48.161   0.431   0.6662
## prop_review_score3     35.156     47.245   0.744   0.4569
## prop_review_score3.5   33.086     46.899   0.705   0.4806
## prop_review_score4     44.191     46.815   0.944   0.3453
## prop_review_score4.5   67.388     46.840   1.439   0.1504
## prop_review_score5    101.942     47.524   2.145   0.0320 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 80.93 on 2597 degrees of freedom
## Multiple R-squared:  0.3073, Adjusted R-squared:  0.3041
## F-statistic: 96.02 on 12 and 2597 DF,  p-value: < 2.2e-16
```

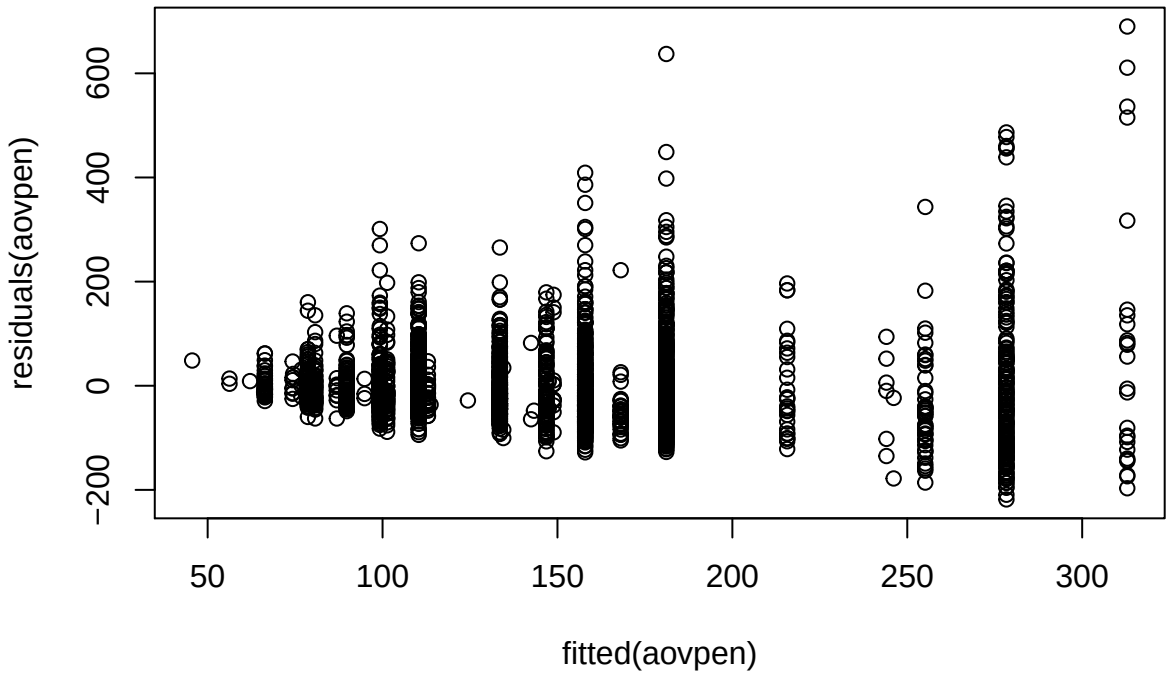
```
drop1(aovpen,test="Chisq")
```

```
## Single term deletions
##
## Model:
## price_usd ~ prop_starrating + prop_review_score
##                   Df Sum of Sq      RSS   AIC  Pr(>Chi)
## <none>                          17008542 22947
## prop_starrating    4   4564659 21573201 23560 < 2.2e-16 ***
## prop_review_score  8    654198 17662741 23030 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
qqnorm(residuals(aovpen))
```




```
plot(fitted(aovpen),residuals(aovpen))
```



prop_starrating is more significant than consumer type and prop_review_score but also both significant

Logistic Regression

An experiment with: an outcome Y that is 0 or 1 ("binary dependent variable"); one or more numerical explanatory variables X1,...,Xp. one or more factor explanatory variables. ("independent variable"). The purpose is to explain Y by a function of X.

