8 Appendix

REGRESSION ANALYSIS

Loading librarys:

```
library(readxl)
library(car)
library(leaps)
library(MASS)
```

Loading the original data:

```
project_data = read.csv("AB_NYC_2019.csv")
```

Omitting null values:

```
nrow(project_data)
```

```
## [1] 48895
```

```
project_data = na.omit(project_data)
nrow(project_data)
```

```
## [1] 38843
```

Random sampling:

```
data_sample = project_data[sample(nrow(project_data),
                                  nrow(project_data)*(5000/nrow(project_data))),]
```

We saved off one randome sample of the data in order to be working with the same data set for analysis:

```
setwd("~/Documents/ISYE 4031 Regression & Forcasting/Project/new-york-city-airbnb-open-data")
project_data_sample = read_excel("sample_data.xlsx")
```

```
## New names:
## * `` -> ...1
```

```
attach(project_data_sample)
```

Creating dataframe of numerical data for correlation:

```
df = project_data_sample[c("price","minimum_nights","number_of_reviews","reviews_per_month"
                           ,"calculated_host_listings_count","availability_365")]
cor(df)
```

```
##                                  price minimum_nights
## price                       1.0000000000   0.0008842091
## minimum_nights              0.0008842091   1.0000000000
## number_of_reviews          -0.0428759061  -0.0830325449
```

```
## reviews_per_month              -0.0418979190  -0.1441522316
## calculated_host_listings_count  0.0644480350   0.0779305734
## availability_365                0.1115295098   0.0763575569
##                                number_of_reviews reviews_per_month
## price                                -0.04287591      -0.041897919
## minimum_nights                       -0.08303254      -0.144152232
## number_of_reviews                     1.00000000       0.524745585
## reviews_per_month                     0.52474559       1.000000000
## calculated_host_listings_count       -0.05849106      -0.004301983
## availability_365                      0.20041460       0.183818170
##                                calculated_host_listings_count
## price                                              0.064448035
## minimum_nights                                     0.077930573
## number_of_reviews                                 -0.058491060
## reviews_per_month                                 -0.004301983
## calculated_host_listings_count                     1.000000000
## availability_365                                   0.185098224
##                                availability_365
## price                                0.11152951
## minimum_nights                       0.07635756
## number_of_reviews                    0.20041460
## reviews_per_month                    0.18381817
## calculated_host_listings_count       0.18509822
## availability_365                     1.00000000
```

There was no severe multicollinearity at this point -> highest being .524

Creation of base model:

```
basemodel = lm(price~minimum_nights+number_of_reviews+reviews_per_month
               +calculated_host_listings_count+availability_365)
summary(basemodel)
```

```
##
## Call:
## lm(formula = price ~ minimum_nights + number_of_reviews + reviews_per_month +
##     calculated_host_listings_count + availability_365)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -162.3  -72.5  -31.4   29.7 4814.6
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    135.25344    3.42564  39.483  < 2e-16 ***
## minimum_nights                  -0.23102    0.15199  -1.520  0.12857
## number_of_reviews               -0.14164    0.05428  -2.610  0.00909 **
## reviews_per_month               -4.09871    1.53334  -2.673  0.00754 **
## calculated_host_listings_count   0.25830    0.09103   2.837  0.00457 **
## availability_365                 0.14704    0.01766   8.324  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 154.7 on 4994 degrees of freedom
```

```
## Multiple R-squared:   0.02,  Adjusted R-squared:  0.01902
## F-statistic: 20.39 on 5 and 4994 DF,  p-value: < 2.2e-16
```

According to the summary, the significant fields (p-value < 0.01) are number_of_reviews, reviews_per_month, calculated_host_listings_count, availability_365(most significant).

Variance Inflation Factor (VIF) for base model:

```
vif(basemodel)
```

```
##                  minimum_nights              number_of_reviews
##                        1.036736                       1.413968
##               reviews_per_month calculated_host_listings_count
##                        1.416381                       1.049445
##                availability_365
##                        1.104509
```

According the VIF test, there is still no severe multicollinearity among the eight independent variables.

Choosing the best model from all subsets

```
all_model<-regsubsets(price~.,data=df,nbest=2,method = "exhaustive")
all_sum = summary(all_model)
Rsq = round(all_sum$rsq*100, digit=1)
adj_Rsq = round(all_sum$adjr2*100, digit=1)
Cp = round(all_sum$cp, digit=1)
SSE = all_sum$rss
k = as.numeric(rownames(all_sum$which))
n = all_model$nn
S = round(sqrt(all_sum$rss/(n-(k+1))), digit=2)
SSTO = sum((price - mean(price))^2)
aic = round(2*(k+1)+n*log(SSE/n),digits=2)
SSE = round(SSE,digits=2)
cbind(Rsq, adj_Rsq, Cp, S, all_sum$outmat)
```

```
##          Rsq   adj_Rsq Cp     S        minimum_nights number_of_reviews
## 1  ( 1 ) "1.2" "1.2"   "36.6" "155.25" " "            " "
## 1  ( 2 ) "0.4" "0.4"   "78.8" "155.9"  " "            " "
## 2  ( 1 ) "1.7" "1.6"   "16"   "154.92" " "            "*"
## 2  ( 2 ) "1.6" "1.6"   "18"   "154.95" " "            " "
## 3  ( 1 ) "1.8" "1.8"   "10.5" "154.82" " "            "*"
## 3  ( 2 ) "1.8" "1.8"   "11"   "154.82" " "            " "
## 4  ( 1 ) "2"   "1.9"   "6.3"  "154.74" " "            "*"
## 4  ( 2 ) "1.9" "1.8"   "10.8" "154.8"  "*"            " "
## 5  ( 1 ) "2"   "1.9"   "6"    "154.71" "*"            "*"
##          reviews_per_month calculated_host_listings_count availability_365
## 1  ( 1 ) " "               " "                             "*"
## 1  ( 2 ) " "               "*"                             " "
## 2  ( 1 ) " "               " "                             "*"
## 2  ( 2 ) "*"               " "                             "*"
## 3  ( 1 ) " "               "*"                             "*"
## 3  ( 2 ) "*"               "*"                             "*"
## 4  ( 1 ) "*"               "*"                             "*"
## 4  ( 2 ) "*"               "*"                             "*"
## 5  ( 1 ) "*"               "*"                             "*"
```

The best models with the lowest C_p that is less than or equal to $k+1$, high adjusted R^2, and lowest variance:

5(1): minimum_nights + number_of_reviews + reviews_per_month + calculated_host_listings_count + availability_365

4(1) number_of_reviews + reviews_per_month + calculated_host_listings_count + availability_365

Creation of the full model:

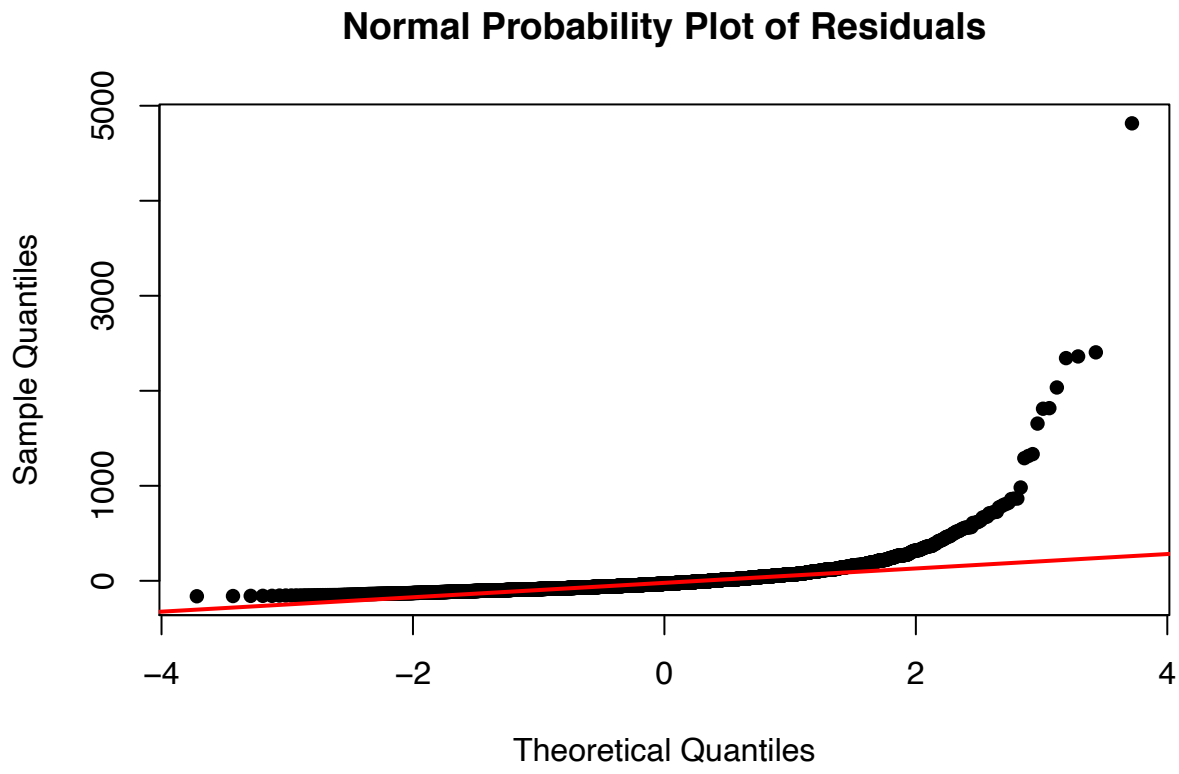
```
full.lm <- lm(price ~ . , data=df)
min.lm <- lm(price ~ 1, data=df)
step_both = step(min.lm, list(upper=full.lm), direction='both')
```

```
## Start:  AIC=50512.86
## price ~ 1
##
##                                  Df Sum of Sq       RSS   AIC
## + availability_365                1   1517286 120462487 50452
## + calculated_host_listings_count  1    506649 121473124 50494
## + number_of_reviews               1    224241 121755532 50506
## + reviews_per_month               1    214128 121765645 50506
## <none>                                        121979773 50513
## + minimum_nights                  1        95 121979678 50515
##
## Step:  AIC=50452.28
## price ~ availability_365
##
##                                  Df Sum of Sq       RSS   AIC
## + number_of_reviews               1    540705 119921782 50432
## + reviews_per_month               1    491555 119970932 50434
## + calculated_host_listings_count  1    242358 120220129 50444
## <none>                                        120462487 50452
## + minimum_nights                  1      7147 120455341 50454
## - availability_365                1   1517286 121979773 50513
##
## Step:  AIC=50431.79
## price ~ availability_365 + number_of_reviews
##
##                                  Df Sum of Sq       RSS   AIC
## + calculated_host_listings_count  1    177558 119744224 50426
## + reviews_per_month               1    145232 119776550 50428
## <none>                                        119921782 50432
## + minimum_nights                  1     25398 119896384 50433
## - number_of_reviews               1    540705 120462487 50452
## - availability_365                1   1833750 121755532 50506
##
## Step:  AIC=50426.38
## price ~ availability_365 + number_of_reviews + calculated_host_listings_count
##
##                                  Df Sum of Sq       RSS   AIC
## + reviews_per_month               1    149260 119594965 50422
## <none>                                        119744224 50426
## + minimum_nights                  1     33530 119710695 50427
## - calculated_host_listings_count  1    177558 119921782 50432
## - number_of_reviews               1    475904 120220129 50444
```

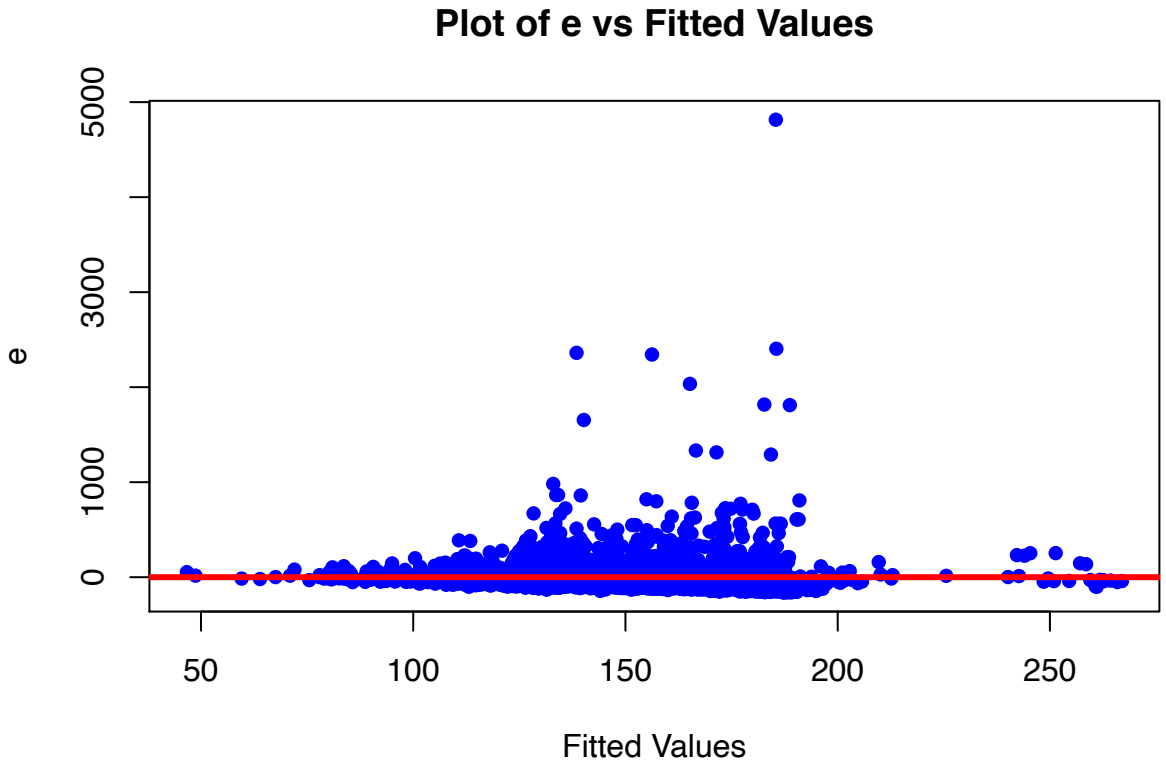
```
## - availability_365                1   1541716 121285940 50488
##
## Step:  AIC=50422.14
## price ~ availability_365 + number_of_reviews + calculated_host_listings_count +
##     reviews_per_month
##
##                                  Df Sum of Sq       RSS   AIC
## + minimum_nights                  1     55303 119539661 50422
## <none>                                        119594965 50422
## - reviews_per_month               1    149260 119744224 50426
## - number_of_reviews               1    159884 119754849 50427
## - calculated_host_listings_count  1    181585 119776550 50428
## - availability_365                1   1616392 121211356 50487
##
## Step:  AIC=50421.83
## price ~ availability_365 + number_of_reviews + calculated_host_listings_count +
##     reviews_per_month + minimum_nights
##
##                                  Df Sum of Sq       RSS   AIC
## <none>                                        119539661 50422
## - minimum_nights                  1     55303 119594965 50422
## - number_of_reviews               1    163020 119702681 50427
## - reviews_per_month               1    171033 119710695 50427
## - calculated_host_listings_count  1    192719 119732380 50428
## - availability_365                1   1658663 121198324 50489
```

The best model has 5 variables:

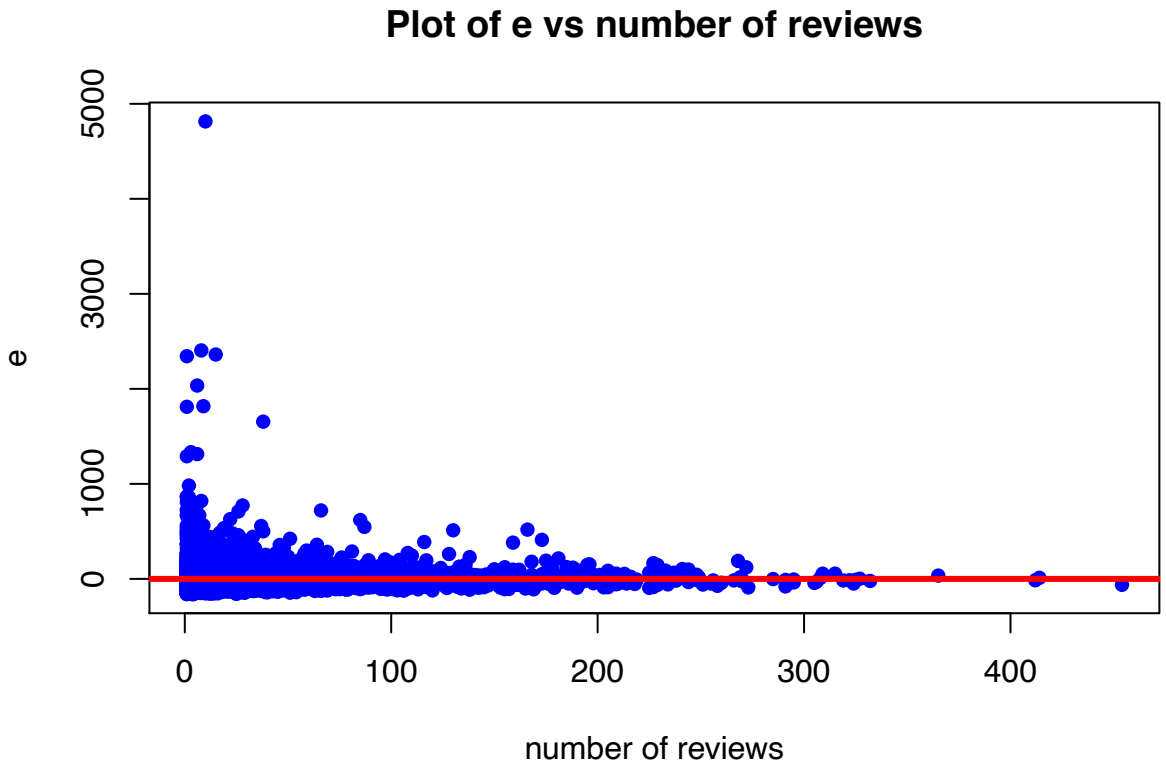
```
bestmodel= lm(price~number_of_reviews+reviews_per_month+calculated_host_listings_count
              +availability_365 + minimum_nights)
qqnorm(resid(bestmodel),pch=16,main="Normal Probability Plot of Residuals")
qqline(resid(bestmodel),col='red',lwd=2)
```



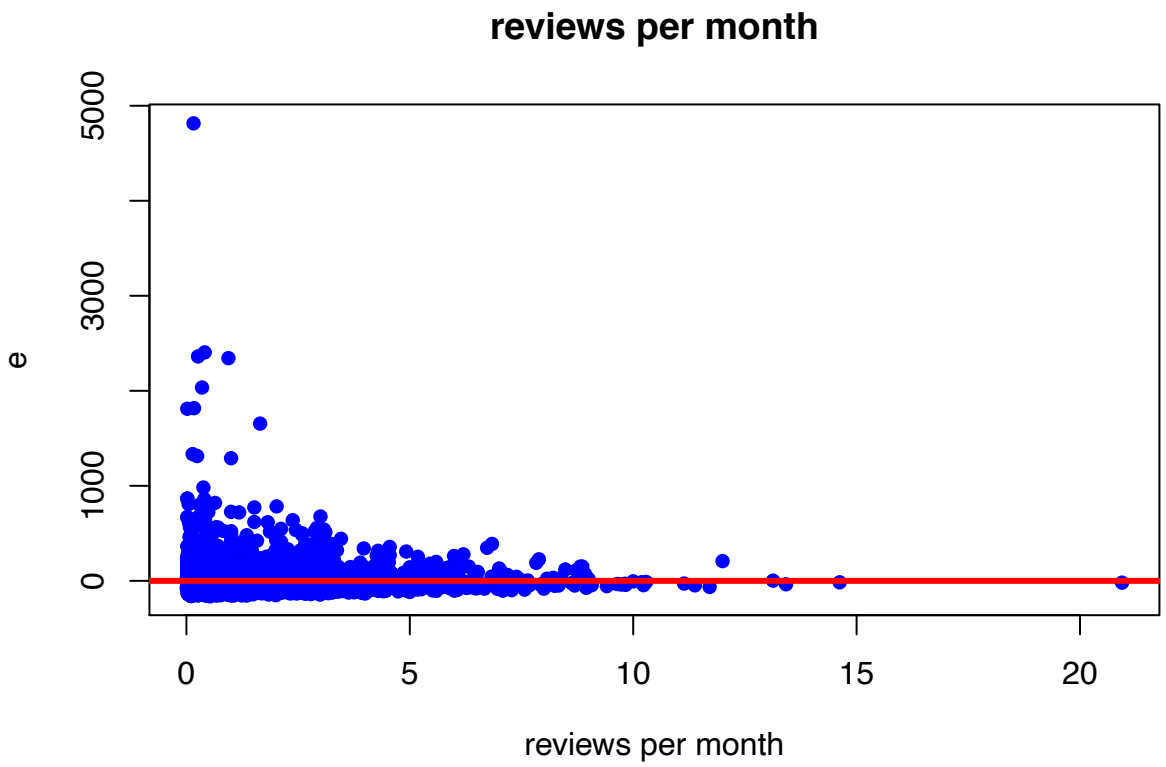

```
plot(fitted(bestmodel),resid(bestmodel), pch=16, col="blue", ylab=bquote(paste("e")),
     xlab=bquote(paste("Fitted Values")),main="Plot of e vs Fitted Values")
abline(0,0,col="red",lwd=3)
```



```
plot(number_of_reviews,resid(bestmodel), pch=16, col="blue", ylab=bquote(paste("e")),
     xlab=bquote(paste("number of reviews")),main="Plot of e vs number of reviews")
abline(0,0,col="red",lwd=3)
```




```
plot(reviews_per_month,resid(bestmodel), pch=16, col="blue", ylab=bquote(paste("e")),
     xlab=bquote(paste("reviews per month")),main="reviews per month")
abline(0,0,col="red",lwd=3)
```