```
# tot=xtabs(~prop_review_score+price_usd,data=mydata);
# hist(mydata$price_usd,main="price_usd");
# round(xtabs(booking_bool~prop_review_score+price_usd,data=mydata)/tot,2)
#
# totage=xtabs(~prop_review_score,data=mydata)
# barplot(xtabs(booking_bool~prop_review_score,data=mydata)/totage)
#
# mydata$prop_review_score2 <- mydata$prop_review_score^2
# myglm=glm(booking_bool~prop_review_score+prop_review_score2+price_usd,data=mydata,family=binomial)
# summary(myglm)
```

```
myglm=glm(booking_bool~
                        prop_starrating
          +prop_review_score
            +prop_location_score1
            +prop_location_score2
            +price_usd
            +promotion_flag
            +consumer
            ,data=mydata,family=binomial)
summary(myglm)
```

```
##
## Call:
## glm(formula = booking_bool ~ prop_starrating + prop_review_score +
##     prop_location_score1 + prop_location_score2 + price_usd +
##     promotion_flag + consumer, family = binomial, data = mydata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9877  -1.2780   0.7871   0.9419   2.2879
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -2.3931195  1.6996472  -1.408 0.159128
## prop_starrating2      2.0123613  1.1719039   1.717 0.085948 .
## prop_starrating3      1.8186350  1.1688833   1.556 0.119738
## prop_starrating4      1.8553442  1.1701929   1.586 0.112852
## prop_starrating5      2.0271625  1.1799129   1.718 0.085785 .
## prop_review_score1.5 -0.7377834  1.6520493  -0.447 0.655173
## prop_review_score2    0.9377906  1.3552031   0.692 0.488942
## prop_review_score2.5  1.2259385  1.2684957   0.966 0.333819
## prop_review_score3    0.7297695  1.2435368   0.587 0.557305
## prop_review_score3.5  1.3953167  1.2354380   1.129 0.258725
## prop_review_score4    1.7001720  1.2332443   1.379 0.168013
## prop_review_score4.5  1.7227357  1.2340611   1.396 0.162718
## prop_review_score5    1.5845126  1.2522512   1.265 0.205753
## prop_location_score1 -0.0897714  0.0307003  -2.924 0.003454 **
## prop_location_score2  1.3253697  0.2705760   4.898 9.67e-07 ***
```

```
## price_usd            -0.0043143  0.0005711  -7.554 4.23e-14 ***
## promotion_flag        0.2115738  0.0962113   2.199 0.027874 *
## consumerother         0.0894607  0.1374709   0.651 0.515201
## consumerParents      -0.0270289  0.1655778  -0.163 0.870329
## consumersingle        0.3819815  0.1050033   3.638 0.000275 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3442.2  on 2609  degrees of freedom
## Residual deviance: 3278.5  on 2590  degrees of freedom
## AIC: 3318.5
##
## Number of Fisher Scoring iterations: 4
```

```
drop1(myglm,test="Chisq")
```

```
## Single term deletions
##
## Model:
## booking_bool ~ prop_starrating + prop_review_score + prop_location_score1 +
##     prop_location_score2 + price_usd + promotion_flag + consumer
##                       Df Deviance    AIC    LRT  Pr(>Chi)
## <none>                     3278.5 3318.5
## prop_starrating        4   3284.7 3316.7  6.151  0.188168
## prop_review_score      8   3315.3 3339.3 36.792 1.257e-05 ***
## prop_location_score1   1   3287.1 3325.1  8.592  0.003377 **
## prop_location_score2   1   3303.8 3341.8 25.332 4.826e-07 ***
## price_usd              1   3341.6 3379.6 63.067 1.998e-15 ***
## promotion_flag         1   3283.4 3321.4  4.875  0.027250 *
## consumer               3   3292.7 3326.7 14.193  0.002654 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
myglm=glm(booking_bool~
            prop_review_score
            +prop_location_score1
            +prop_location_score2
            +price_usd
            +promotion_flag
            +consumer
            ,data=mydata,family=binomial)
summary(myglm)
```

```
##
## Call:
## glm(formula = booking_bool ~ prop_review_score + prop_location_score1 +
##     prop_location_score2 + price_usd + promotion_flag + consumer,
##     family = binomial, data = mydata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9782  -1.2881   0.7901   0.9427   2.2252
##
```