Outlier analysis:

```
k = 5
n = length(price)
LV_cutoff = 2*(k+1)/n; print(LV_cutoff)
```

```
## [1] 0.0024
```

```
Hi = hatvalues(bestmodel)
Hi[Hi>LV_cutoff]
```

```
##          14          26          40         115         140         149
## 0.002522602 0.003711449 0.008459252 0.007991201 0.003234863 0.002476020
##         198         209         224         227         249         259
## 0.002963222 0.006947654 0.002417892 0.007845635 0.005940952 0.003610938
##         281         283         290         306         312         320
## 0.003035470 0.003065521 0.004348396 0.004043015 0.006471384 0.003510556
##         324         345         350         356         364         381
## 0.003448336 0.008302446 0.003133159 0.013510081 0.034922588 0.003267111
##         383         385         393         433         440         468
## 0.003598141 0.003948391 0.003069451 0.004664993 0.004639866 0.007036337
##         473         478         494         512         516         521
## 0.036936159 0.003720652 0.002431800 0.004708325 0.002574757 0.004018389
##         522         551         552         559         564         574
## 0.004224196 0.003493510 0.002849927 0.003221705 0.006683083 0.005913257
##         601         613         644         650         660         666
## 0.003801395 0.003198287 0.034677305 0.002839477 0.003546620 0.006819212
##         703         759         760         767         793         813
## 0.005270799 0.003479479 0.004488949 0.004585076 0.003979616 0.005230298
##         818         821         822         834         865         869
```

```
## 0.002707626 0.006624475 0.004254303 0.004142646 0.003199051 0.004437243
##         883         890         900         910         926         967
## 0.003969310 0.005393451 0.007296868 0.003304665 0.003078140 0.004987843
##         970         975         976         986         990         996
## 0.002619482 0.008391394 0.002738862 0.003497561 0.003001551 0.003599175
##        1015        1022        1027        1031        1064        1068
## 0.003113545 0.122966053 0.003010231 0.034896745 0.014751771 0.003858320
##        1112        1132        1157        1158        1168        1182
## 0.064638450 0.002494741 0.002587536 0.003621971 0.002509404 0.003400794
##        1203        1213        1246        1268        1272        1287
## 0.006896052 0.003380493 0.002817283 0.003225680 0.083071968 0.035310538
##        1292        1294        1345        1367        1396        1409
## 0.004168601 0.003387739 0.035324329 0.003089018 0.003510130 0.035417123
##        1413        1418        1442        1445        1458        1464
## 0.003126688 0.007642430 0.003776359 0.016705329 0.006644867 0.003342389
##        1487        1512        1537        1539        1540        1557
## 0.006962231 0.003219815 0.003190514 0.003028388 0.003500428 0.034846487
##        1561        1586        1599        1608        1634        1648
## 0.034665204 0.003254317 0.003269651 0.002849715 0.002860008 0.003097908
##        1650        1663        1696        1712        1752        1753
## 0.067625450 0.003568238 0.003648083 0.003215460 0.002836581 0.003120561
##        1765        1766        1771        1779        1786        1797
## 0.003498316 0.034868869 0.005797592 0.002795953 0.008666333 0.003025721
##        1824        1828        1901        1932        1940        1968
## 0.003350459 0.003958937 0.003305205 0.004033948 0.003595417 0.003406886
##        1976        1983        2001        2046        2053        2065
## 0.034975235 0.004864847 0.008228342 0.002808369 0.002680854 0.003522957
##        2083        2114        2134        2146        2161        2213
## 0.005302469 0.003190124 0.008766591 0.002493261 0.004233086 0.034901888
##        2224        2233        2289        2320        2366        2371
## 0.003652673 0.003158702 0.002814818 0.003261535 0.004876405 0.005248680
##        2373        2382        2398        2415        2442        2448
## 0.003422079 0.003786494 0.005505313 0.003018490 0.004560327 0.002844196
##        2449        2470        2479        2491        2495        2498
## 0.003592405 0.125091106 0.006656775 0.002993852 0.035225785 0.020018802
##        2499        2512        2557        2565        2575        2589
## 0.003068758 0.002599592 0.029139743 0.004000230 0.005518019 0.002667048
##        2591        2594        2616        2620        2630        2632
## 0.002543322 0.003602259 0.003107967 0.003176713 0.004221576 0.002659103
##        2643        2649        2663        2664        2685        2688
## 0.003783856 0.004010869 0.002910607 0.125200682 0.004482128 0.003573110
##        2689        2707        2733        2752        2763        2781
## 0.014131511 0.003132450 0.004755574 0.011753062 0.003912254 0.003770303
##        2785        2794        2808        2830        2851        2863
## 0.010508066 0.004921253 0.002532225 0.003239942 0.003103512 0.034868610
##        2865        2909        2934        2946        2987        2994
## 0.005107823 0.003641210 0.003888108 0.002558039 0.004236793 0.004761857
##        3009        3021        3023        3039        3043        3059
## 0.002801115 0.005446694 0.003233720 0.002976330 0.003120704 0.003154562
##        3079        3140        3154        3164        3172        3198
## 0.004199816 0.003337111 0.003953768 0.004208732 0.004105032 0.003709710
##        3212        3216        3224        3226        3232        3251
## 0.008602744 0.003719287 0.002663286 0.003817642 0.004294326 0.003237697
##        3277        3285        3355        3357        3364        3367
```

```
## 0.002842208 0.005540077 0.016101913 0.013771660 0.005001712 0.007993835
##        3382        3392        3403        3405        3418        3430
## 0.003245554 0.002429079 0.002828763 0.004489871 0.002926780 0.002550042
##        3435        3465        3475        3502        3504        3511
## 0.002424768 0.003804483 0.004341065 0.002435752 0.006708951 0.002479718
##        3546        3560        3588        3634        3640        3650
## 0.034927465 0.002481044 0.006075799 0.007416557 0.011095788 0.017474412
##        3668        3714        3723        3728        3733        3755
## 0.004042200 0.007851366 0.003642627 0.003253954 0.002792981 0.004427914
##        3791        3808        3828        3840        3873        3874
## 0.009101531 0.002448022 0.003917530 0.003258894 0.005045912 0.005106068
##        3884        3899        3906        3918        3931        3933
## 0.003233893 0.002713257 0.003145530 0.011508215 0.003545213 0.003052742
##        3953        3959        3963        3970        3984        3994
## 0.004105375 0.002731368 0.002903346 0.004691024 0.002510677 0.003904864
##        3995        3999        4000        4015        4020        4032
## 0.007209701 0.002472497 0.002691892 0.003190979 0.003926032 0.006406253
##        4035        4051        4070        4085        4100        4113
## 0.005310442 0.004635526 0.035553976 0.003172733 0.005355637 0.003913515
##        4126        4138        4202        4228        4276        4285
## 0.006955530 0.005052855 0.002551104 0.005160906 0.036128130 0.003012734
##        4286        4351        4373        4404        4419        4436
## 0.003604519 0.002652881 0.002917745 0.003508809 0.007294479 0.002523768
##        4446        4453        4505        4506        4518        4531
## 0.005229064 0.005305419 0.002732241 0.035063160 0.008220801 0.003673717
##        4543        4565        4588        4597        4601        4603
## 0.002636776 0.007908950 0.035408256 0.003761733 0.002632938 0.034882621
##        4614        4627        4629        4661        4676        4688
## 0.007684276 0.006803763 0.002499270 0.003356588 0.003471265 0.010023581
##        4693        4694        4698        4704        4711        4748
## 0.003369665 0.002919855 0.035151555 0.004770149 0.006324688 0.004117794
##        4777        4785        4790        4795        4800        4836
## 0.003165602 0.034834351 0.006048057 0.006983270 0.034901892 0.002560851
##        4850        4857        4881        4890        4894        4931
## 0.003037584 0.005810815 0.034896129 0.003349645 0.003227326 0.004827617
##        4934        4945        4965        4993
## 0.003091229 0.003583784 0.010605291 0.035284258
```

These are the outliers.

Studentized Deleted Residuals (SDR)

```
Res_SE = summary(bestmodel)$sigma
di = resid(bestmodel)/(1-Hi)
SSE = Res_SE^2*(n-(k+1))
SDR = resid(bestmodel)*sqrt((n-k-2)/(SSE*(1-Hi)-(resid(bestmodel))^2))
SDR[abs(SDR)>qt(0.975,n-k-2)] #some evidence
```

```
##        21        41       112       202       206       319       369
##  4.070703  5.239872  8.405900  3.544375  3.941335  2.098437  3.311446
##       401       424       439       459       477       478       549
##  4.132448  2.731495  2.328101  2.836344  2.071854  2.251589  2.766181
##       600       604       611       697       751       753       790
##  5.010102 15.940243  2.756368  1.996238  4.616233  2.028928  5.579848
```

```
##       843      1000      1154      1161      1240      1295      1318
##  3.549353 15.510904  2.097619  3.202641  3.020367  8.554335  2.310004
##      1360      1425      1434      1451      1457      1472      1492
##  2.339152  2.391363  2.376218  2.324857  2.497322  4.012644  1.991918
##      1539      1583      1725      1730      1732      1746      1748
##  2.515631  3.496112 10.820696  3.626003  4.667683  2.280833  2.345261
##      1780      1817      1849      1868      1896      1943      2004
##  2.029912  2.129898  2.733191  2.145636  2.107037  3.939377 34.684247
##      2185      2187      2259      2312      2344      2361      2362
##  4.340589  2.207392  2.512124  2.236311  3.601311  2.055105  3.638736
##      2400      2408      2444      2475      2561      2652      2661
##  2.192896  3.626056  5.178456  3.403189  2.046218  2.518616  2.360450
##      2791      2879      3028      3042      3066      3091      3119
##  4.388774  2.053870  3.241396  4.309396  5.614878  2.096660  4.601583
##      3180      3182      3222      3269      3279      3300      3312
##  6.373757  5.077773  3.358769  2.037009  3.107381  3.248337  2.233702
##      3341      3348      3393      3489      3502      3560      3564
##  3.460408  2.043322  2.082849  5.315740  2.659211  2.470611  4.351110
##      3614      3630      3715      3717      3760      3805      3830
##  3.060194  2.376522  3.002642  3.648465  3.026963  2.287340  2.382893
##      3863      3997      4007      4139      4162      4252      4264
##  3.355454  2.862761  2.947511  4.707467  3.011097  3.994691 15.637837
##      4271      4318      4319      4328      4337      4355      4396
##  4.691184  3.942548  2.864306 13.388104  2.067308  2.791614  3.667013
##      4409      4450      4475      4496      4540      4552      4572
##  8.684772  2.691685  1.981647 11.878671  3.656419  2.601080  2.700536
##      4589      4677      4728      4738      4751      4759      4816
##  2.360054  3.380080  2.080073  3.139684 11.920139  2.153474  2.973391
##      4821      4873      4907      4948
##  5.611364  2.334515  2.208886  2.562440
```

```
SDR[abs(SDR)>qt(0.995,n-k-2)] #strong evidence
```

```
##        21        41       112       202       206       369       401
##  4.070703  5.239872  8.405900  3.544375  3.941335  3.311446  4.132448
##       424       459       549       600       604       611       751
##  2.731495  2.836344  2.766181  5.010102 15.940243  2.756368  4.616233
##       790       843      1000      1161      1240      1295      1472
##  5.579848  3.549353 15.510904  3.202641  3.020367  8.554335  4.012644
##      1583      1725      1730      1732      1849      1943      2004
##  3.496112 10.820696  3.626003  4.667683  2.733191  3.939377 34.684247
##      2185      2344      2362      2408      2444      2475      2791
##  4.340589  3.601311  3.638736  3.626056  5.178456  3.403189  4.388774
##      3028      3042      3066      3119      3180      3182      3222
##  3.241396  4.309396  5.614878  4.601583  6.373757  5.077773  3.358769
##      3279      3300      3341      3489      3502      3564      3614
##  3.107381  3.248337  3.460408  5.315740  2.659211  4.351110  3.060194
##      3715      3717      3760      3863      3997      4007      4139
##  3.002642  3.648465  3.026963  3.355454  2.862761  2.947511  4.707467
##      4162      4252      4264      4271      4318      4319      4328
##  3.011097  3.994691 15.637837  4.691184  3.942548  2.864306 13.388104
##      4355      4396      4409      4450      4496      4540      4552
##  2.791614  3.667013  8.684772  2.691685 11.878671  3.656419  2.601080
##      4572      4677      4738      4751      4816      4821
##  2.700536  3.380080  3.139684 11.920139  2.973391  5.611364
```

This test outputs a list of data points that show some and strong evidence of being an outlier with respect to its y value.

Cook's Distance Measure

```
CooksD = cooks.distance(bestmodel)
CooksD[CooksD>qf(0.5,k+1, n-k-1)] #Influential
```

```
## named numeric(0)
```

```
#CooksD[CooksD<qf(0.2,k+1, n-k-1)] #Not Influential
CooksD[CooksD<qf(0.5,k+1, n-k-1) & CooksD>qf(0.2,k+1, n-k-1)]
```

```
## named numeric(0)
```

This test outputs a list of data points that show influential/non-influential evidence of being an outlier.

Creation of dummy variables (made of room type and all location related variables)

```
attach(project_data_sample)
```

```
## The following objects are masked from project_data_sample (pos = 3):
##
##     ...1, availability_365, calculated_host_listings_count,
##     host_id, host_name, id, last_review, latitude, longitude,
##     minimum_nights, name, neighbourhood, neighbourhood_group,
##     number_of_reviews, price, reviews_per_month, room_type
```

```
brooklyn_dummy = as.numeric(neighbourhood_group == 'Brooklyn')
queens_dummy = as.numeric(neighbourhood_group == 'Queens')
bronx_dummy = as.numeric(neighbourhood_group == 'Bronx')
staten_dummy = as.numeric(neighbourhood_group == 'Staten Island')
private_room_dummy = as.numeric(room_type =='Private room')
shared_room_dummy = as.numeric(room_type == 'Shared room')
```

Creation of Location/Price Model and Price/Staten Dummy Model:

```
location_price_model = lm(price ~ + brooklyn_dummy +
                            queens_dummy + bronx_dummy + staten_dummy)

summary(location_price_model)
```

```
##
## Call:
## lm(formula = price ~ +brooklyn_dummy + queens_dummy + bronx_dummy +
##     staten_dummy)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -163.0  -64.4  -29.0   25.6 4876.6
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     178.999      3.316  53.982  < 2e-16 ***
## brooklyn_dummy  -55.605      4.677 -11.888  < 2e-16 ***
## queens_dummy    -85.849      7.130 -12.040  < 2e-16 ***
```

```
## bronx_dummy     -91.286     15.061  -6.061 1.45e-09 ***
## staten_dummy   -101.621     23.000  -4.418 1.02e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 152.7 on 4995 degrees of freedom
## Multiple R-squared:  0.04546,    Adjusted R-squared:  0.0447
## F-statistic: 59.48 on 4 and 4995 DF,  p-value: < 2.2e-16
```

```
anova(location_price_model)
```

```
## Analysis of Variance Table
##
## Response: price
##                   Df    Sum Sq Mean Sq F value    Pr(>F)
## brooklyn_dummy     1   1331938 1331938  57.140 4.801e-14 ***
## queens_dummy       1   2940495 2940495 126.147 < 2.2e-16 ***
## bronx_dummy        1    818008  818008  35.092 3.355e-09 ***
## staten_dummy       1    455051  455051  19.522 1.016e-05 ***
## Residuals       4995 116434281   23310
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
staten_model = lm(price~staten_dummy)

summary(staten_model)
```

```
##
## Call:
## lm(formula = price ~ staten_dummy)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -142.8  -73.8  -37.8   32.2 4857.2
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   142.837      2.218   64.41  < 2e-16 ***
## staten_dummy  -65.459     23.376   -2.80  0.00513 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 156.1 on 4998 degrees of freedom
## Multiple R-squared:  0.001567,   Adjusted R-squared:  0.001367
## F-statistic: 7.842 on 1 and 4998 DF,  p-value: 0.005125
```

```
anova(staten_model)
```

```
## Analysis of Variance Table
##
## Response: price
##                Df    Sum Sq Mean Sq F value   Pr(>F)
## staten_dummy    1    191083  191083  7.8417 0.005125 **
## Residuals    4998 121788690   24367
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Creation of the BASE model that includes dummy variables

```
overall = lm(price ~number_of_reviews + minimum_nights + reviews_per_month
             + calculated_host_listings_count+ availability_365 + shared_room_dummy
             + staten_dummy+ brooklyn_dummy + queens_dummy + bronx_dummy + private_room_dummy)

full.lm = lm(price ~ number_of_reviews + minimum_nights + reviews_per_month
             + calculated_host_listings_count +availability_365 + shared_room_dummy
             + staten_dummy+ brooklyn_dummy + queens_dummy + bronx_dummy
             + private_room_dummy, data = project_data_sample)


summary(full.lm)
```

```
##
## Call:
## lm(formula = price ~ number_of_reviews + minimum_nights + reviews_per_month +
##     calculated_host_listings_count + availability_365 + shared_room_dummy +
##     staten_dummy + brooklyn_dummy + queens_dummy + bronx_dummy +
##     private_room_dummy, data = project_data_sample)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -191.7  -53.5  -15.1   19.1 4876.5
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     213.86270    4.22492  50.619  < 2e-16 ***
## number_of_reviews                -0.20184    0.04956  -4.072 4.73e-05 ***
## minimum_nights                   -0.64761    0.13913  -4.655 3.33e-06 ***
## reviews_per_month                -1.40665    1.41241  -0.996    0.319
## calculated_host_listings_count   -0.03833    0.08366  -0.458    0.647
## availability_365                  0.19493    0.01632  11.946  < 2e-16 ***
## shared_room_dummy              -135.87966   14.41519  -9.426  < 2e-16 ***
## staten_dummy                   -107.97891   21.32911  -5.063 4.29e-07 ***
## brooklyn_dummy                  -46.55858    4.36708 -10.661  < 2e-16 ***
## queens_dummy                    -66.63348    6.77516  -9.835  < 2e-16 ***
## bronx_dummy                     -84.93433   13.99659  -6.068 1.39e-09 ***
## private_room_dummy             -108.38674    4.11035 -26.369  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 140.9 on 4988 degrees of freedom
## Multiple R-squared:  0.1877, Adjusted R-squared:  0.1859
## F-statistic: 104.8 on 11 and 4988 DF,  p-value: < 2.2e-16
```

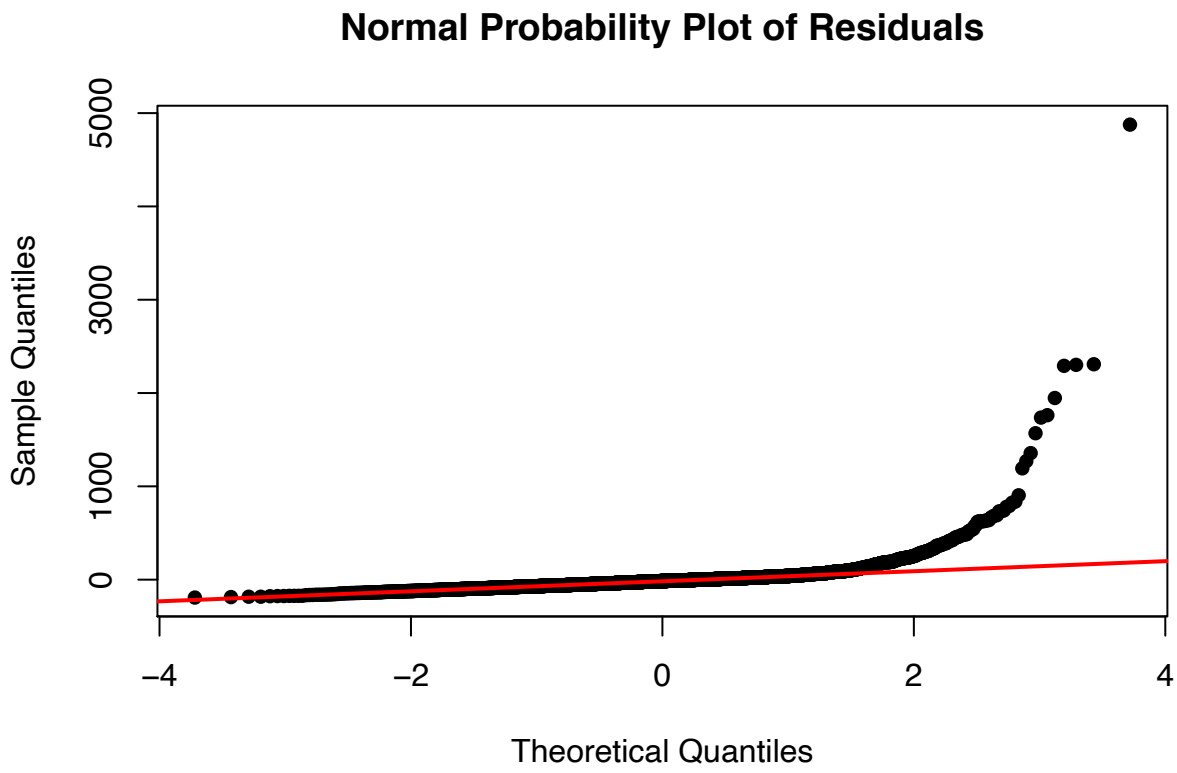
Variance Inflation Factor (VIF) for base model:

```
vif(full.lm)
```

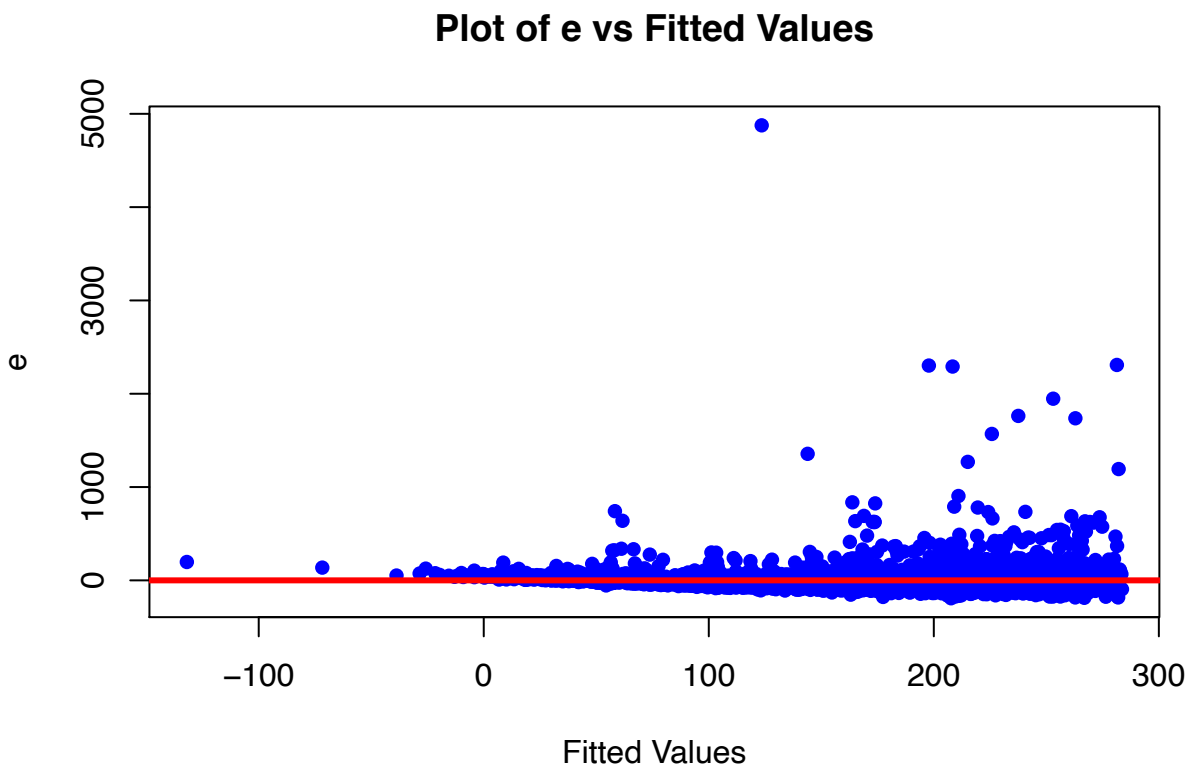
```
##              number_of_reviews                minimum_nights
##                       1.420853                      1.046777
##              reviews_per_month calculated_host_listings_count
##                       1.448094                      1.068111
```