```
## Coefficients:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -0.5089489  1.2359990  -0.412 0.680507
## prop_review_score1.5 -0.7238342  1.6527538  -0.438 0.661418
## prop_review_score2    0.9868408  1.3573111   0.727 0.467192
## prop_review_score2.5  1.2568074  1.2699084   0.990 0.322329
## prop_review_score3    0.7441285  1.2467621   0.597 0.550608
## prop_review_score3.5  1.3632721  1.2391255   1.100 0.271250
## prop_review_score4    1.6587396  1.2369201   1.341 0.179913
## prop_review_score4.5  1.6905400  1.2376793   1.366 0.171972
## prop_review_score5    1.5343434  1.2556226   1.222 0.221716
## prop_location_score1 -0.0920050  0.0302119  -3.045 0.002324 **
## prop_location_score2  1.2830149  0.2686645   4.776 1.79e-06 ***
## price_usd            -0.0041031  0.0005139  -7.985 1.41e-15 ***
## promotion_flag        0.2190510  0.0944278   2.320 0.020353 *
## consumerother         0.0929271  0.1373123   0.677 0.498560
## consumerParents      -0.0220893  0.1652853  -0.134 0.893684
## consumersingle        0.3807132  0.1048163   3.632 0.000281 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3442.2  on 2609  degrees of freedom
## Residual deviance: 3284.7  on 2594  degrees of freedom
## AIC: 3316.7
##
## Number of Fisher Scoring iterations: 4
```

```
drop1(myglm,test="Chisq")
```

```
## Single term deletions
##
## Model:
## booking_bool ~ prop_review_score + prop_location_score1 + prop_location_score2 +
##     price_usd + promotion_flag + consumer
##                       Df Deviance    AIC    LRT  Pr(>Chi)
## <none>                     3284.7 3316.7
## prop_review_score      8   3322.5 3338.5 37.891 7.884e-06 ***
## prop_location_score1   1   3294.0 3324.0  9.316  0.002271 **
## prop_location_score2   1   3308.7 3338.7 24.016 9.555e-07 ***
## price_usd              1   3355.6 3385.6 70.994 < 2.2e-16 ***
## promotion_flag         1   3290.1 3320.1  5.431  0.019781 *
## consumer               3   3298.8 3324.8 14.097  0.002776 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
mydata$consumer=factor(mydata$consumer)
mydata$prop_review_score=factor(mydata$prop_review_score)
myglm=glm(booking_bool~
            prop_review_score
            +prop_location_score2
            +price_usd
            +promotion_flag
            +consumer
```