```
##               availability_365             shared_room_dummy
##                       1.135628                      1.025125
##                   staten_dummy                brooklyn_dummy
##                       1.021271                      1.175448
##                   queens_dummy                   bronx_dummy
##                       1.193617                      1.042063
##            private_room_dummy
##                       1.053551
```

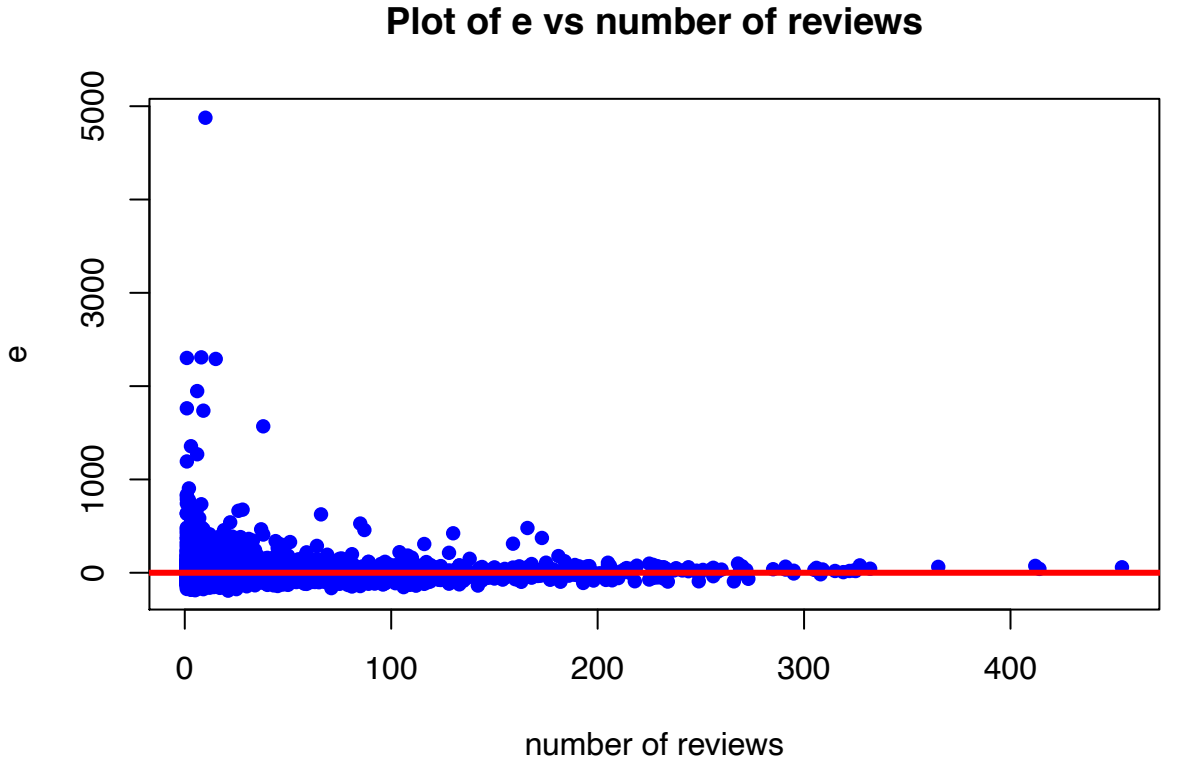
```
qqnorm(resid(full.lm),pch=16,main="Normal Probability Plot of Residuals")
qqline(resid(full.lm),col='red',lwd=2)
```



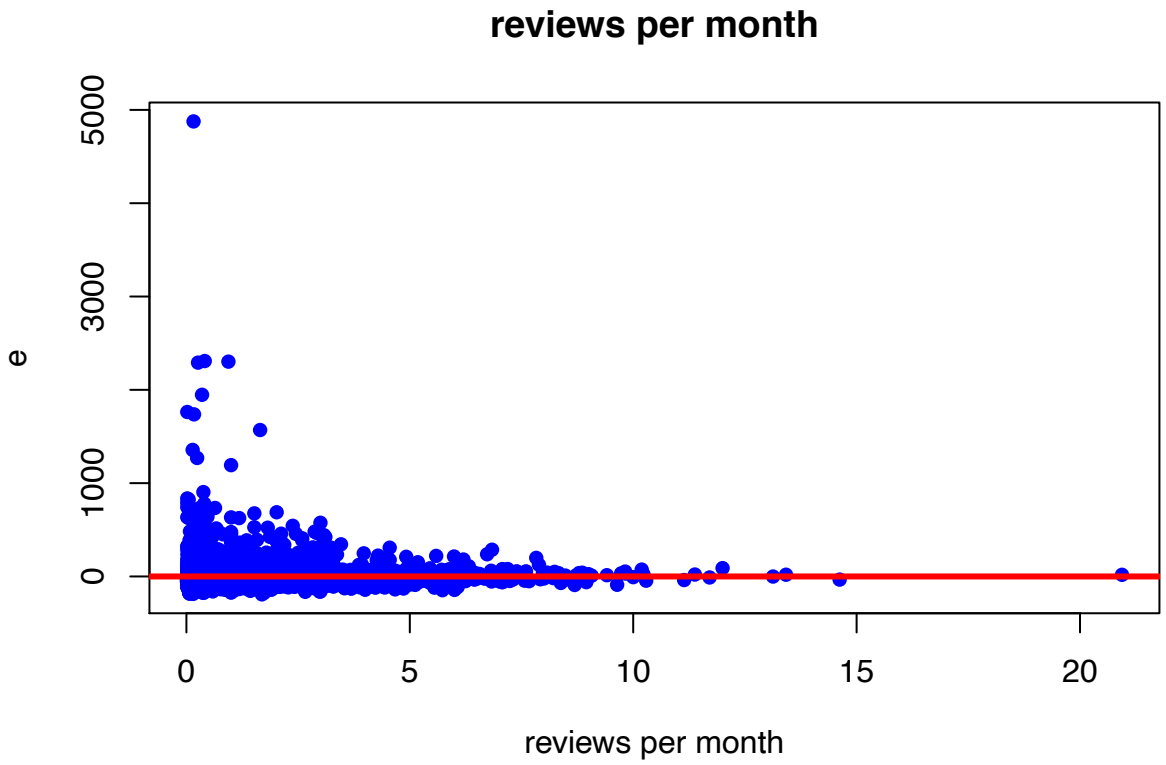

```
plot(fitted(full.lm),resid(full.lm), pch=16, col="blue", ylab=bquote(paste("e")),
     xlab=bquote(paste("Fitted Values")),main="Plot of e vs Fitted Values")
abline(0,0,col="red",lwd=3)
```




```
plot(number_of_reviews,resid(full.lm), pch=16, col="blue", ylab=bquote(paste("e")),
     xlab=bquote(paste("number of reviews")),main="Plot of e vs number of reviews")
abline(0,0,col="red",lwd=3)
```



```
plot(reviews_per_month,resid(full.lm), pch=16, col="blue", ylab=bquote(paste("e")),
     xlab=bquote(paste("reviews per month")),main="reviews per month")
abline(0,0,col="red",lwd=3)
```



Checking for outliers using Cutoff

```
k = 7
n = length(price)
LV_cutoff = 2*(k+1)/n; print(LV_cutoff)
```

```
## [1] 0.0032
```

```
Hi = hatvalues(full.lm)
Hi[Hi>LV_cutoff]
```

```
##          16          26          30          40          49          50
## 0.010753016 0.004153212 0.010749984 0.008998285 0.011855027 0.011723032
##          57          65          66          86         115         138
## 0.010682609 0.011701607 0.011991981 0.010812465 0.008766859 0.009661109
##         140         149         168         190         191         198
## 0.003744112 0.003958574 0.003635246 0.012624820 0.011036110 0.003337397
##         209         227         237         249         259         281
## 0.016259779 0.008775704 0.022787477 0.006426755 0.003780122 0.003293959
##         283         290         306         312         320         324
## 0.003522848 0.005000955 0.004528270 0.007173413 0.003675939 0.004450859
##         336         345         350         356         364         376
## 0.010522118 0.009150562 0.003360925 0.014317056 0.034947399 0.023028936
##         381         383         385         393         399         433
## 0.003775176 0.003776373 0.004502464 0.003469903 0.010639670 0.005229369
##         440         446         468         473         478         484
```

```
## 0.005125129 0.011692510 0.008354252 0.037237642 0.004451337 0.011036397
##         488         508         512         521         522         542
## 0.010596026 0.010421299 0.005098637 0.013089689 0.013618413 0.012099225
##         550         551         552         559         564         574
## 0.009472801 0.004081218 0.003591173 0.003674819 0.006879180 0.006414093
##         595         601         606         609         613         640
## 0.010579469 0.005896609 0.022723728 0.011136620 0.003770590 0.011444782
##         644         650         660         664         666         690
## 0.034713776 0.003601003 0.004677004 0.010186889 0.007491634 0.010193266
##         703         735         759         760         767         793
## 0.005803744 0.022894159 0.003647555 0.004861574 0.005198161 0.004479088
##         813         821         822         828         830         834
## 0.005360150 0.007232055 0.004747477 0.010706980 0.009923756 0.005440392
##         835         840         864         865         869         883
## 0.009921844 0.011203488 0.022890519 0.003917640 0.004933833 0.005106898
##         888         890         895         896         900         910
## 0.011403571 0.006257268 0.010040299 0.009866207 0.007450186 0.003911328
##         926         937         959         967         970         971
## 0.003227223 0.011678319 0.023582873 0.005989406 0.003237657 0.022518180
##         973         975         978         986         990         996
## 0.022668990 0.008894404 0.023233183 0.004236789 0.003632074 0.003776902
##        1008        1009        1015        1022        1027        1031
## 0.009558528 0.009792137 0.004738085 0.123161284 0.004380590 0.034918594
##        1064        1068        1071        1090        1102        1112
## 0.015349825 0.004533171 0.022640935 0.022530075 0.010735937 0.065608506
##        1122        1138        1143        1157        1158        1178
## 0.011282216 0.009860108 0.009449471 0.003351321 0.004235294 0.009776862
##        1182        1198        1203        1210        1213        1224
## 0.003823747 0.003397033 0.007370527 0.022650470 0.003522730 0.011032838
##        1231        1239        1246        1258        1268        1272
## 0.010483316 0.022674103 0.004203338 0.009694523 0.003789039 0.084444317
##        1287        1292        1294        1332        1345        1359
## 0.035345827 0.004613061 0.003924473 0.022995283 0.035352672 0.010779429
##        1363        1367        1394        1396        1409        1413
## 0.009954241 0.003431350 0.012508609 0.003932213 0.035447626 0.003348650
##        1418        1442        1445        1448        1458        1464
## 0.008282527 0.003908583 0.017792035 0.003266771 0.007259814 0.004082017
##        1479        1487        1503        1512        1516        1537
## 0.010087256 0.007125246 0.010886469 0.003877799 0.012101398 0.003803285
##        1539        1540        1557        1561        1572        1573
## 0.003642561 0.003659769 0.034869346 0.034701169 0.022930194 0.011700636
##        1586        1599        1600        1608        1634        1646
## 0.003427779 0.003887280 0.010017862 0.003397023 0.003334893 0.003834268
##        1648        1650        1663        1664        1679        1696
## 0.004313083 0.067734515 0.004224180 0.011015235 0.009840358 0.003826208
##        1697        1704        1712        1726        1735        1752
## 0.011084439 0.011967600 0.003349067 0.011186293 0.010124188 0.003460467
##        1753        1760        1763        1765        1766        1771
## 0.003758942 0.010693379 0.010922014 0.012228122 0.034890852 0.006186104
##        1779        1786        1794        1795        1797        1821
## 0.011681184 0.009503956 0.003426615 0.022983549 0.004283238 0.023848855
##        1824        1828        1836        1888        1901        1931
## 0.003496194 0.004406487 0.011902204 0.010927131 0.003905742 0.003285345
##        1932        1940        1968        1976        1983        1992
```

```
## 0.014331038 0.003763932 0.004389029 0.035000381 0.005297108 0.010078125
##        2001        2020        2026        2039        2046        2053
## 0.008833166 0.023114331 0.022606057 0.003297626 0.003925900 0.003415119
##        2064        2065        2074        2083        2110        2114
## 0.010558481 0.003686670 0.009764693 0.005434211 0.009583924 0.003323825
##        2134        2157        2161        2163        2170        2213
## 0.009314193 0.010644893 0.004868485 0.022885996 0.022788282 0.034925395
##        2224        2230        2233        2277        2289        2305
## 0.003825407 0.011993175 0.003682578 0.009841296 0.003319054 0.003483420
##        2320        2321        2330        2356        2366        2371
## 0.003581965 0.010693980 0.022760481 0.019417068 0.005449789 0.006987913
##        2373        2382        2389        2398        2399        2415
## 0.004035310 0.004369094 0.009851213 0.006098956 0.003221635 0.004171037
##        2420        2422        2427        2434        2442        2448
## 0.010250618 0.011008885 0.010627008 0.009724013 0.005053274 0.003495117
##        2449        2454        2462        2470        2479        2480
## 0.003762193 0.009672918 0.003200198 0.126888125 0.007495722 0.012370818
##        2491        2495        2496        2498        2499        2512
## 0.012228031 0.035253040 0.010000261 0.021150931 0.011749509 0.003237129
##        2551        2557        2559        2562        2565        2575
## 0.009781585 0.029753501 0.010919353 0.019445580 0.004522459 0.006263095
##        2576        2594        2597        2599        2600        2610
## 0.010187610 0.003728098 0.011596218 0.009913633 0.009682665 0.011126226
##        2616        2620        2630        2643        2649        2659
## 0.003248445 0.003596003 0.004592816 0.005778894 0.004558177 0.010458315
##        2663        2664        2668        2685        2688        2689
## 0.003523621 0.125512815 0.010028723 0.004921618 0.004070638 0.014772862
##        2693        2694        2695        2707        2721        2722
## 0.009554856 0.010661466 0.011172972 0.003860310 0.010123150 0.009696686
##        2733        2752        2763        2764        2765        2781
## 0.005168970 0.012684871 0.004408112 0.009988032 0.003567708 0.005838214
##        2785        2787        2794        2803        2830        2851
## 0.011131032 0.009984499 0.006707922 0.009683745 0.003721286 0.003692232
##        2863        2865        2869        2880        2905        2908
## 0.034891395 0.006791601 0.003311255 0.010055881 0.010708041 0.009940452
##        2909        2912        2913        2929        2934        2946
## 0.003982093 0.009897299 0.010095706 0.010082501 0.005290308 0.004025483
##        2987        2992        2994        3000        3001        3009
## 0.005221378 0.010683075 0.005363721 0.022829245 0.010221483 0.003405276
##        3021        3023        3036        3038        3039        3043
## 0.006098312 0.003850818 0.022889335 0.010253346 0.003422586 0.003800537
##        3050        3059        3064        3079        3084        3097
## 0.012234039 0.003291012 0.011120593 0.004777507 0.010706980 0.034856707
##        3117        3129        3140        3154        3162        3164
## 0.010625459 0.010693301 0.003516718 0.004471839 0.011099719 0.004675283
##        3172        3198        3206        3212        3216        3226
## 0.004537947 0.005292913 0.023010290 0.009213593 0.003897922 0.004402816
##        3231        3232        3234        3247        3251        3252
## 0.009776686 0.004939594 0.022752637 0.011560584 0.003432296 0.022683966
##        3277        3285        3298        3302        3308        3339
## 0.003622330 0.006856673 0.011557544 0.010518922 0.011082031 0.023281796
##        3355        3357        3362        3364        3367        3382
## 0.016664316 0.015163343 0.009628228 0.007141471 0.008429832 0.004378786
##        3394        3403        3405        3410        3416        3418
```

```
## 0.010918552 0.004053142 0.005158292 0.010676233 0.009687828 0.004122655
##        3419        3424        3428        3430        3435        3454
## 0.010010249 0.023051629 0.009569324 0.004356077 0.003737174 0.009929745
##        3465        3475        3484        3493        3503        3504
## 0.004387322 0.004771084 0.010738152 0.010299677 0.010082435 0.007247328
##        3511        3515        3523        3532        3546        3549
## 0.003902462 0.009640459 0.011510743 0.011093850 0.034950125 0.011680526
##        3555        3564        3566        3588        3598        3621
## 0.010481672 0.011268702 0.010880864 0.007961612 0.011526847 0.009750784
##        3629        3634        3640        3650        3653        3668
## 0.009935446 0.007570148 0.011743978 0.028615149 0.004393772 0.004496806
##        3705        3709        3714        3723        3728        3730
## 0.010800842 0.010085430 0.008261051 0.005649495 0.003892918 0.010022077
##        3733        3753        3755        3768        3773        3777
## 0.003284348 0.022580718 0.005206439 0.009800853 0.010111479 0.011734376
##        3791        3796        3797        3800        3804        3817
## 0.009480714 0.010275364 0.009967630 0.009582013 0.010159455 0.010458402
##        3828        3840        3871        3873        3874        3884
## 0.004036301 0.003432532 0.011804560 0.005633076 0.005220060 0.003850833
##        3898        3899        3906        3918        3921        3931
## 0.009860257 0.003298858 0.003610823 0.011606491 0.009823913 0.003708826
##        3933        3953        3959        3963        3970        3981
## 0.003649881 0.004593938 0.003415169 0.003574218 0.005129310 0.010231848
##        3984        3987        3989        3994        3995        3999
## 0.003929948 0.011569587 0.023025354 0.004336732 0.008044228 0.011550955
##        4000        4006        4013        4014        4015        4017
## 0.003288779 0.011880265 0.010631924 0.010491100 0.003804565 0.022929678
##        4020        4029        4032        4035        4042        4051
## 0.005826988 0.003239657 0.007275256 0.005442055 0.009955581 0.005435228
##        4052        4055        4070        4081        4085        4088
## 0.010139043 0.011066315 0.035587128 0.009892478 0.003307321 0.022830201
##        4100        4113        4114        4126        4128        4138
## 0.005865225 0.004680846 0.003627415 0.007582640 0.011151512 0.005447072
##        4147        4198        4205        4213        4226        4228
## 0.010151320 0.023597413 0.009741800 0.011590852 0.023281021 0.005653171
##        4233        4253        4265        4276        4285        4286
## 0.024498183 0.010301229 0.009913726 0.036172393 0.004220481 0.004297219
##        4287        4294        4308        4323        4351        4357
## 0.010099203 0.003805582 0.009913471 0.022604952 0.003210539 0.010004946
##        4361        4364        4365        4366        4369        4373
## 0.022781376 0.010472924 0.003915324 0.009943694 0.009526060 0.003420634
##        4382        4392        4404        4419        4436        4446
## 0.011763696 0.011167905 0.004131137 0.007448526 0.004268072 0.005356459
##        4453        4456        4467        4481        4486        4505
## 0.014312685 0.022908750 0.011933111 0.009764674 0.011208146 0.003970006
##        4506        4512        4517        4518        4531        4535
## 0.035088378 0.010720241 0.010968219 0.009476691 0.004154854 0.023048724
##        4543        4555        4559        4565        4582        4588
## 0.004141082 0.010665732 0.011138990 0.009024801 0.010333320 0.035447136
##        4593        4597        4601        4602        4603        4614
## 0.010693143 0.005811301 0.003242164 0.011052002 0.034904989 0.008304959
##        4616        4627        4629        4661        4676        4688
## 0.009960611 0.016028921 0.003206251 0.003538445 0.003627481 0.010926749
##        4693        4694        4698        4704        4711        4725
```

```
## 0.003747562 0.003511218 0.035181140 0.005416740 0.007033313 0.012617618
##        4737        4747        4748        4777        4785        4790
## 0.009991684 0.022609782 0.004630244 0.003653147 0.034857817 0.006794442
##        4795        4800        4803        4833        4836        4850
## 0.016600370 0.034928758 0.010031667 0.009950993 0.003812592 0.003633373
##        4857        4868        4881        4884        4890        4893
## 0.006200659 0.003320502 0.034918613 0.003836872 0.013329351 0.010007924
##        4894        4910        4923        4931        4934        4945
## 0.003900093 0.003746695 0.010910042 0.005466427 0.003237071 0.005379513
##        4952        4957        4958        4961        4965        4991
## 0.023580901 0.022743243 0.023712754 0.010706980 0.010738167 0.010831242
##        4993
## 0.035312272
```

These are the outliers.

Studentized Deleted Residuals (SDR)

```
Res_SE = summary(full.lm)$sigma
di = resid(full.lm)/(1-Hi)
SSE = Res_SE^2*(n-(k+1))
SDR = resid(full.lm)*sqrt((n-k-2)/(SSE*(1-Hi)-(resid(full.lm))^2))
SDR[abs(SDR)>qt(0.975,n-k-2)] #some evidence
```

```
##        21        41        57       112       202       206       292
##  3.840474  5.879217  1.970867  8.531874  3.255321  4.450823  2.257411
##       369       401       424       439       459       549       600
##  3.005770  3.858117  2.336190  1.999103  2.588921  2.714026  4.812918
##       604       611       677       751       790       843      1000
## 16.853226  2.857142  2.367642  4.404025  5.556061  4.542620 16.794963
##      1092      1161      1240      1295      1318      1360      1425
##  2.107011  3.226858  2.772334  9.088746  2.189291  2.290561  2.357198
##      1434      1451      1457      1472      1539      1583      1725
##  2.061002  2.044910  2.577996  3.748673  2.037627  3.142260 11.277178
##      1730      1732      1748      1780      1849      1943      2004
##  3.453233  4.451259  2.025062  1.979400  2.787585  4.449010 39.724870
##      2185      2259      2344      2362      2408      2444      2475
##  4.170508  2.188172  3.307926  3.437014  3.445016  5.209225  3.206000
##      2538      2613      2652      2661      2791      3028      3042
##  2.406145  2.286629  2.154374  2.038190  4.091448  2.909875  4.515425
##      3066      3091      3119      3180      3182      3222      3279
##  5.955942  2.166938  4.724410  6.442902  4.894943  3.410965  2.751256
##      3300      3341      3489      3502      3560      3564      3614
##  3.102705  3.243999  5.225723  2.651402  2.214295  5.306768  2.988102
##      3630      3715      3717      3760      3830      3863      3997
##  2.082725  2.618805  3.335943  2.968248  2.058708  3.014280  2.928838
##      4007      4139      4162      4252      4264      4271      4318
##  2.655966  4.501436  2.754245  3.713762 16.716136  4.916308  4.455322
##      4319      4328      4355      4396      4409      4450      4486
##  2.446670 14.091333  2.594594  3.472396  9.716556  2.403656  2.132986
##      4496      4540      4552      4572      4589      4677      4738
## 12.716730  3.657422  2.605854  2.608957  2.040661  3.381107  2.762539
##      4751      4816      4821      4873      4907      4948
## 12.528049  2.562962  5.624146  2.348138  2.167482  2.153366
```

```
SDR[abs(SDR)>qt(0.995,n-k-2)] #strong evidence
```

```
##        21        41       112       202       206       369       401
##  3.840474  5.879217  8.531874  3.255321  4.450823  3.005770  3.858117
##       459       549       600       604       611       751       790
##  2.588921  2.714026  4.812918 16.853226  2.857142  4.404025  5.556061
##       843      1000      1161      1240      1295      1457      1472
##  4.542620 16.794963  3.226858  2.772334  9.088746  2.577996  3.748673
##      1583      1725      1730      1732      1849      1943      2004
##  3.142260 11.277178  3.453233  4.451259  2.787585  4.449010 39.724870
##      2185      2344      2362      2408      2444      2475      2791
##  4.170508  3.307926  3.437014  3.445016  5.209225  3.206000  4.091448
##      3028      3042      3066      3119      3180      3182      3222
##  2.909875  4.515425  5.955942  4.724410  6.442902  4.894943  3.410965
##      3279      3300      3341      3489      3502      3564      3614
##  2.751256  3.102705  3.243999  5.225723  2.651402  5.306768  2.988102
##      3715      3717      3760      3863      3997      4007      4139
##  2.618805  3.335943  2.968248  3.014280  2.928838  2.655966  4.501436
##      4162      4252      4264      4271      4318      4328      4355
##  2.754245  3.713762 16.716136  4.916308  4.455322 14.091333  2.594594
##      4396      4409      4496      4540      4552      4572      4677
##  3.472396  9.716556 12.716730  3.657422  2.605854  2.608957  3.381107
##      4738      4751      4821
##  2.762539 12.528049  5.624146
```

This test outputs a list of data points that show some and strong evidence of being an outlier with respect to its y value.

Cook's Distance Measure

```
CooksD = cooks.distance(full.lm)
CooksD[CooksD>qf(0.5,k+1, n-k-1)] #Influential
```

```
## named numeric(0)
```

```
#CooksD[CooksD<qf(0.2,k+1, n-k-1)] #Not Influential
CooksD[CooksD<qf(0.5,k+1, n-k-1) & CooksD>qf(0.2,k+1, n-k-1)]
```

```
## named numeric(0)
```

This test outputs a list of data points that show influential/non-influential evidence of being an outlier.

Stepwise selection of variables from BASE model

```
min.lm = lm(price ~1, data = project_data_sample)

step_both = step(min.lm, list(upper = full.lm), direction = 'both')
```

```
## Start:  AIC=50512.86
## price ~ 1
##
##                                 Df Sum of Sq       RSS   AIC
## + private_room_dummy             1  14865376 107114397 49865
## + queens_dummy                   1   1596999 120382774 50449
## + availability_365               1   1517286 120462487 50452
```

```
## + brooklyn_dummy                   1   1331938 120647835 50460
## + shared_room_dummy                1    571494 121408279 50491
## + calculated_host_listings_count   1    506649 121473124 50494
## + bronx_dummy                      1    328283 121651490 50501
## + number_of_reviews                1    224241 121755532 50506
## + reviews_per_month                1    214128 121765645 50506
## + staten_dummy                     1    191083 121788690 50507
## <none>                                         121979773 50513
## + minimum_nights                   1        95 121979678 50515
##
## Step:  AIC=49865.07
## price ~ private_room_dummy
##
##                                  Df Sum of Sq       RSS   AIC
## + availability_365                1   1670550 105443847 49788
## + shared_room_dummy               1   1606675 105507723 49792
## + brooklyn_dummy                  1    993491 106120906 49820
## + queens_dummy                    1    649257 106465140 49837
## + bronx_dummy                     1    206735 106907662 49857
## + calculated_host_listings_count  1    201270 106913127 49858
## + number_of_reviews               1    184344 106930054 49858
## + staten_dummy                    1    155207 106959190 49860
## + minimum_nights                  1     83991 107030406 49863
## + reviews_per_month               1     72624 107041774 49864
## <none>                                        107114397 49865
## - private_room_dummy              1  14865376 121979773 50513
##
## Step:  AIC=49788.48
## price ~ private_room_dummy + availability_365
##
##                                  Df Sum of Sq       RSS   AIC
## + shared_room_dummy               1   1834033 103609814 49703
## + queens_dummy                    1    904942 104538906 49747
## + brooklyn_dummy                  1    851172 104592675 49750
## + number_of_reviews               1    493415 104950432 49767
## + bronx_dummy                     1    301774 105142073 49776
## + reviews_per_month               1    265335 105178512 49778
## + staten_dummy                    1    239026 105204821 49779
## + minimum_nights                  1    153334 105290513 49783
## + calculated_host_listings_count  1     44569 105399278 49788
## <none>                                        105443847 49788
## - availability_365                1   1670550 107114397 49865
## - private_room_dummy              1  15018640 120462487 50452
##
## Step:  AIC=49702.75
## price ~ private_room_dummy + availability_365 + shared_room_dummy
##
##                                  Df Sum of Sq       RSS   AIC
## + brooklyn_dummy                  1    893513 102716301 49661
## + queens_dummy                    1    779753 102830061 49667
## + number_of_reviews               1    507281 103102533 49680
## + bronx_dummy                     1    305131 103304683 49690
## + reviews_per_month               1    262215 103347599 49692
## + staten_dummy                    1    241305 103368509 49693
```

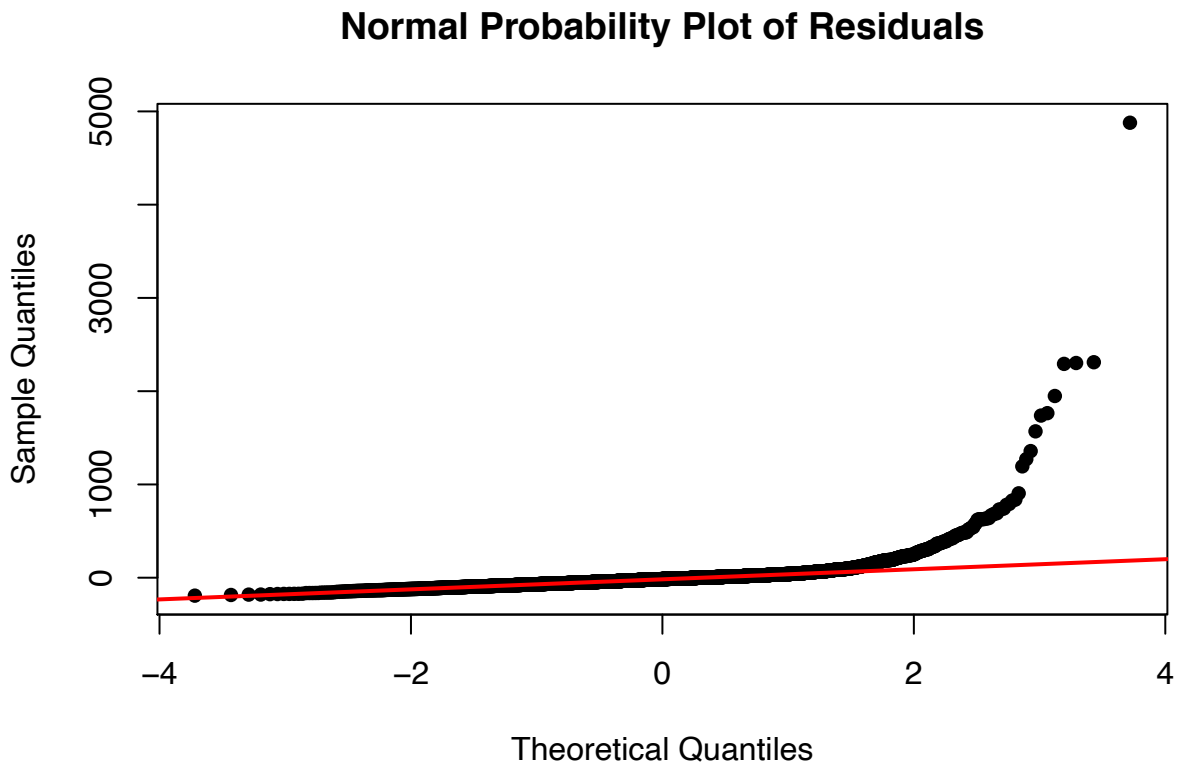
```
## + minimum_nights                   1    182313 103427501 49696
## <none>                                         103609814 49703
## + calculated_host_listings_count  1     34743 103575071 49703
## - shared_room_dummy               1   1834033 105443847 49788
## - availability_365                1   1897908 105507723 49792
## - private_room_dummy              1  16156589 119766403 50425
##
## Step:  AIC=49661.44
## price ~ private_room_dummy + availability_365 + shared_room_dummy +
##     brooklyn_dummy
##
##                                  Df Sum of Sq       RSS   AIC
## + queens_dummy                    1   1559894 101156408 49587
## + number_of_reviews               1    507137 102209164 49639
## + bronx_dummy                     1    458788 102257513 49641
## + reviews_per_month               1    330473 102385828 49647
## + staten_dummy                    1    322454 102393847 49648
## + minimum_nights                  1    209596 102506705 49653
## <none>                                         102716301 49661
## + calculated_host_listings_count  1     13202 102703100 49663
## - brooklyn_dummy                  1    893513 103609814 49703
## - availability_365                1   1745332 104461633 49744
## - shared_room_dummy               1   1876374 104592675 49750
## - private_room_dummy              1  15833013 118549314 50376
##
## Step:  AIC=49586.93
## price ~ private_room_dummy + availability_365 + shared_room_dummy +
##     brooklyn_dummy + queens_dummy
##
##                                  Df Sum of Sq       RSS   AIC
## + bronx_dummy                     1    679912 100476496 49555
## + number_of_reviews               1    481001 100675406 49565
## + staten_dummy                    1    437947 100718461 49567
## + minimum_nights                  1    282382 100874026 49575
## + reviews_per_month               1    195950 100960457 49579
## <none>                                         101156408 49587
## + calculated_host_listings_count  1      1274 101155133 49589
## - queens_dummy                    1   1559894 102716301 49661
## - brooklyn_dummy                  1   1673654 102830061 49667
## - shared_room_dummy               1   1709934 102866342 49669
## - availability_365                1   2044232 103200640 49685
## - private_room_dummy              1  14113067 115269474 50238
##
## Step:  AIC=49555.21
## price ~ private_room_dummy + availability_365 + shared_room_dummy +
##     brooklyn_dummy + queens_dummy + bronx_dummy
##
##                                  Df Sum of Sq       RSS   AIC
## + staten_dummy                    1    482195  99994301 49533
## + number_of_reviews               1    466743 100009753 49534
## + minimum_nights                  1    306198 100170298 49542
## + reviews_per_month               1    167672 100308824 49549
## <none>                                         100476496 49555
## + calculated_host_listings_count  1         6 100476490 49557
```

```
## - bronx_dummy                      1    679912 101156408 49587
## - shared_room_dummy                1   1707491 102183987 49637
## - queens_dummy                     1   1781017 102257513 49641
## - brooklyn_dummy                   1   1978364 102454860 49651
## - availability_365                 1   2214704 102691200 49662
## - private_room_dummy               1  13764783 114241280 50195
##
## Step:  AIC=49533.15
## price ~ private_room_dummy + availability_365 + shared_room_dummy +
##     brooklyn_dummy + queens_dummy + bronx_dummy + staten_dummy
##
##                                  Df Sum of Sq       RSS   AIC
## + number_of_reviews               1    464098  99530204 49512
## + minimum_nights                  1    331906  99662396 49519
## + reviews_per_month               1    160669  99833632 49527
## <none>                                         99994301 49533
## + calculated_host_listings_count  1       780  99993522 49535
## - staten_dummy                    1    482195 100476496 49555
## - bronx_dummy                     1    724159 100718461 49567
## - shared_room_dummy               1   1706433 101700735 49616
## - queens_dummy                    1   1916797 101911099 49626
## - brooklyn_dummy                  1   2163311 102157612 49638
## - availability_365                1   2363787 102358088 49648
## - private_room_dummy              1  13624902 113619203 50170
##
## Step:  AIC=49511.89
## price ~ private_room_dummy + availability_365 + shared_room_dummy +
##     brooklyn_dummy + queens_dummy + bronx_dummy + staten_dummy +
##     number_of_reviews
##
##                                  Df Sum of Sq       RSS   AIC
## + minimum_nights                  1    418815  99111389 49493
## <none>                                         99530204 49512
## + calculated_host_listings_count  1      9067  99521136 49513
## + reviews_per_month               1      3916  99526287 49514
## - number_of_reviews               1    464098  99994301 49533
## - staten_dummy                    1    479550 100009753 49534
## - bronx_dummy                     1    709363 100239567 49545
## - shared_room_dummy               1   1720512 101250716 49596
## - queens_dummy                    1   1885368 101415572 49604
## - brooklyn_dummy                  1   2149149 101679352 49617
## - availability_365                1   2693086 102223290 49643
## - private_room_dummy              1  13601976 113132180 50150
##
## Step:  AIC=49492.81
## price ~ private_room_dummy + availability_365 + shared_room_dummy +
##     brooklyn_dummy + queens_dummy + bronx_dummy + staten_dummy +
##     number_of_reviews + minimum_nights
##
##                                  Df Sum of Sq       RSS   AIC
## <none>                                         99111389 49493
## + reviews_per_month               1     20183  99091206 49494
## + calculated_host_listings_count  1      4649  99106740 49495
## - minimum_nights                  1    418815  99530204 49512
```

```
## - staten_dummy                    1    508356  99619745 49516
## - number_of_reviews               1    551007  99662396 49519
## - bronx_dummy                     1    738046  99849435 49528
## - shared_room_dummy               1   1761571 100872960 49579
## - queens_dummy                    1   1989449 101100838 49590
## - brooklyn_dummy                  1   2248835 101360224 49603
## - availability_365                1   2889215 102000604 49634
## - private_room_dummy              1  13867786 112979175 50146
```

Best model with dummies (location, roomtype) = price ~ private_room_dummy + availability_365 + shared_room_dummy + brooklyn_dummy + bronx_dummy + number_of_reviews + minimum_nights + queens_dummy + staten_dummy

```
newbestmodel= lm(price ~ private_room_dummy + availability_365 +
                   shared_room_dummy + brooklyn_dummy + bronx_dummy +
                   number_of_reviews + minimum_nights + queens_dummy +
                   staten_dummy)
qqnorm(resid(newbestmodel),pch=16,main="Normal Probability Plot of Residuals")
qqline(resid(newbestmodel),col='red',lwd=2)
```




```
summary(newbestmodel)
```

```
##
## Call:
## lm(formula = price ~ private_room_dummy + availability_365 +
##     shared_room_dummy + brooklyn_dummy + bronx_dummy + number_of_reviews +
##     minimum_nights + queens_dummy + staten_dummy)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -192.3  -53.6  -15.0   19.1 4878.4
```

```
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)         212.55929    4.05706  52.392  < 2e-16 ***
## private_room_dummy -108.39142    4.10207 -26.424  < 2e-16 ***
## availability_365      0.19200    0.01592  12.061  < 2e-16 ***
## shared_room_dummy  -135.72689   14.41210  -9.418  < 2e-16 ***
## brooklyn_dummy      -46.21379    4.34315 -10.641  < 2e-16 ***
## bronx_dummy         -85.16244   13.97069  -6.096 1.17e-09 ***
## number_of_reviews    -0.22470    0.04266  -5.267 1.44e-07 ***
## minimum_nights       -0.63347    0.13795  -4.592 4.50e-06 ***
## queens_dummy        -67.19520    6.71403 -10.008  < 2e-16 ***
## staten_dummy       -107.82482   21.31308  -5.059 4.36e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 140.9 on 4990 degrees of freedom
## Multiple R-squared:  0.1875, Adjusted R-squared:  0.186
## F-statistic: 127.9 on 9 and 4990 DF,  p-value: < 2.2e-16
```

The above plot is for the best model with dummies

Checking for outliers using Cutoff

```
k = 7
n = length(price)
LV_cutoff = 2*(k+1)/n; print(LV_cutoff)
```

```
## [1] 0.0032
```

```
Hi = hatvalues(newbestmodel)
Hi[Hi>LV_cutoff]
```

```
##          16          26          30          40          49          50
## 0.010295099 0.003580248 0.010708091 0.008801343 0.010958321 0.011506680
##          57          65          66          86         138         140
## 0.010622078 0.011546727 0.011962369 0.010800933 0.009654897 0.003525011
##         149         168         190         191         209         237
## 0.003840322 0.003497515 0.012562061 0.011022621 0.016238858 0.022664212
##         249         283         290         306         336         350
## 0.005386329 0.003472463 0.004514577 0.004395417 0.010420508 0.003315117
##         376         381         393         399         440         446
## 0.022859433 0.003746894 0.003430099 0.010455347 0.004509451 0.011654737
##         484         488         508         512         521         522
## 0.010839399 0.010584059 0.010314380 0.005045478 0.010642129 0.013532977
##         542         550         551         559         564         574
## 0.011858203 0.009470571 0.004066207 0.003459526 0.006741544 0.005822696
##         595         606         609         640         664         666
## 0.010551873 0.022697295 0.010957079 0.011430447 0.010153258 0.006195028
##         690         703         735         760         793         821
## 0.009773882 0.005657417 0.022829862 0.004583740 0.004329470 0.006205029
##         822         828         830         835         840         864
## 0.004272088 0.010653301 0.009853165 0.009711298 0.010478385 0.022766622
##         869         888         895         896         900         910
## 0.004911291 0.011111108 0.009843056 0.009842786 0.007332060 0.003731103
```

```
##         937         959         967         971         973         975
## 0.011630582 0.022916760 0.004098918 0.022514552 0.022663327 0.008299023
##         978         990        1008        1009        1015        1022
## 0.023166159 0.003480826 0.009554413 0.009756069 0.004138170 0.121442438
##        1068        1071        1090        1102        1112        1122
## 0.004414267 0.022431218 0.022468100 0.010696497 0.064895379 0.011264908
##        1138        1143        1158        1178        1182        1203
## 0.009856390 0.009447411 0.003773607 0.009742422 0.003457355 0.007308783
##        1210        1224        1231        1239        1258        1272
## 0.022645861 0.010402877 0.009593017 0.022591634 0.009570620 0.083468832
##        1292        1294        1332        1359        1363        1367
## 0.003973433 0.003544460 0.022965213 0.010609887 0.009944586 0.003228448
##        1394        1396        1413        1418        1458        1479
## 0.010577998 0.003307723 0.003323726 0.008155576 0.007099998 0.010082193
##        1487        1503        1512        1516        1572        1573
## 0.007048381 0.010781020 0.003840108 0.011818130 0.022654448 0.011688052
##        1600        1608        1646        1650        1664        1679
## 0.009934889 0.003380397 0.003530683 0.066920314 0.010911278 0.009819500
##        1697        1704        1726        1735        1760        1763
## 0.009864161 0.011732147 0.011009082 0.009930212 0.010644413 0.010851518
##        1765        1771        1779        1795        1821        1828
## 0.009511177 0.005429146 0.009993707 0.022946301 0.022494449 0.004114601
##        1836        1888        1901        1931        1932        1983
## 0.011751257 0.010750965 0.003662231 0.003270666 0.014078821 0.004682932
##        1992        2001        2020        2026        2039        2064
## 0.009962258 0.008780184 0.023021315 0.022590153 0.003283511 0.010550276
##        2074        2110        2134        2157        2163        2170
## 0.009607951 0.009560068 0.009097691 0.010610993 0.022703120 0.022735659
##        2230        2233        2277        2289        2320        2321
## 0.011747510 0.003580589 0.009801758 0.003238564 0.003246061 0.010449365
##        2330        2356        2366        2371        2373        2389
## 0.022680565 0.019321319 0.005370212 0.005967216 0.003307317 0.009721691
##        2420        2422        2427        2434        2442        2448
## 0.010146758 0.010853376 0.010564146 0.009564968 0.004389631 0.003213941
##        2454        2470        2480        2491        2496        2498
## 0.009644958 0.124941356 0.010915675 0.012205170 0.009630020 0.021025304
##        2499        2551        2557        2559        2562        2565
## 0.009602797 0.009748085 0.029370522 0.010438569 0.019404967 0.004503662
##        2576        2597        2599        2600        2610        2630
## 0.009987161 0.011444471 0.009855128 0.009611969 0.010420672 0.004454952
##        2659        2664        2668        2685        2688        2689
## 0.010445793 0.123670142 0.009919850 0.004862202 0.003928554 0.013859287
##        2693        2694        2695        2721        2722        2733
## 0.009504615 0.010637174 0.011064230 0.010021540 0.009564772 0.004891647
##        2763        2764        2785        2787        2794        2803
## 0.003920231 0.009828888 0.010840750 0.009824247 0.005678595 0.009673527
##        2830        2851        2865        2880        2905        2908
## 0.003272698 0.003567350 0.006633250 0.009905950 0.010589388 0.009894792
##        2909        2912        2913        2929        2946        2992
## 0.003553916 0.009842659 0.010068043 0.009581903 0.003450845 0.010641817
##        2994        3000        3001        3021        3023        3036
## 0.004196322 0.022630023 0.010147569 0.005911329 0.003838247 0.022730526
##        3038        3039        3050        3064        3079        3084
## 0.009558404 0.003410303 0.011863699 0.010977942 0.004726713 0.010653301
```