```
            ,data=mydata,family=binomial)
summary(myglm)
```

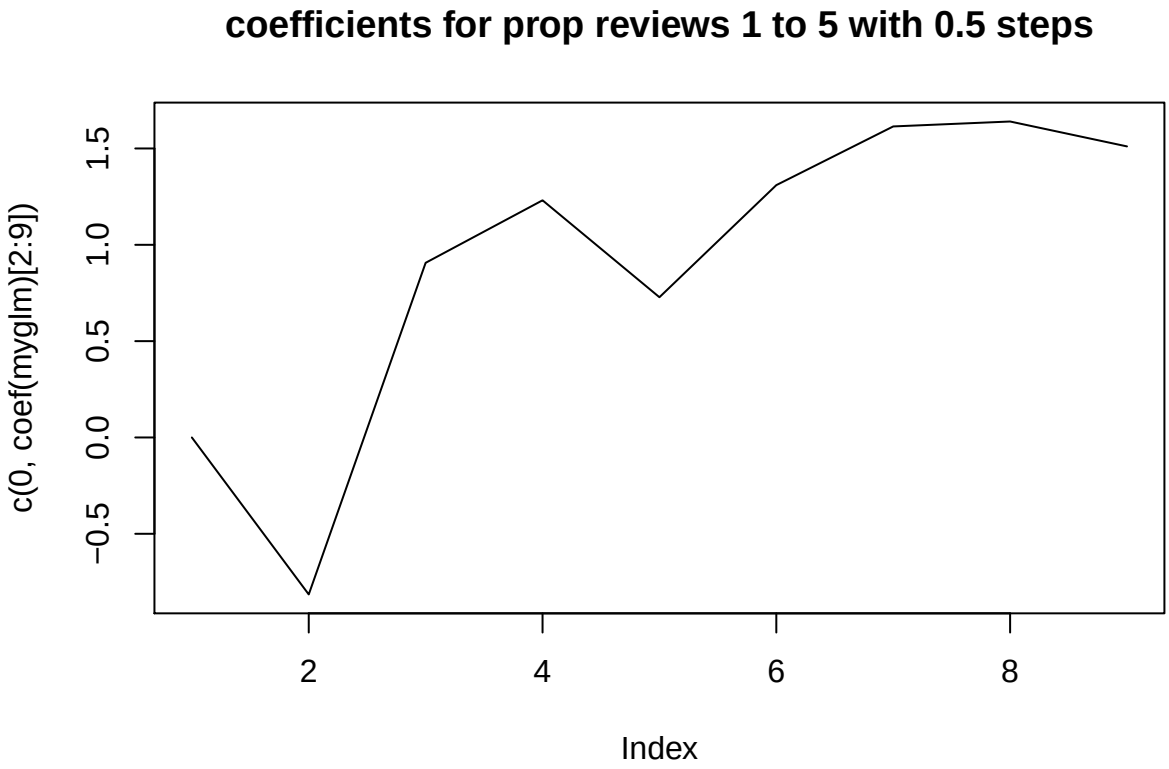
```
##
## Call:
## glm(formula = booking_bool ~ prop_review_score + prop_location_score2 +
##     price_usd + promotion_flag + consumer, family = binomial,
##     data = mydata)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9566  -1.3009   0.8048   0.9368   2.2769
##
## Coefficients:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.625446   1.231149  -0.508 0.611440
## prop_review_score1.5 -0.814697   1.648238  -0.494 0.621106
## prop_review_score2    0.906527   1.352144   0.670 0.502579
## prop_review_score2.5  1.230928   1.265531   0.973 0.330724
## prop_review_score3    0.728006   1.242430   0.586 0.557907
## prop_review_score3.5  1.309675   1.234693   1.061 0.288813
## prop_review_score4    1.614361   1.232521   1.310 0.190262
## prop_review_score4.5  1.639964   1.233256   1.330 0.183589
## prop_review_score5    1.510766   1.251291   1.207 0.227291
## prop_location_score2  1.050305   0.254956   4.120  3.8e-05 ***
## price_usd            -0.004498   0.000503  -8.943  < 2e-16 ***
## promotion_flag        0.167049   0.092677   1.802 0.071469 .
## consumerother         0.076274   0.136896   0.557 0.577409
## consumerParents      -0.004631   0.164779  -0.028 0.977580
## consumersingle        0.382782   0.104743   3.654 0.000258 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3442.2  on 2609  degrees of freedom
## Residual deviance: 3294.0  on 2595  degrees of freedom
## AIC: 3324
##
## Number of Fisher Scoring iterations: 4
```

```
drop1(myglm,test="Chisq")
```

```
## Single term deletions
##
## Model:
## booking_bool ~ prop_review_score + prop_location_score2 + price_usd +
##     promotion_flag + consumer
##                       Df Deviance    AIC    LRT  Pr(>Chi)
## <none>                     3294.0 3324.0
## prop_review_score      8   3330.9 3344.9 36.934 1.184e-05 ***
## prop_location_score2   1   3311.7 3339.7 17.682 2.611e-05 ***
## price_usd              1   3384.7 3412.7 90.688 < 2.2e-16 ***
## promotion_flag         1   3297.2 3325.2  3.271  0.070501 .
```

```
## consumer              3   3308.1 3332.1 14.138  0.002723 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(c(0,coef(myglm)[2:9]),type="l",main = "coefficients for prop reviews 1 to 5 with 0.5 steps" )
```




```
drop1(myglm,test="Chisq")
```

```
## Single term deletions
##
## Model:
## booking_bool ~ prop_review_score + prop_location_score2 + price_usd +
##     promotion_flag + consumer
##                      Df Deviance    AIC    LRT  Pr(>Chi)
## <none>                    3294.0 3324.0
## prop_review_score     8   3330.9 3344.9 36.934 1.184e-05 ***
## prop_location_score2  1   3311.7 3339.7 17.682 2.611e-05 ***
## price_usd             1   3384.7 3412.7 90.688 < 2.2e-16 ***
## promotion_flag        1   3297.2 3325.2  3.271  0.070501 .
## consumer              3   3308.1 3332.1 14.138  0.002723 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```