```
##        3097        3117        3129        3154        3162        3164
## 0.032823822 0.010620107 0.010643939 0.004437352 0.011060748 0.004485908
##        3172        3198        3206        3212        3231        3234
## 0.004117100 0.004368017 0.022981744 0.008722026 0.009743956 0.022616399
##        3247        3252        3285        3298        3302        3308
## 0.011506568 0.022679324 0.006263807 0.011432548 0.010513401 0.010891318
##        3339        3355        3357        3362        3364        3367
## 0.022640597 0.016441186 0.014819034 0.009590828 0.006728899 0.007825808
##        3394        3405        3410        3416        3419        3424
## 0.010857225 0.004378259 0.010619964 0.009672650 0.009865656 0.023044455
##        3428        3430        3454        3475        3484        3493
## 0.009499726 0.004125753 0.009868733 0.004070367 0.010658189 0.010095227
##        3503        3504        3515        3523        3532        3549
## 0.009962258 0.007092474 0.009549090 0.011490444 0.010868122 0.011667007
##        3555        3564        3566        3588        3598        3621
## 0.010480829 0.011249343 0.010466709 0.007066860 0.011514995 0.009710331
##        3629        3634        3650        3653        3668        3705
## 0.009896001 0.007327116 0.026675471 0.004345575 0.004233035 0.010714082
##        3709        3714        3723        3728        3730        3733
## 0.010005272 0.007797415 0.005359558 0.003578373 0.009865656 0.003238431
##        3753        3768        3773        3777        3791        3796
## 0.022533415 0.009782794 0.009878379 0.011528866 0.008337898 0.010059935
##        3797        3800        3804        3817        3871        3873
## 0.009954379 0.009556631 0.010099366 0.010457045 0.011647689 0.005571411
##        3884        3898        3906        3918        3921        3953
## 0.003837472 0.009647144 0.003548395 0.011600822 0.009791340 0.003815292
##        3970        3981        3987        3989        3994        3995
## 0.004458836 0.010024995 0.011519160 0.022984550 0.004235562 0.008030979
##        3999        4006        4013        4014        4017        4020
## 0.010963828 0.011735352 0.010627645 0.010465608 0.022743248 0.005729851
##        4042        4052        4055        4081        4088        4100
## 0.009852242 0.010093333 0.011009047 0.009838037 0.022689492 0.005857919
##        4126        4128        4138        4147        4198        4205
## 0.007039947 0.010973915 0.004896825 0.010014529 0.023576812 0.009615079
##        4213        4226        4228        4233        4253        4265
## 0.011525167 0.023279327 0.005635443 0.022699229 0.010243212 0.009784257
##        4287        4308        4323        4357        4361        4364
## 0.009891446 0.009828521 0.022542922 0.009965049 0.022710005 0.009692862
##        4366        4369        4382        4392        4419        4436
## 0.009908615 0.009494837 0.011757319 0.010987074 0.007415582 0.003919361
##        4453        4456        4467        4481        4486        4512
## 0.009558403 0.022709406 0.011787942 0.009639946 0.011082241 0.010470174
##        4517        4518        4531        4535        4555        4559
## 0.010621190 0.008552161 0.004038480 0.022993509 0.010076738 0.010961942
##        4565        4582        4593        4602        4614        4616
## 0.008258742 0.010090721 0.010680279 0.010567583 0.007246476 0.009859232
##        4627        4693        4725        4737        4747        4748
## 0.015175585 0.003721506 0.012543245 0.009863520 0.022559979 0.004319770
##        4777        4795        4803        4833        4857        4890
## 0.003396378 0.016600238 0.009953749 0.009863026 0.005632152 0.013061928
##        4893        4894        4910        4923        4945        4952
## 0.009932485 0.003425796 0.003657655 0.010788923 0.005128471 0.023544421
##        4957        4958        4961        4965        4991
## 0.022724764 0.023694048 0.010653301 0.010705755 0.010589198
```

These are the outliers.

Studentized Deleted Residuals (SDR)

```
Res_SE = summary(newbestmodel)$sigma
di = resid(newbestmodel)/(1-Hi)
SSE = Res_SE^2*(n-(k+1))
SDR = resid(newbestmodel)*sqrt((n-k-2)/(SSE*(1-Hi)-(resid(newbestmodel))^2))
SDR[abs(SDR)>qt(0.975,n-k-2)] #some evidence
```

```
##        21        41        57       112       202       206       292
##  3.853657  5.892351  1.979116  8.538694  3.262445  4.463722  2.263725
##       369       401       424       439       459       549       600
##  3.009309  3.848844  2.347303  2.008181  2.592684  2.709101  4.818513
##       604       611       677       751       790       843      1000
## 16.867655  2.873079  2.365211  4.415477  5.561931  4.553753 16.796701
##      1092      1161      1240      1295      1318      1360      1425
##  2.114810  3.226870  2.781198  9.099605  2.160651  2.299968  2.365744
##      1434      1451      1457      1472      1539      1583      1725
##  2.069323  2.057379  2.588667  3.762961  1.983599  3.126510 11.278966
##      1730      1732      1748      1780      1849      1943      2004
##  3.448920  4.466615  2.035191  1.976892  2.791414  4.462136 39.745394
##      2185      2259      2344      2362      2408      2444      2475
##  4.182580  2.183472  3.296828  3.445494  3.438025  5.202624  3.197826
##      2538      2613      2652      2661      2791      3028      3042
##  2.398785  2.293178  2.167217  2.047135  4.077212  2.902987  4.521918
##      3066      3091      3119      3180      3182      3222      3279
##  5.962354  2.170818  4.738610  6.448606  4.890060  3.420201  2.756332
##      3300      3341      3489      3502      3560      3564      3614
##  3.094489  3.221710  5.232924  2.669620  2.220639  5.312045  2.981829
##      3630      3715      3717      3760      3830      3863      3997
##  2.090807  2.631627  3.351504  2.972100  2.060612  3.008673  2.935692
##      4007      4139      4162      4252      4264      4271      4318
##  2.664286  4.506514  2.762643  3.709251 16.725313  4.919260  4.468221
##      4319      4328      4355      4396      4409      4450      4486
##  2.431705 14.102615  2.599374  3.481171  9.728200  2.411823  2.145445
##      4496      4540      4552      4572      4589      4677      4738
## 12.731293  3.665871  2.612446  2.612771  2.049298  3.383142  2.753379
##      4751      4816      4821      4873      4907      4948
## 12.539492  2.551592  5.632746  2.354783  2.163355  2.140510
```

```
SDR[abs(SDR)>qt(0.995,n-k-2)] #strong evidence
```

```
##        21        41       112       202       206       369       401
##  3.853657  5.892351  8.538694  3.262445  4.463722  3.009309  3.848844
##       459       549       600       604       611       751       790
##  2.592684  2.709101  4.818513 16.867655  2.873079  4.415477  5.561931
##       843      1000      1161      1240      1295      1457      1472
##  4.553753 16.796701  3.226870  2.781198  9.099605  2.588667  3.762961
##      1583      1725      1730      1732      1849      1943      2004
##  3.126510 11.278966  3.448920  4.466615  2.791414  4.462136 39.745394
##      2185      2344      2362      2408      2444      2475      2791
##  4.182580  3.296828  3.445494  3.438025  5.202624  3.197826  4.077212
##      3028      3042      3066      3119      3180      3182      3222
##  2.902987  4.521918  5.962354  4.738610  6.448606  4.890060  3.420201
```

```
##      3279      3300      3341      3489      3502      3564      3614
##  2.756332  3.094489  3.221710  5.232924  2.669620  5.312045  2.981829
##      3715      3717      3760      3863      3997      4007      4139
##  2.631627  3.351504  2.972100  3.008673  2.935692  2.664286  4.506514
##      4162      4252      4264      4271      4318      4328      4355
##  2.762643  3.709251 16.725313  4.919260  4.468221 14.102615  2.599374
##      4396      4409      4496      4540      4552      4572      4677
##  3.481171  9.728200 12.731293  3.665871  2.612446  2.612771  3.383142
##      4738      4751      4821
##  2.753379 12.539492  5.632746
```

This test outputs a list of data points that show some and strong evidence of being an outlier with respect to its y value.

Cook's Distance Measure

```
CooksD = cooks.distance(newbestmodel)
CooksD[CooksD>qf(0.5,k+1, n-k-1)] #Influential
```

```
## named numeric(0)
```

```
#CooksD[CooksD<qf(0.2,k+1, n-k-1)] #Not Influential
CooksD[CooksD<qf(0.5,k+1, n-k-1) & CooksD>qf(0.2,k+1, n-k-1)]
```

```
## named numeric(0)
```

This test outputs a list of data points that show influential/non-influential evidence of being an outlier.

DATA EXPLORATION PLOTS

Load packages:

```
library(ggmap)
library(dplyr)
library("ggcorrplot")
library(gridExtra)
#library(ggplot)
library(plotrix)
register_google([redacted])
```

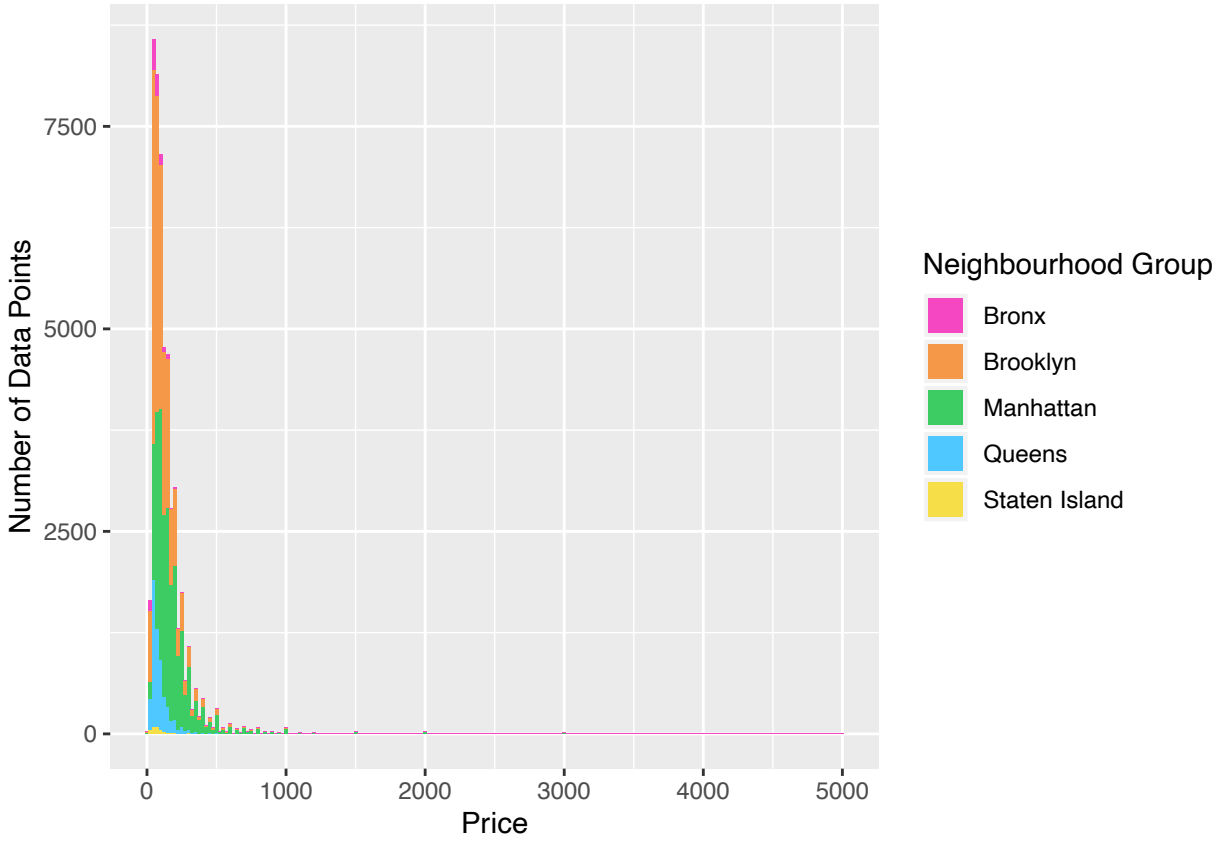
Custom Colors:

```
pink = "#f547c1"
orange = "#f59847"
yellow = "#f5de47"
green = "#3dcc64"
blue = "#4fc7ff"
customcolors = c(pink,orange,green,blue,yellow)
```

Before cutting down the data:

```
airbnb = read.csv("AB_NYC_2019.csv")
attach(airbnb)
```

```
histdata = airbnb[airbnb$price <= 5000,]
ggplot(histdata, aes(histdata$price, fill = histdata$neighbourhood_group)) +
  geom_histogram(binwidth = 25, size = 2) +
  scale_fill_manual(values=customcolors) +
  labs(x = "Price", y = "Number of Data Points", fill="Neighbourhood Group")
```



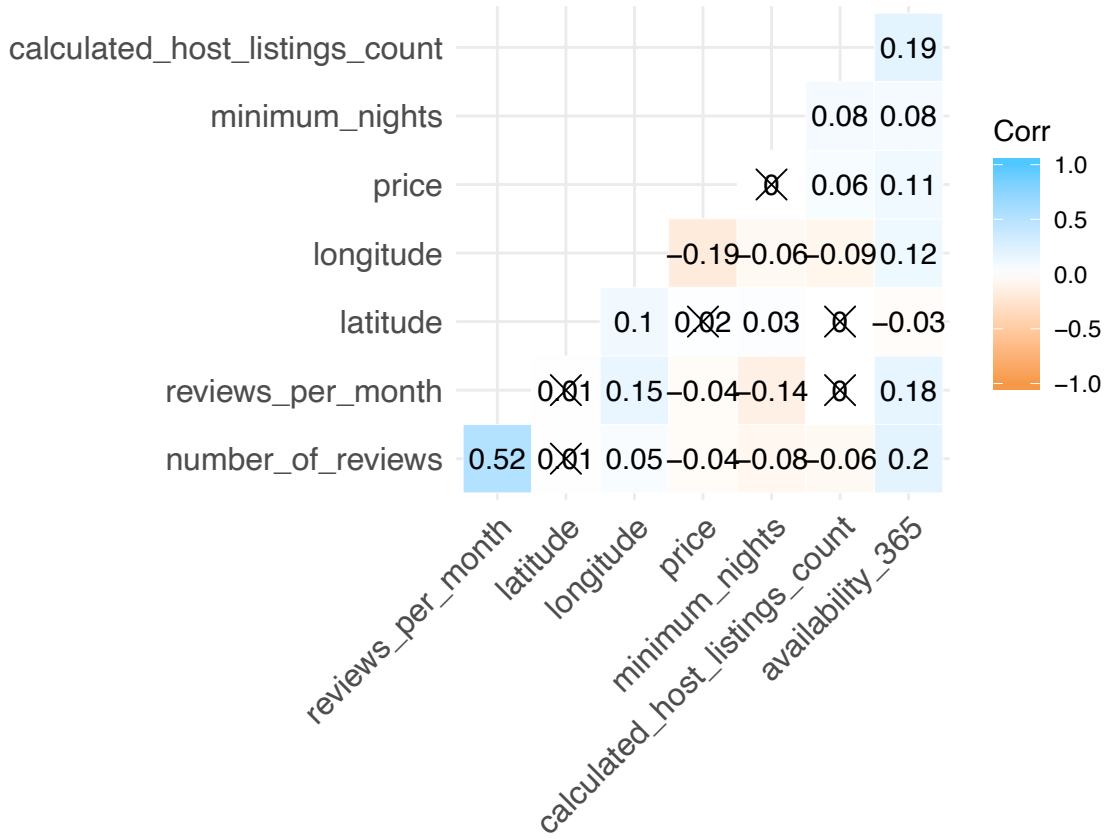

```
#ggsave("Hist_Price_NG_Before Random Sampling.png", dpi=1000)
```

Data Sample:

```
data_sample_final = read.csv('sample_data.csv')
data_sample_final = data_sample_final[,c(6:13,15:17)]
```

Correlation Matrix:

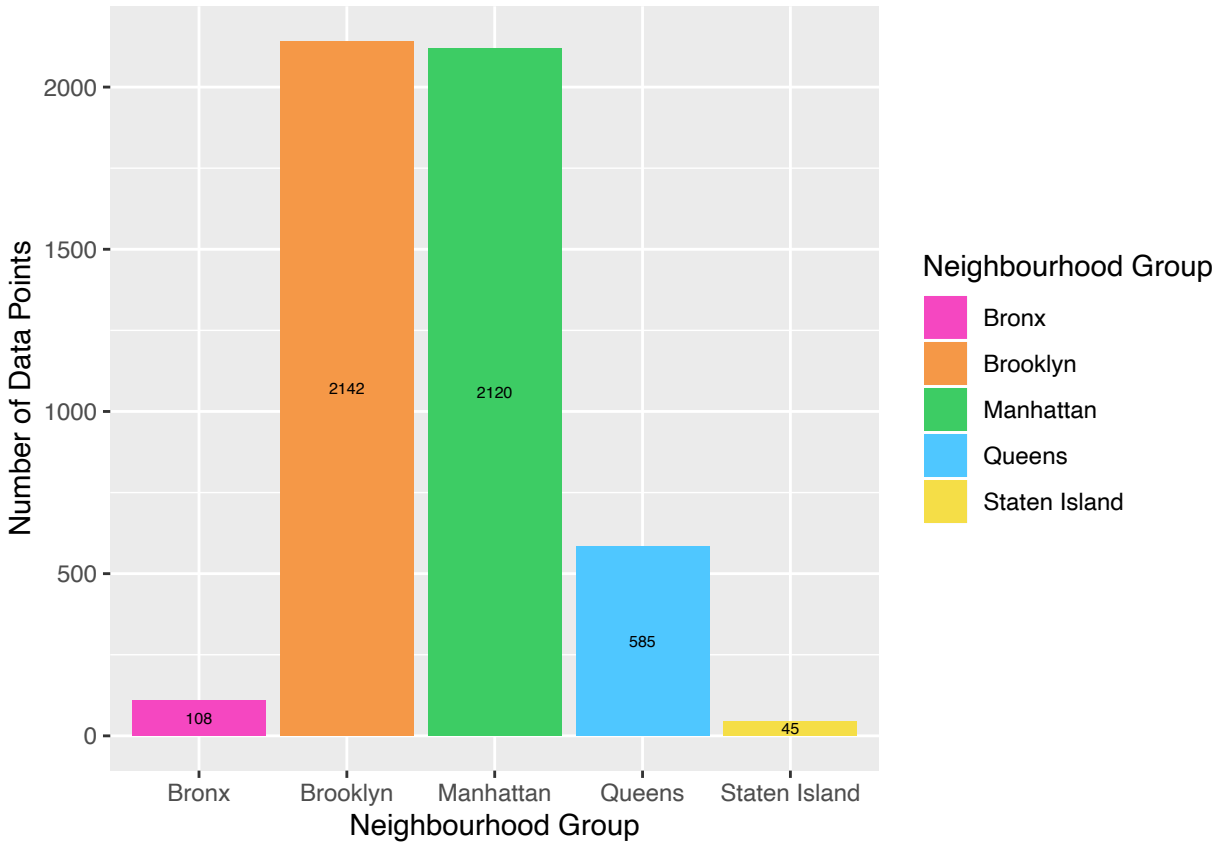
```
corr_data = data_sample_final[,c(1,3:11)]
corr_data = data.frame(corr_data)

corr <- round(cor(corr_data[,c(2,3,5,6,7,8,9,10)]),2)
ggcorrplot(corr, p.mat = cor_pmat(corr_data[,c(2,3,5,6,7,8,9,10)]),
           hc.order = TRUE, type = "lower",
           color = c(orange, "white", blue),
           outline.col = "white",
           lab = TRUE)
```




```
#ggsave("corr_matrix.png", dpi=1000)
```

Counts per room type:

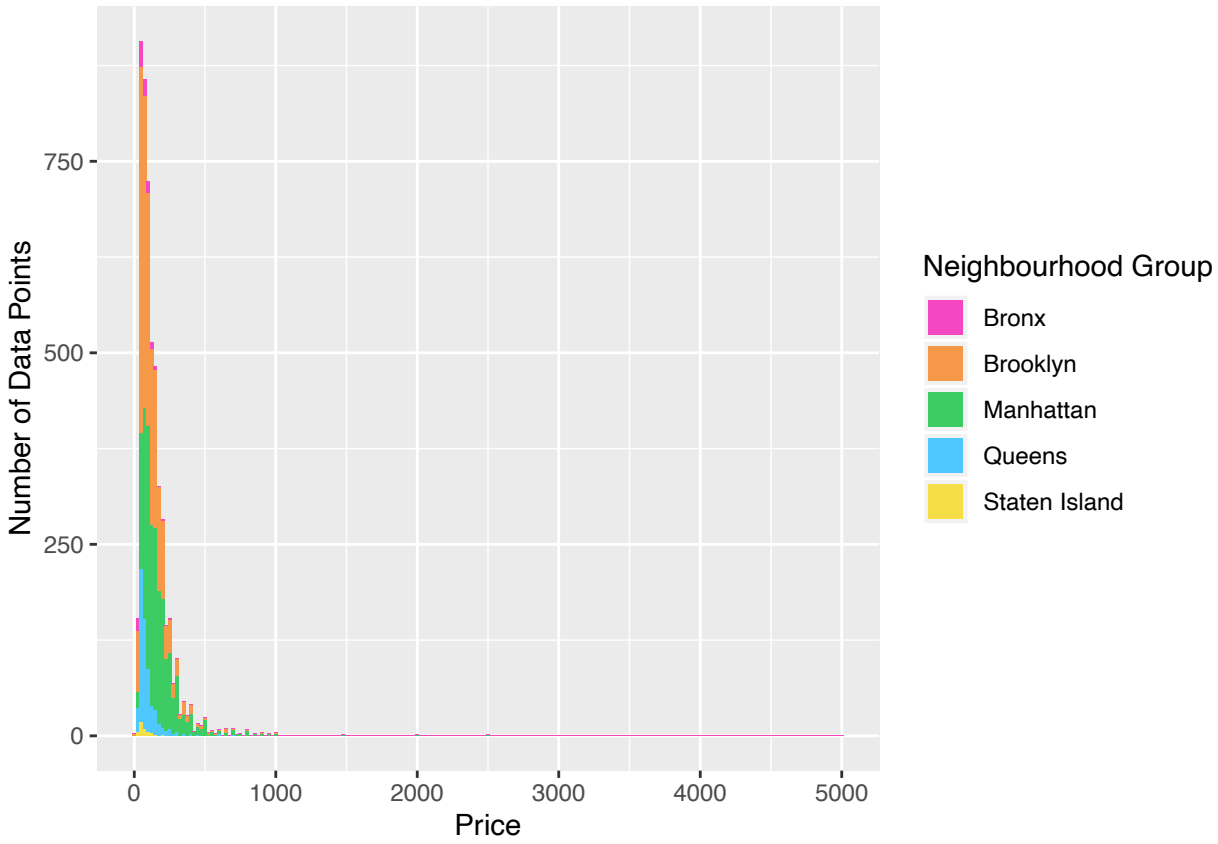
```
counts = count(data_sample_final, neighbourhood_group)

ggplot(counts, aes(x = counts$neighbourhood_group, y = counts$n, fill = counts$neighbourhood_group, labe
  geom_bar(stat = "identity") +
  geom_text(size = 2, position = position_stack(vjust = 0.5)) +
  scale_fill_manual(values=customcolors) +
  labs(x = "Neighbourhood Group", y = "Number of Data Points", fill="Neighbourhood Group")
```




```
#ggsave("num_of_room_type.png", dpi=1000)
```

Histogram of all Prices points:

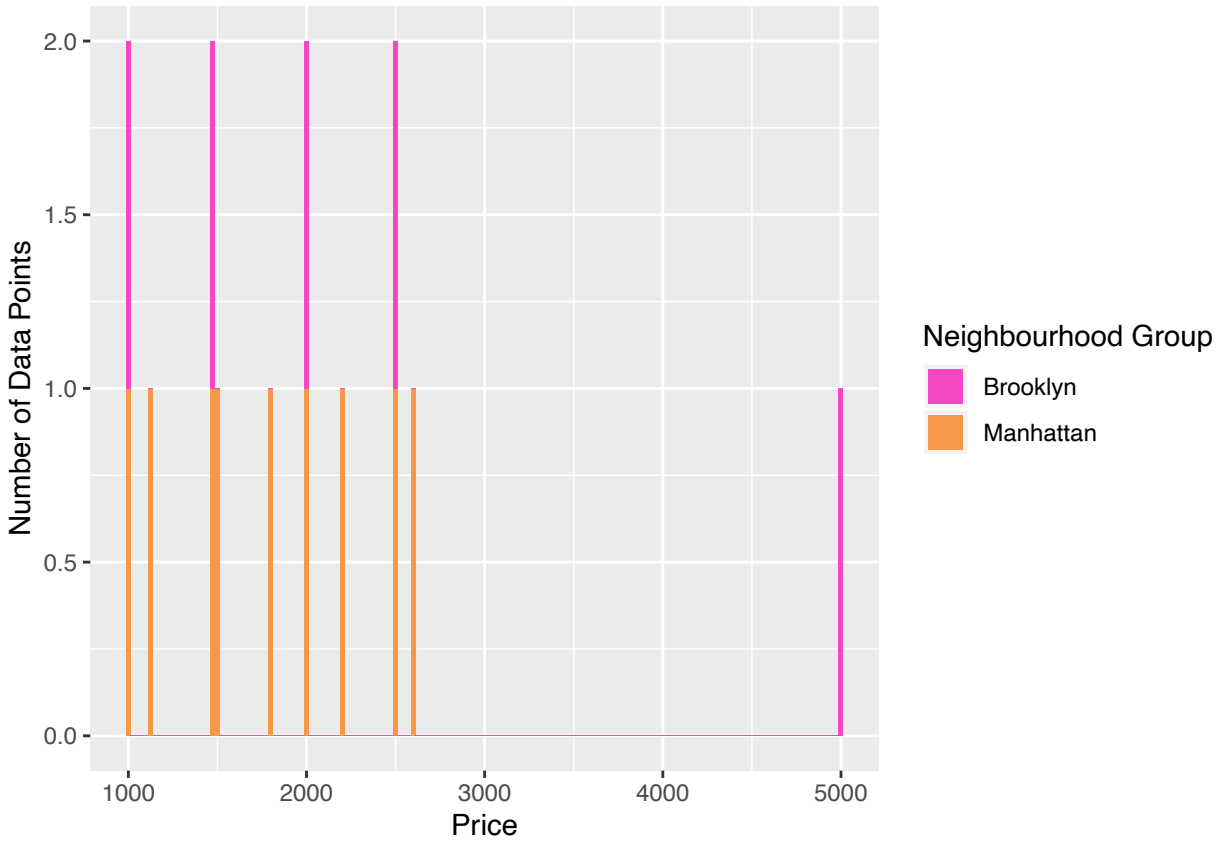
```
histdata = data_sample_final
ggplot(histdata, aes(histdata$price, fill = histdata$neighbourhood_group)) +
  geom_histogram(binwidth = 25, size = 2) +
  scale_fill_manual(values=customcolors) +
  labs(x = "Price", y = "Number of Data Points", fill="Neighbourhood Group")
```




```
#ggsave("Hist_Price_NG.png", dpi=1000)
```

Histogram of the 14 points that are greater than 1000

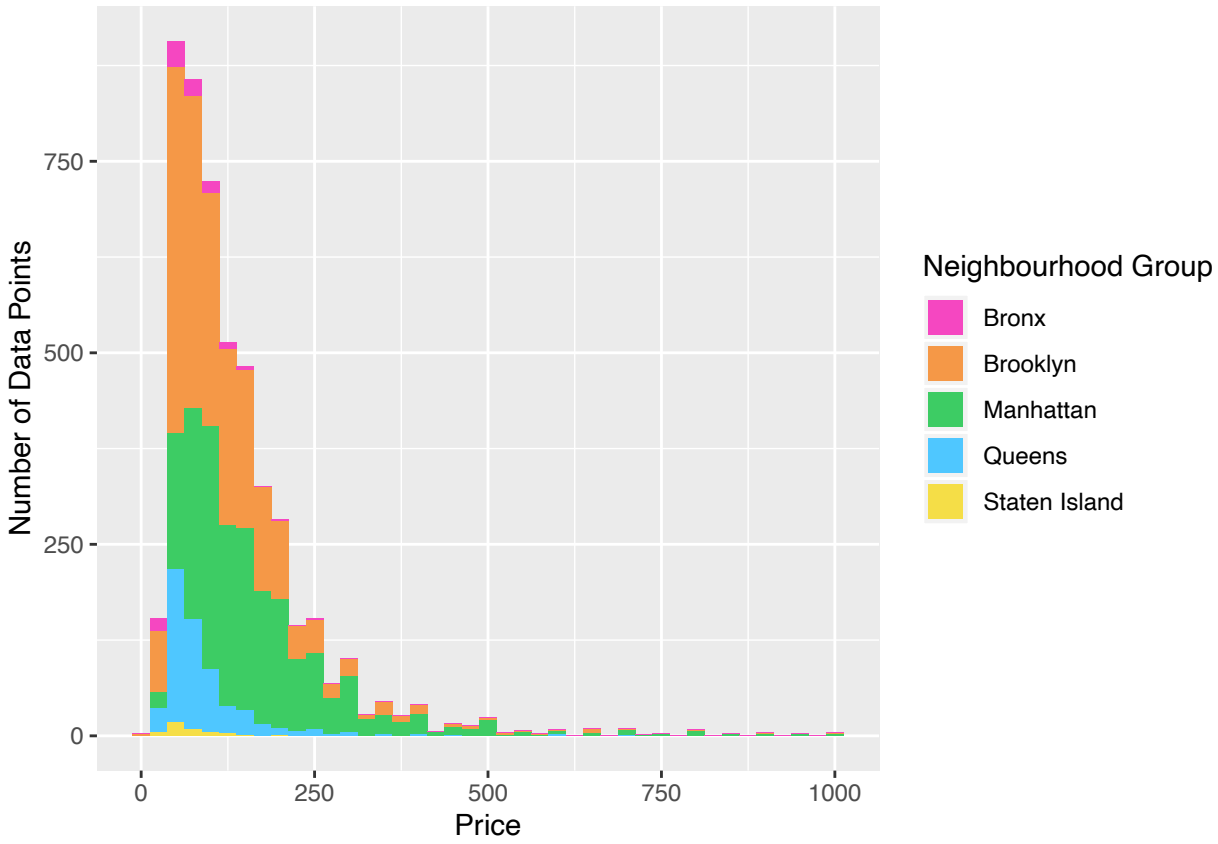
```
histdata = data_sample_final[data_sample_final$price >= 1000,]
ggplot(histdata, aes(histdata$price, fill = histdata$neighbourhood_group)) +
  geom_histogram(binwidth = 25, size = 2) +
  scale_fill_manual(values=customcolors) +
  labs(x = "Price", y = "Number of Data Points", fill="Neighbourhood Group")
```




```
#ggsave("Hist_Price_gt_1000_NG.png", dpi=1000)
```

Histogram excluding the 14 points that are greater than 1000

```
histdata = data_sample_final[data_sample_final$price <= 1000,]
ggplot(histdata, aes(histdata$price, fill = histdata$neighbourhood_group)) +
  geom_histogram(binwidth = 25, size = 2) +
  scale_fill_manual(values=customcolors) +
  labs(x = "Price", y = "Number of Data Points", fill="Neighbourhood Group")
```




```
#ggsave("Hist_Price_lt_1000_NG.png", dpi=1000)
```

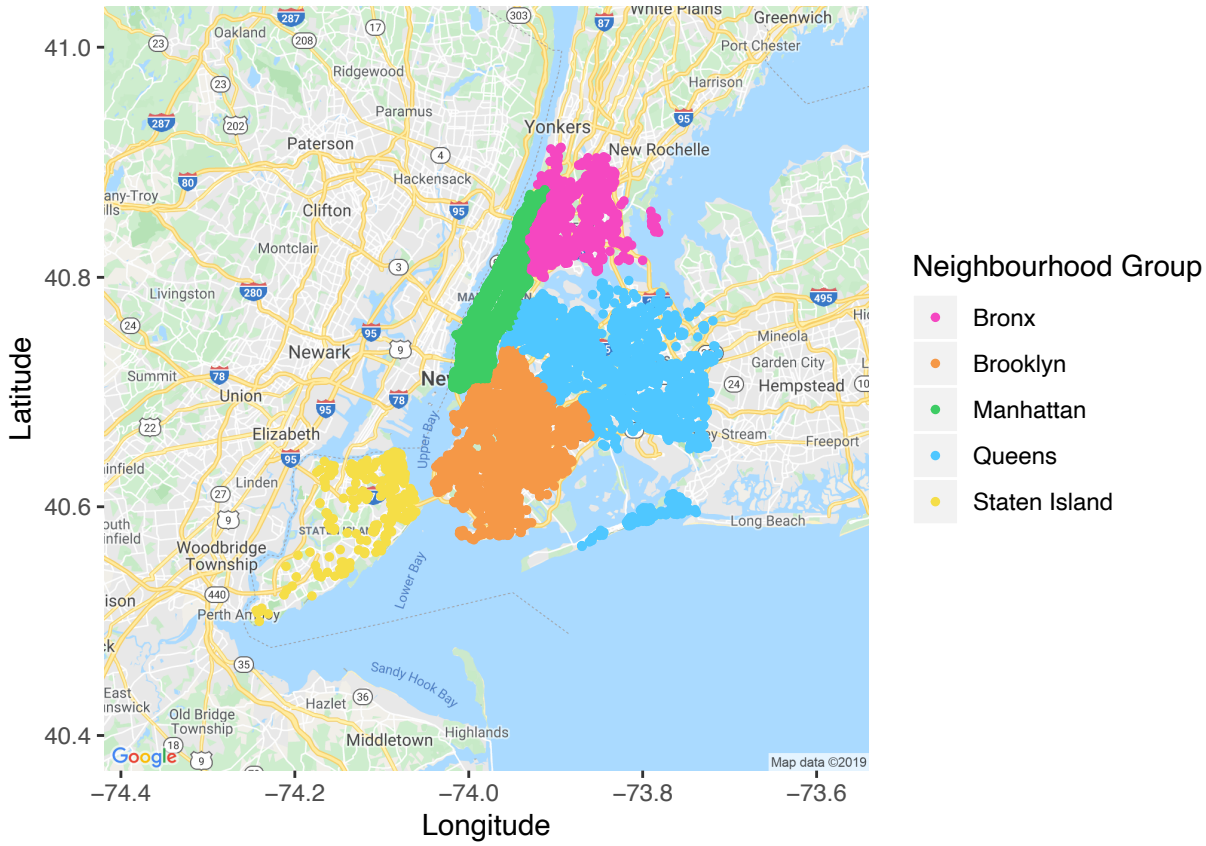
Some variables for maps:

```
# lat/long centers
ALL_centerlong = (min(data_sample_final$longitude) + max(data_sample_final$longitude))/2
ALL_centerlat = (min(data_sample_final$latitude) + max(data_sample_final$latitude))/2

# neighbourhood group centers
NG_centerlong = c()
NG_centerlat = c()

neighbourhood_groups = as.character(unique(data_sample_final$neighbourhood_group))

for (i in 1:length(neighbourhood_groups)) {
  lat = data_sample_final$latitude[data_sample_final$neighbourhood_group == neighbourhood_groups[i]]
  long = data_sample_final$longitude[data_sample_final$neighbourhood_group == neighbourhood_groups[i]]
  NG_centerlong[i] = (min(long) + max(long))/2
  NG_centerlat[i] = (min(lat) + max(lat))/2
}

NG_centers = data.frame(neighbourhood_groups, NG_centerlong, NG_centerlat)

#neighbourhood centers
N_centerlong = c()
N_centerlat = c()
```

```
neighbourhoods = as.character(unique(data_sample_final$neighbourhood))

for (i in 1:length(neighbourhoods)) {
  lat = data_sample_final$latitude[data_sample_final$neighbourhood == neighbourhoods[i]]
  long = data_sample_final$longitude[data_sample_final$neighbourhood == neighbourhoods[i]]
  N_centerlong[i] = (min(long) + max(long))/2
  N_centerlat[i] = (min(lat) + max(lat))/2
}

N_centers = data.frame(neighbourhoods, N_centerlong, N_centerlat)
```

Map of Neighbourhoods FULL DATA:

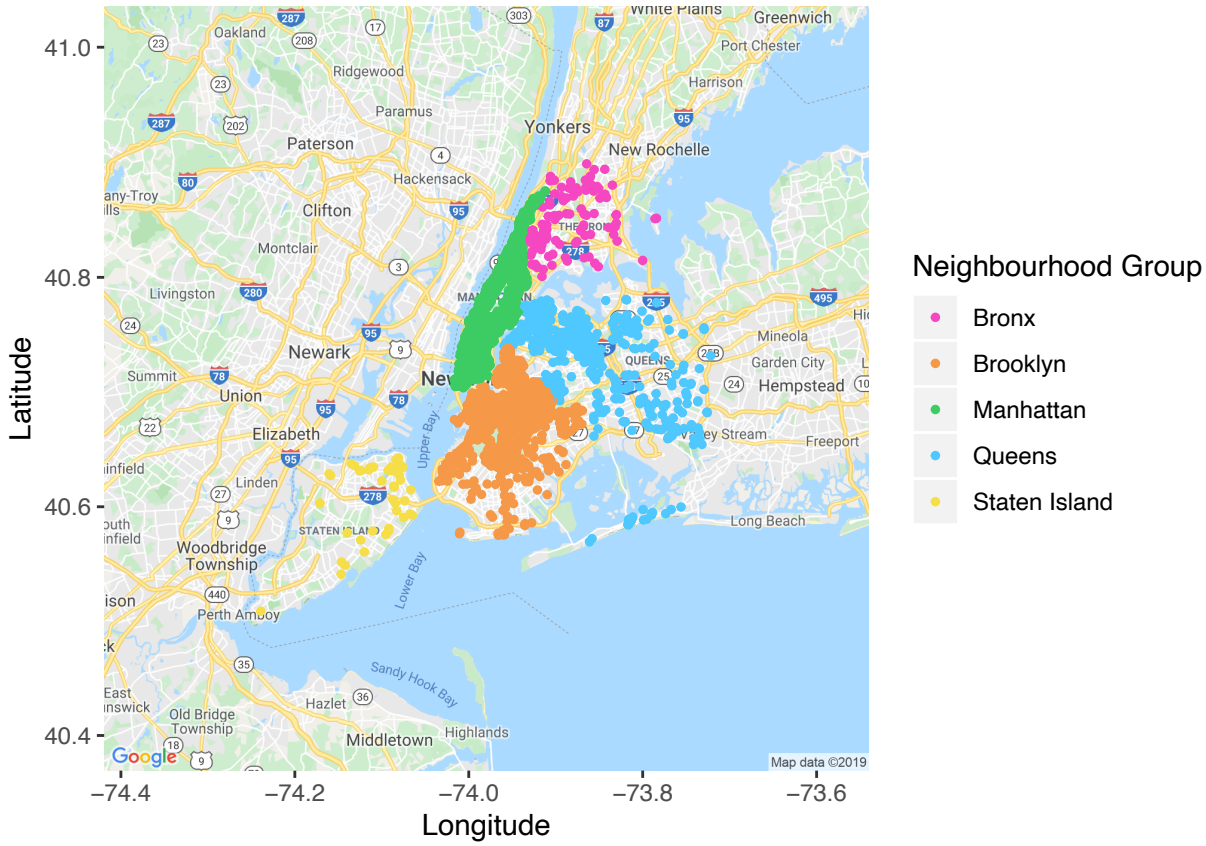
```
map = get_map(location = c(ALL_centerlong, ALL_centerlat),
              source = "google",
              zoom = 10,
              maptype = "roadmap",
              size = c(640, 640),
              scale = 2)

print(ggmap(map)
      + geom_point(data = airbnb,
                   aes(x = airbnb$longitude,
                       y = airbnb$latitude,
                       colour = factor(airbnb$neighbourhood_group)
                       ),
                   size = 1)
      + labs(x = "Longitude",
             y = "Latitude",
             colour="Neighbourhood Group")
      + scale_color_manual(values=customcolors)

)
```




```
#ggsave("map_of_neighbourhoods_FULLDATA.png", dpi=1000)
```

Map of Neibourhoods SAMPLE:

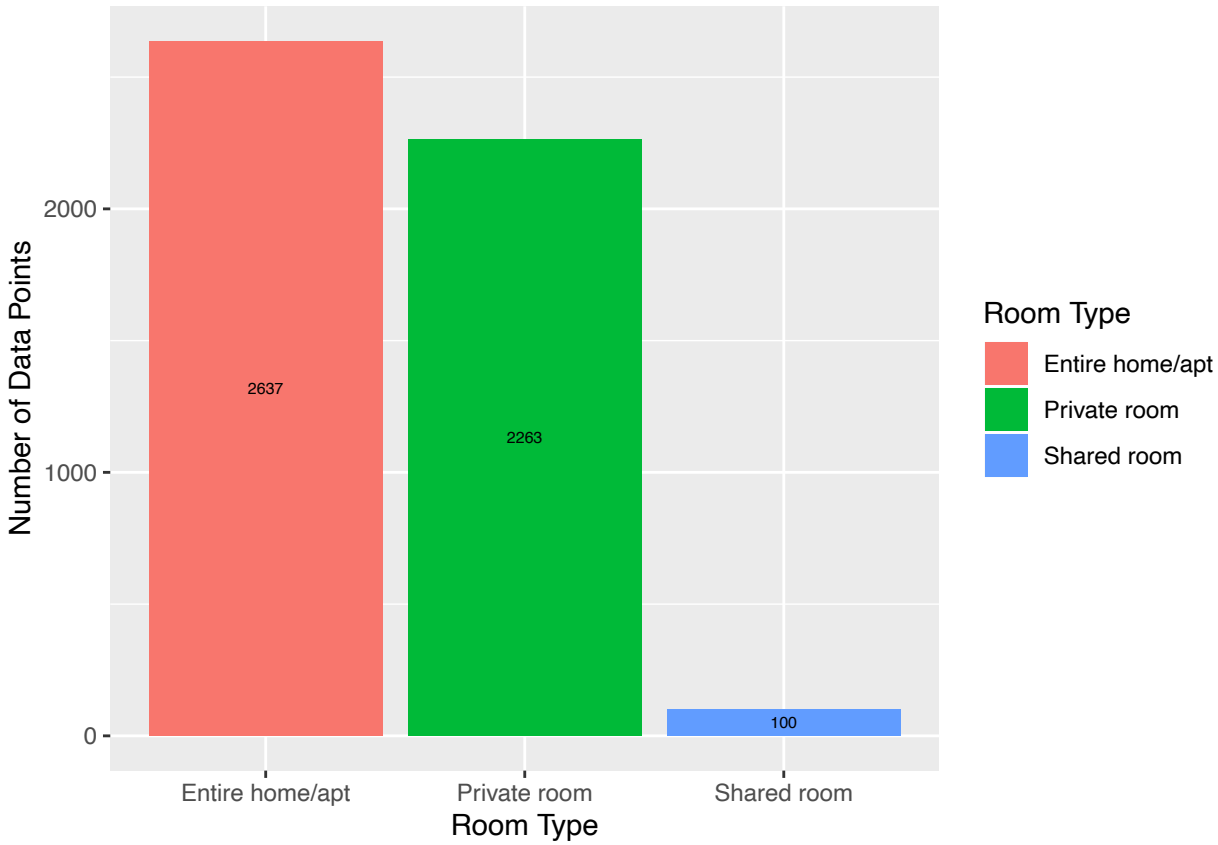
```
map = get_map(location = c(ALL_centerlong, ALL_centerlat),
              source = "google",
              zoom = 10,
              maptype = "roadmap",
              size = c(640, 640),
              scale = 2)

print(ggmap(map)
      + geom_point(data = data_sample_final,
                   aes(x = data_sample_final$longitude,
                       y = data_sample_final$latitude,
                       colour = factor(data_sample_final$neighbourhood_group)
                       ),
                   size = 1)
      + labs(x = "Longitude",
             y = "Latitude",
             colour="Neighbourhood Group")
      + scale_color_manual(values=customcolors)

)
```




```
#ggsave("map_of_neighbourhoods_SAMPLE.png", dpi=1000)
```

Number of Room types:

```
counts = count(data_sample_final, room_type)

ggplot(counts, aes(x = counts$room_type, y = counts$n, fill = counts$room_type, label = counts$n)) +
  geom_bar(stat = "identity") +
  geom_text(size = 2, position = position_stack(vjust = 0.5)) +
  labs(x = "Room Type", y = "Number of Data Points", fill="Room Type")
```




```
#ggsave("num_of_Room_type.png", dpi=1000)
```

Getting Top 10 neighbourhoods:

```
counts = count(data_sample_final, neighbourhood_group, neighbourhood)
counts[order(counts$neighbourhood_group, counts$neighbourhood, -counts$n),]
```

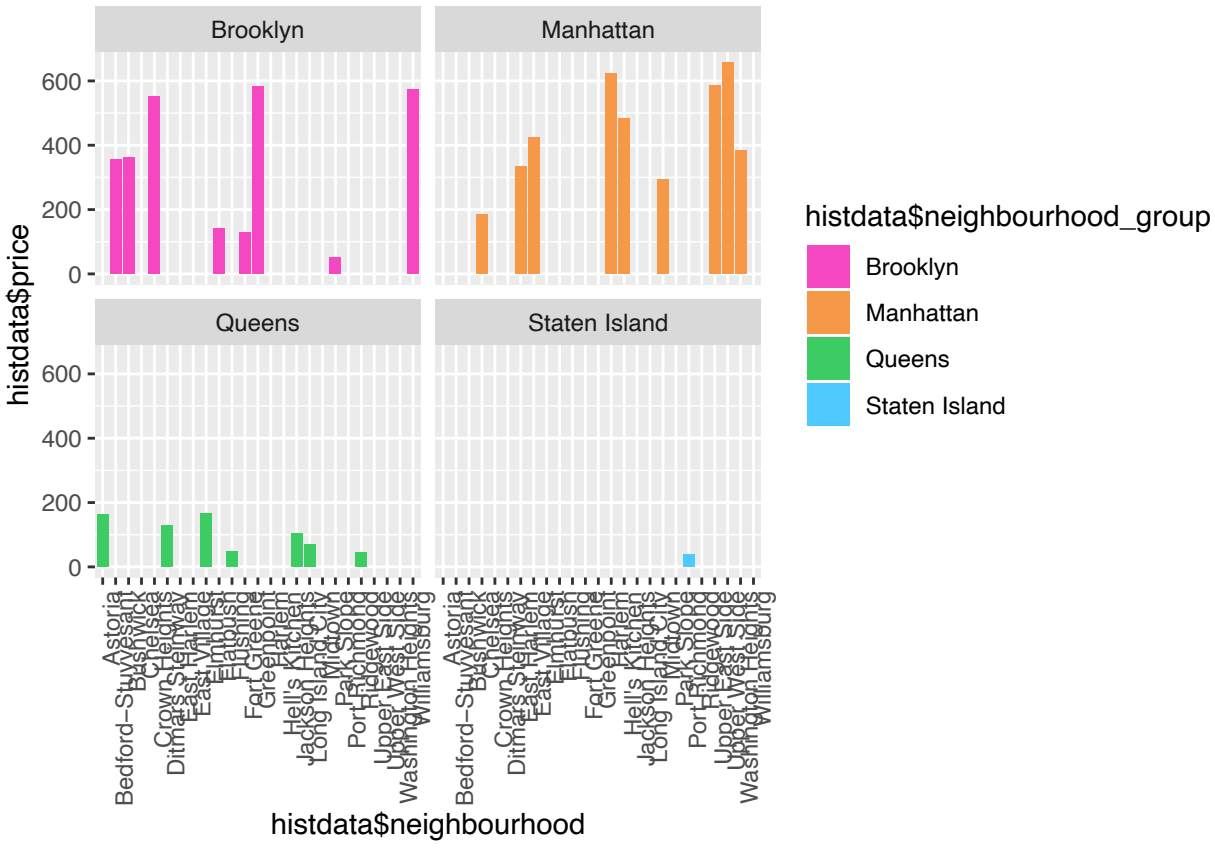
```
## # A tibble: 178 x 3
##    neighbourhood_group neighbourhood         n
##    <fct>               <fct>             <int>
##  1 Bronx               Allerton              3
##  2 Bronx               Baychester            2
##  3 Bronx               Belmont               2
##  4 Bronx               Bronxdale             2
##  5 Bronx               City Island           2
##  6 Bronx               Claremont Village     5
##  7 Bronx               Clason Point          4
##  8 Bronx               Concourse             6
##  9 Bronx               Concourse Village     4
## 10 Bronx               East Morrisania       1
## # ... with 168 more rows
```

```
brooklyn = counts[counts$neighbourhood_group == 'Brooklyn',]
manhattan = counts[counts$neighbourhood_group == 'Manhattan',]
queens = counts[counts$neighbourhood_group == 'Queens',]
statenIsland = counts[counts$neighbourhood_group == 'Staten Island',]
bronx = counts[counts$neighbourhood_group == 'Bronx',]
```

```
nsi = statenIsland[order(statenIsland$neighbourhood_group, -statenIsland$n),][1:10,]
nq = queens[order(queens$neighbourhood_group, -queens$n),][1:10,]
nm = manhattan[order(manhattan$neighbourhood_group, -manhattan$n),][1:10,]
nbn = brooklyn[order(brooklyn$neighbourhood_group, -brooklyn$n),][1:10,]
nbx = bronx[order(bronx$neighbourhood_group, -bronx$n),][1:10,]

top10 = rbind(nsi,nq,nm,nbn,nbx)
```

Price distribution for top 10 neighbourhoods:

```
histdata = data_sample_final[data_sample_final$neighbourhood == top10$neighbourhood,]
histdata = histdata[histdata$price <= 1000,]

ggplot(histdata, aes(x=histdata$neighbourhood, y=histdata$price, fill = histdata$neighbourhood_group)) +
  geom_bar(stat = "identity") +
  facet_wrap(~histdata$neighbourhood_group) +
  scale_fill_manual(values=customcolors) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```



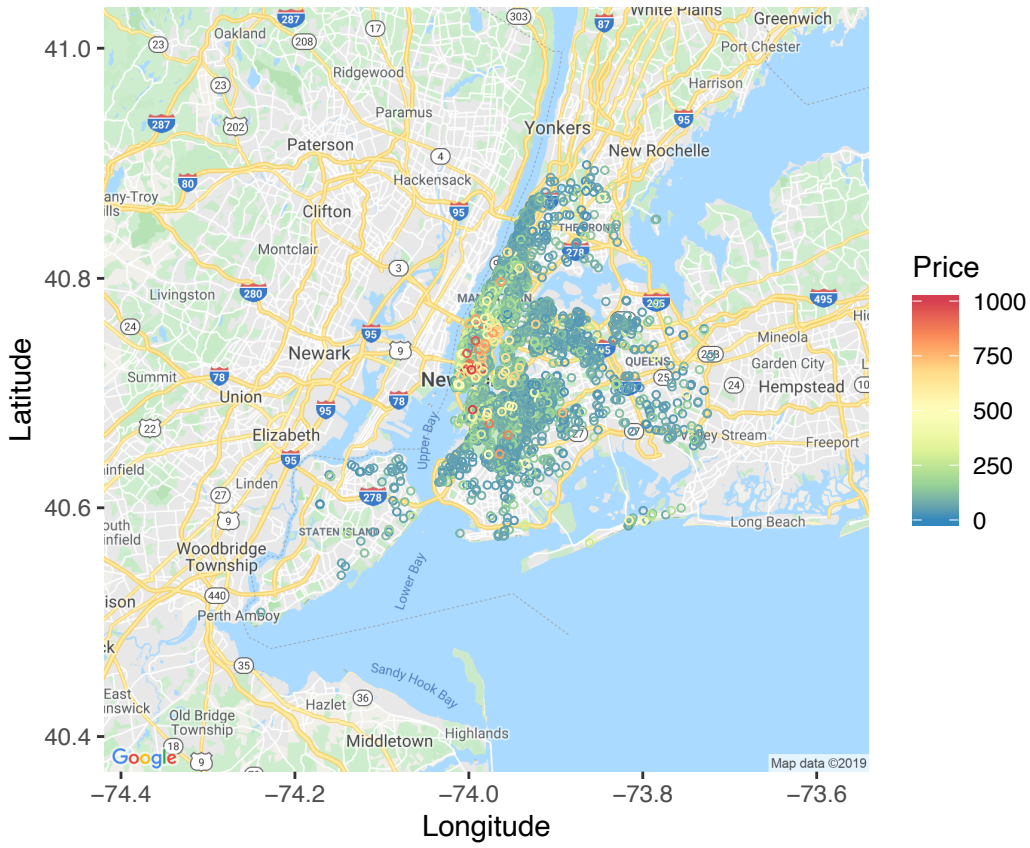
Prices on map:

```
data = data_sample_final[data_sample_final$price<=1000,]

map = get_map(location = c(ALL_centerlong, ALL_centerlat),
              source = "google",
```

```
              zoom = 10,
              maptype = "roadmap",
              size = c(640, 640),
              scale = 2)
```

```
## Source : https://maps.googleapis.com/maps/api/staticmap?center=40.70373,-73.980465&zoom=10&size=640x
```

```
print(ggmap(map)
      + geom_point(data = data[data$price<=500,],
                   aes(x = data$longitude[data$price<=500],
                       y = data$latitude[data$price<=500],
                       colour = data$price[data$price<=500]#,
                       #size = data_sample_final$price
                       ),
                   shape = 1, size = 1)
      + geom_point(data = data[data$price>500,],
                   aes(x = data$longitude[data$price>500],
                       y = data$latitude[data$price>500],
                       colour = data$price[data$price>500]#,
                       #size = data_sample_final$price
                       ),
                   shape = 1, size = 1)
      + scale_colour_distiller(palette = "Spectral")
      + labs(x = "Longitude",
             y = "Latitude",
             colour="Price")
)
```



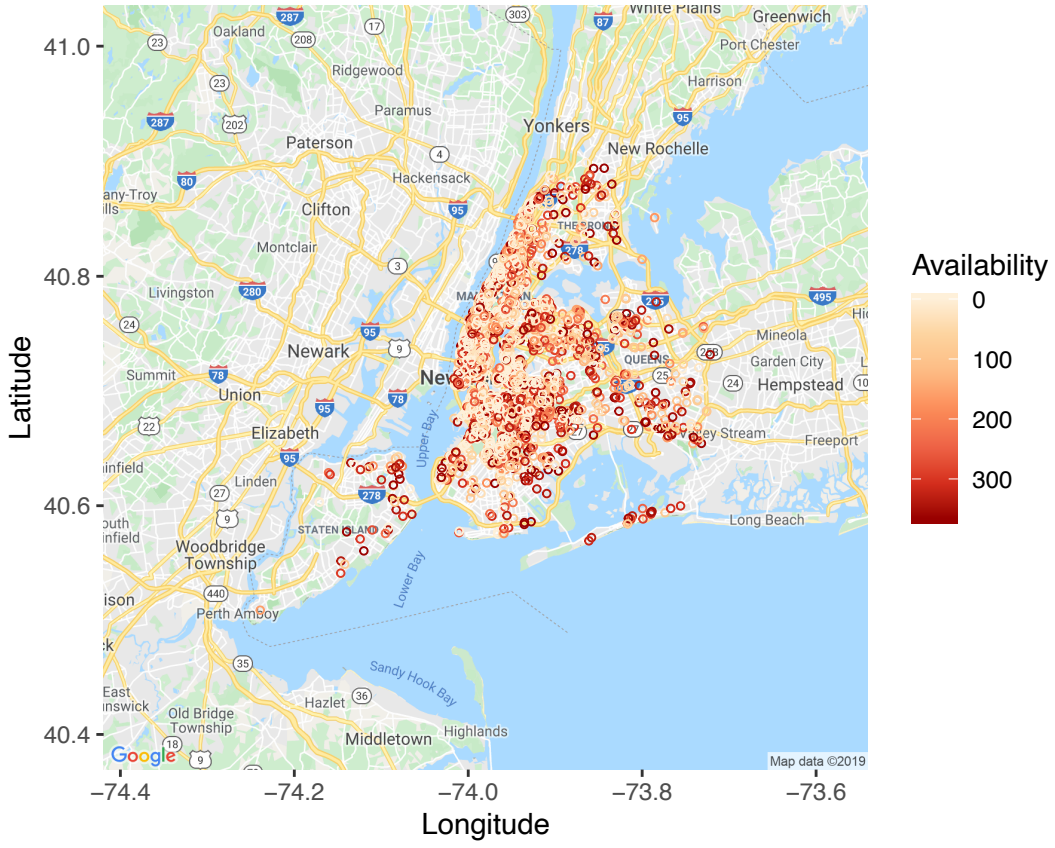
```
#ggsave("map_of_prices.png", dpi=1000)
```

Availability on map:

```
data = data_sample_final
map = get_map(location = c(ALL_centerlong, ALL_centerlat),
              source = "google",
              zoom = 10,
              maptype = "roadmap",
              size = c(640, 640),
              scale = 2)
```

```
## Source : https://maps.googleapis.com/maps/api/staticmap?center=40.70373,-73.980465&zoom=10&size=640x
```

```
print(ggmap(map)
      + geom_point(data = data,
                   aes(x = data$longitude,
                       y = data$latitude,
                       colour = data$availability_365
                       ),
                   shape = 1, size = 1)
      + scale_colour_distiller(palette = "OrRd", trans = 'reverse')
      + labs(x = "Longitude",
             y = "Latitude",
             colour="Availability"
             )
)
```



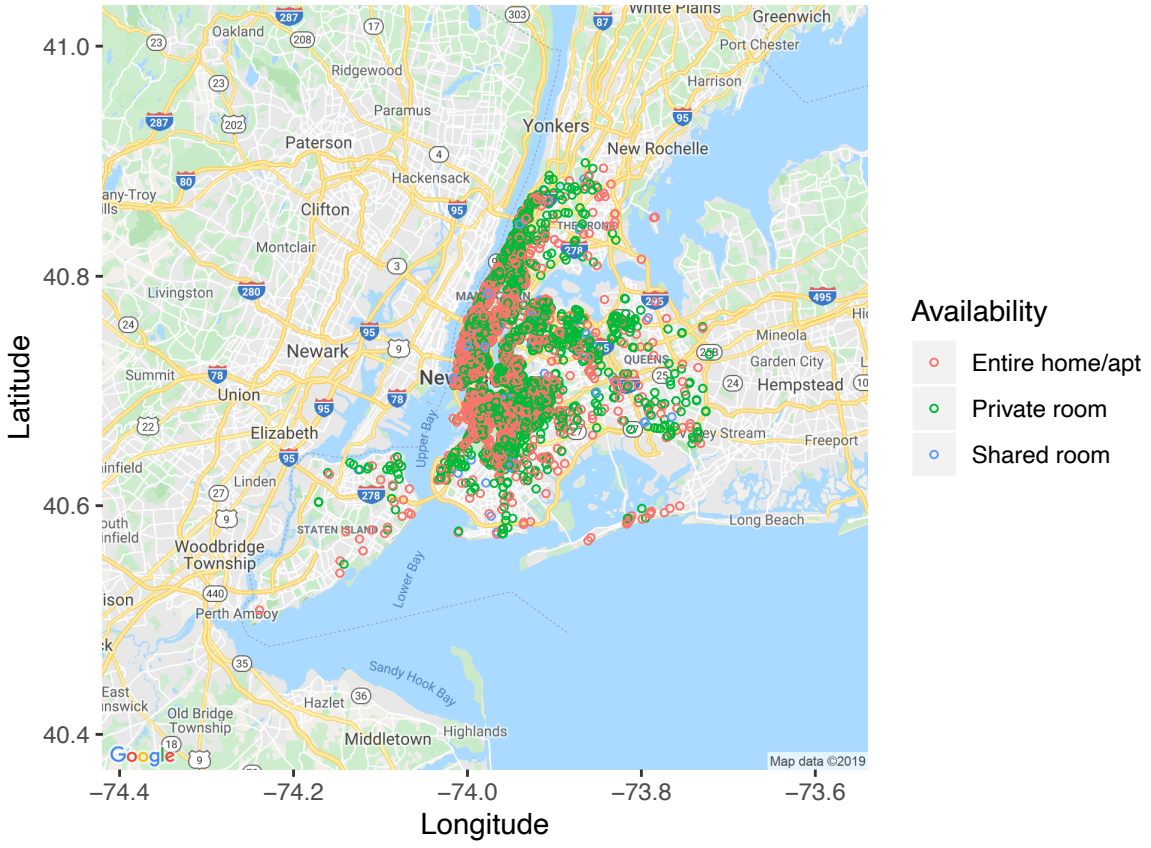
```
#ggsave("map_of_availability.png", dpi=1000)
```

Room Type on Map:

```
data = data_sample_final
map = get_map(location = c(ALL_centerlong, ALL_centerlat),
              source = "google",
              zoom = 10,
              maptype = "roadmap",
              size = c(640, 640),
              scale = 2)
```

```
## Source : https://maps.googleapis.com/maps/api/staticmap?center=40.70373,-73.980465&zoom=10&size=640x
```

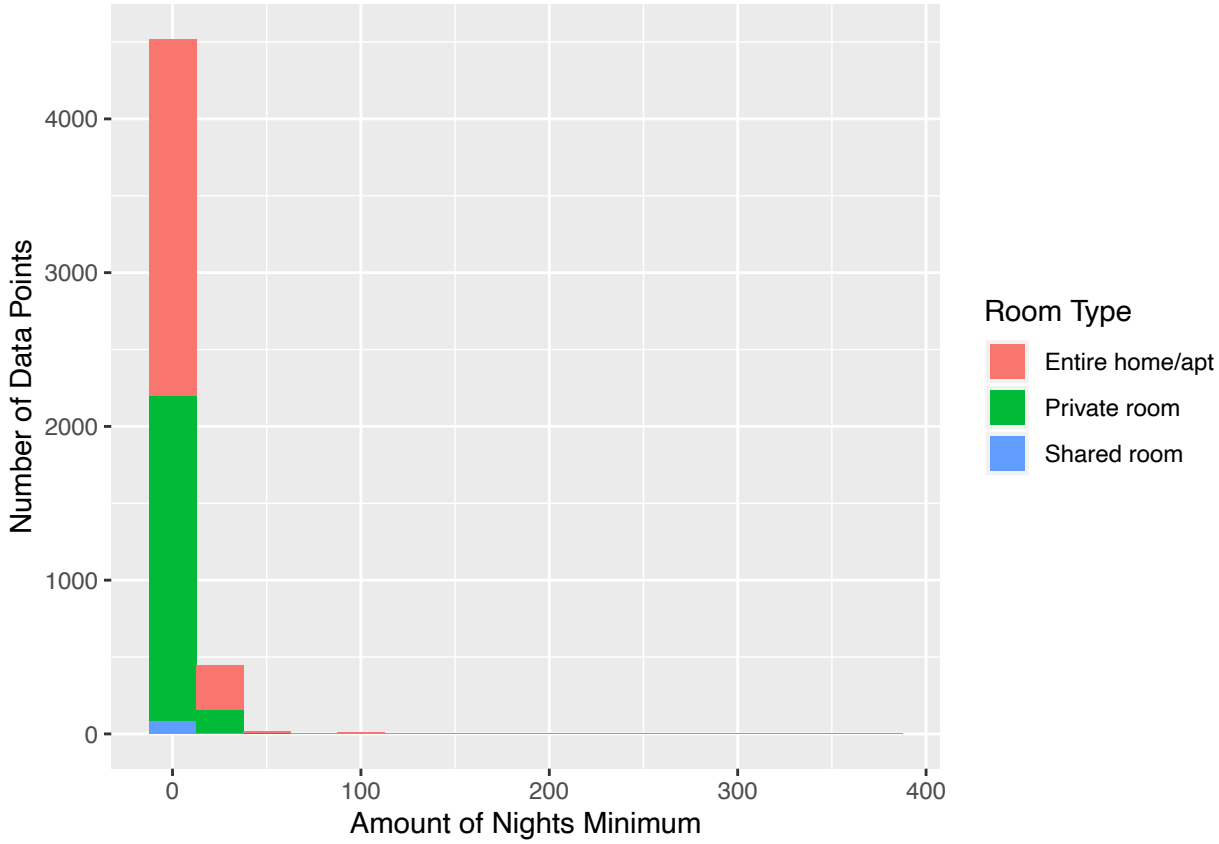
```
print(ggmap(map)
      + geom_point(data = data,
                   aes(x = data$longitude,
                       y = data$latitude,
                       colour = data$room_type
                       ),
                   shape = 1, size = 1)
      #+ scale_colour_distiller(palette = "OrRd", trans = 'reverse')
      + labs(x = "Longitude",
             y = "Latitude",
             colour="Availability"
             )
)
```



```
#ggsave("map_of_roomtype.png", dpi=1000)
```

Histogram of Minimum nights:

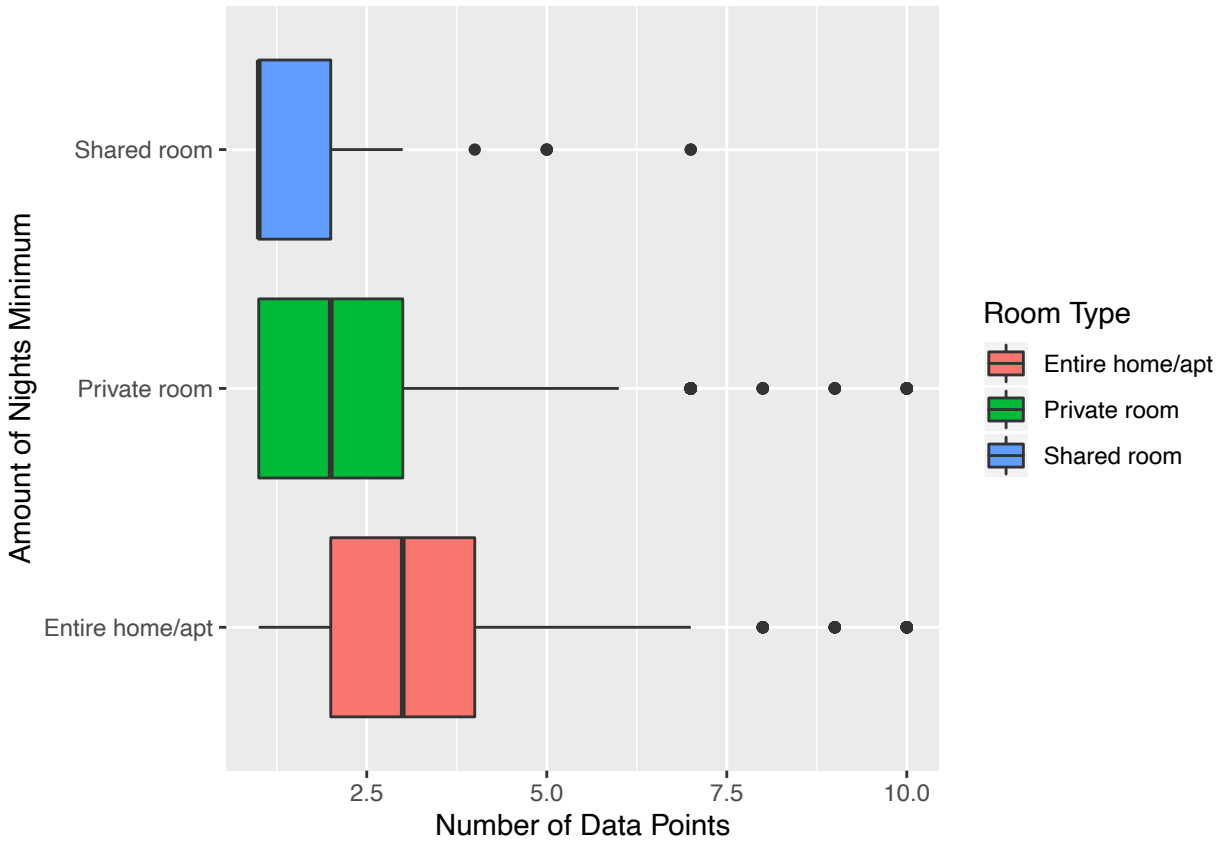
```
histdata = data_sample_final
ggplot(histdata, aes(histdata$minimum_nights, fill = histdata$room_type)) +
  geom_histogram(binwidth = 25, size = 2) +
  labs(x = "Amount of Nights Minimum", y = "Number of Data Points", fill="Room Type")
```




```
#ggsave("Hist_MinNights_RoomType.png", dpi=1000)
```

Box Plot of Minimum Nights:

```
data = data_sample_final[data_sample_final$minimum_nights <= 10,]
ggplot(data, aes(x=data$room_type, y=data$minimum_nights, fill=data$room_type)) +
  geom_boxplot() +
  coord_flip() +
  labs(x = "Amount of Nights Minimum", y = "Number of Data Points", fill="Room Type")
```

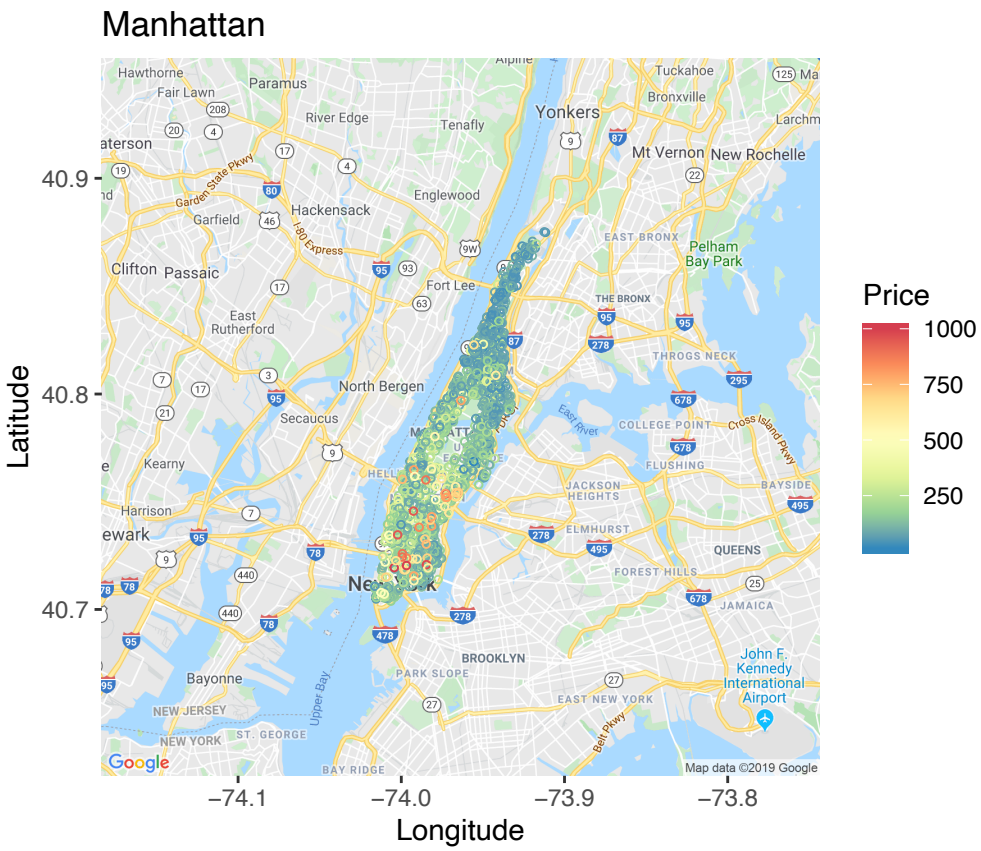



```
#ggsave("Box_MinNights_RoomType.png", dpi=1000)
```

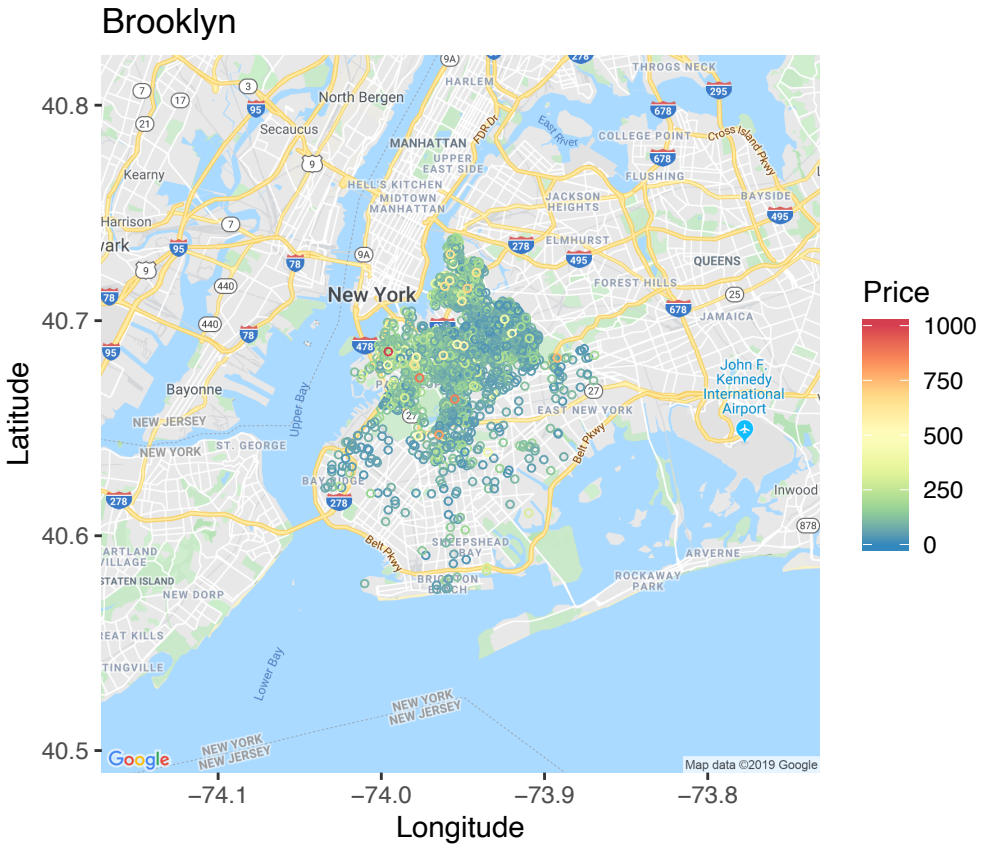
Price by location broken out by neighbourhood_group:

```
data_cut = data_sample_final[data_sample_final$price<=1000,]

for (i in 1:length(neighbourhood_groups)) {
  NG = as.character(NG_centers[i,1])
  data = data_cut[data_cut$neighbourhood_group == NG,]
  centerlong = (min(data$longitude) + max(data$longitude))/2
  centerlat = (min(data$latitude) + max(data$latitude))/2

  map = get_map(location = c(centerlong, centerlat),
                source = "google",
                zoom = 11,
                maptype = "roadmap",
                size = c(640, 640),
                scale = 2)

  print(ggmap(map)
        + geom_point(data = data[data$price<=500,],
                     aes(x = data$longitude[data$price<=500],
                         y = data$latitude[data$price<=500],
                         colour = data$price[data$price<=500]
                         ),
                     shape = 1, size = 1)
```

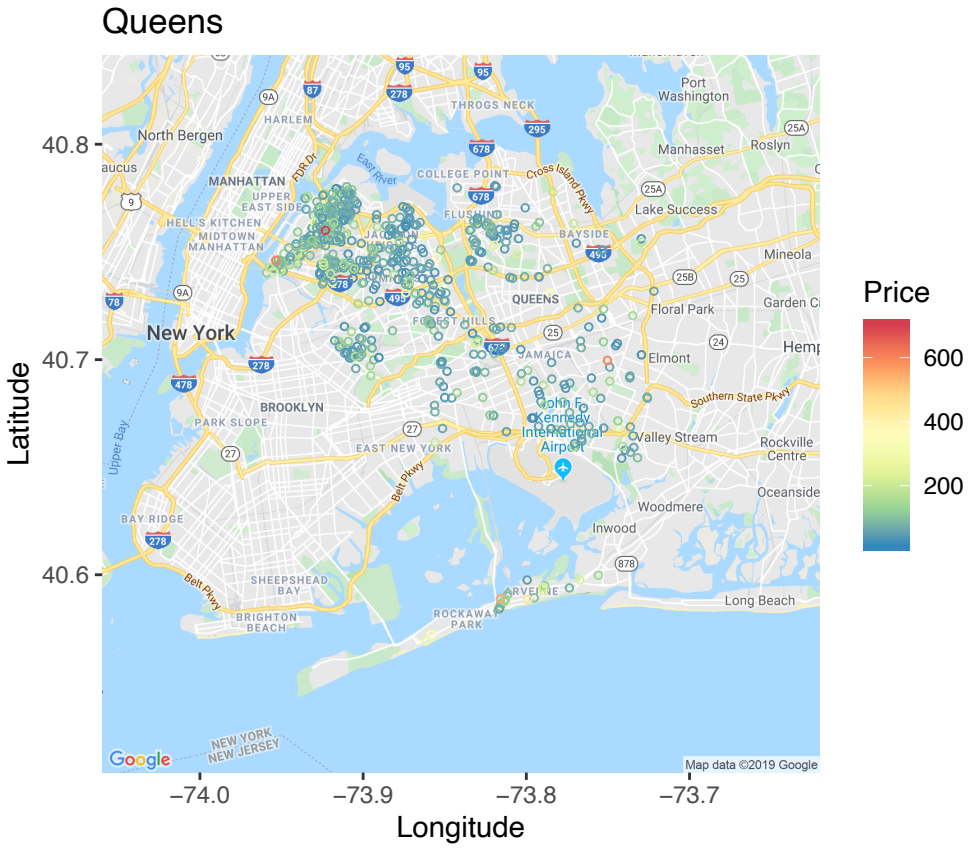
```
        + geom_point(data = data[data$price>500,],
                     aes(x = data$longitude[data$price>500],
                         y = data$latitude[data$price>500],
                         colour = data$price[data$price>500]
                         ),
                     shape = 1, size = 1)
       + scale_colour_distiller(palette = "Spectral")
        + labs(x = "Longitude",
               y = "Latitude",
               colour="Price",
               title = NG)
  )

  print(cat('\n'))
}
```



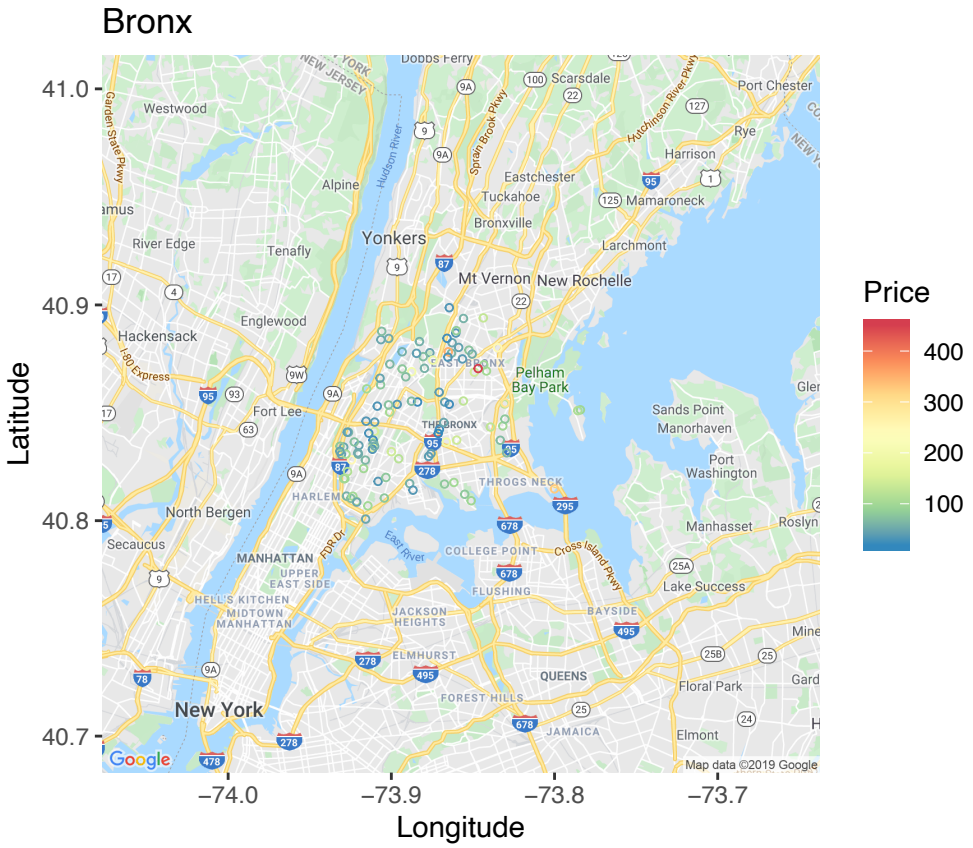

```
##
## NULL
```


Brooklyn
Latitude
40.8
40.7
40.6
40.5
−74.1
−74.0
−73.9
−73.8
Longitude
Price
1000
750
500
250
0
New York
North Bergen
Secaucus
Kearny
Harrison
Bayonne
MANHATTAN
HARLEM
UPPER EAST SIDE
HELL'S KITCHEN
MIDTOWN MANHATTAN
JACKSON HEIGHTS
ELMHURST
QUEENS
FOREST HILLS
JAMAICA
COLLEGE POINT
FLUSHING
BAYSIDE
THROGS NECK
EAST NEW YORK
John F. Kennedy International Airport
Inwood
ROCKAWAY PARK
ARVERNE
SHEEPSHEAD BAY
BRIGHTON BEACH
NEW DORP
STATEN ISLAND
NEW JERSEY
NEW YORK
ST. GEORGE
Upper Bay
Lower Bay
East River
FDR Dr
Cross Island Pkwy
Belt Pkwy
Google
Map data ©2019 Google

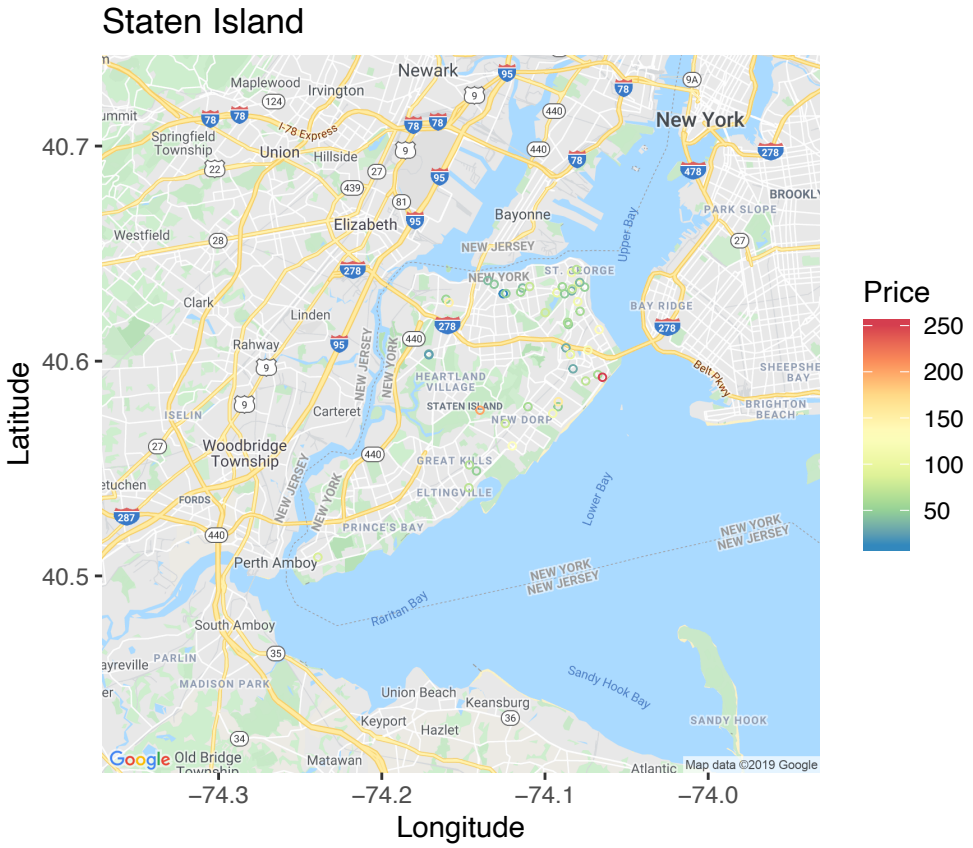
```
##
## NULL
```


Queens
Latitude
40.8
40.7
40.6
Longitude
−74.0
−73.9
−73.8
−73.7
Price
600
400
200
New York
North Bergen
MANHATTAN
BROOKLYN
QUEENS
Port Washington
Manhasset
Roslyn
Lake Success
Mineola
Floral Park
Elmont
Valley Stream
Rockville Centre
Oceanside
Woodmere
Inwood
Long Beach
Southern State Pkwy
Belt Pkwy
Upper Bay
East River
Cross Island Pkwy
Google
Map data ©2019 Google

```
##
## NULL
```


Bronx
Latitude
41.0
40.9
40.8
40.7
−74.0
−73.9
−73.8
−73.7
Longitude
Price
400
300
200
100
Map data ©2019 Google
Google
Yonkers
Mt Vernon
New Rochelle
Scarsdale
Port Chester
Rye
Harrison
Eastchester
Tuckahoe
Mamaroneck
Bronxville
Larchmont
Westwood
Alpine
River Edge
Tenafly
Englewood
Hackensack
Fort Lee
North Bergen
Secaucus
Pelham Bay Park
Sands Point
Manorhaven
Port Washington
Manhasset
Roslyn
Lake Success
MANHATTAN
UPPER EAST SIDE
HELL'S KITCHEN
MIDTOWN MANHATTAN
HARLEM
THROGS NECK
COLLEGE POINT
FLUSHING
JACKSON HEIGHTS
BAYSIDE
ELMHURST
QUEENS
FOREST HILLS
JAMAICA
Floral Park
Elmont
New York
East River
FDR Dr
Cross Island Pkwy
Hudson River
Garden State Pkwy
Sprain Brook Pkwy
Hutchinson River Pkwy
I-80 Express

```
##
## NULL
```


Staten Island
Latitude
40.7
40.6
40.5
−74.3
−74.2
−74.1
−74.0
Longitude
Price
250
200
150
100
50
Newark
New York
Maplewood
Irvington
Springfield Township
Union
Hillside
Elizabeth
Bayonne
Westfield
Clark
Linden
Rahway
Carteret
Woodbridge Township
Perth Amboy
South Amboy
Union Beach
Keansburg
Keyport
Hazlet
Matawan
Old Bridge
Atlantic
Upper Bay
Lower Bay
Raritan Bay
Sandy Hook Bay
NEW JERSEY
NEW YORK
ST. GEORGE
BAY RIDGE
PARK SLOPE
BROOKLYN
HEARTLAND VILLAGE
STATEN ISLAND
NEW DORP
GREAT KILLS
ELTINGVILLE
PRINCE'S BAY
ISELIN
FORDS
PARLIN
MADISON PARK
SANDY HOOK
BRIGHTON BEACH
SHEEPSHEAD BAY
Belt Pkwy
I-78 Express
Google
Map data ©2019 Google

```
##
## NULL
```

ISYE 4031 Regression/Forecasting

Regression Analysis on New York City Airbnb Open Data

Milandi Bezuidenhout, Erica Cho, Savannah Chunn
Ethan Kreager, Karen Loscocco, Samantha White

December 4, 2019

Contents

1 Executive Summary

In this paper, we examine a dataset related to Airbnb rental properties in New York City and perform regression analysis to determine the best predictors of price. Regression is a powerful approach used in a wide variety of applications for predictive analysis in both industry and academia. After exploring multiple regression models using R, we have come to the conclusion that ___ are the best predictors of price. Below, we include our data exploration, mathematical regression models, and implementations in R, as well as our solutions and comments on the applications of our findings.

2 Introduction

Since its inception in 2008, Airbnb has become one of the world's largest marketplaces to connect people who want to rent out their homes with travelers. It began as a small operation in downtown San Francisco, but quickly grew into the multinational corporation that it is today. Airbnb is very unique because the corporation itself does not actually own any of the properties that it rents out. Instead they are owned and maintained by common people, who make money by renting out their space to temporary tenants. The price of one night's rent at an Airbnb property can vary wildly based on factors such as location, reviews, and amenities. Our project attempts to determine which factors have the most impact on the final listed price.

3 Problem Description

Our analysis proposes to determine which variables have the most effect on the observed differences in price. We tested various multiple linear regression models with price as the dependent variable in order to find the model which contains the most statistically significant predictor variables. We also made observations on the data itself and included visuals to give a deeper understanding of the data. We also identified outliers and included potential justifications for why these outliers could exist.

4 Data Exploration

4.1 Data Description

The dataset includes 48,895 listings for rental properties in New York City from the year 2019. There are 16 columns that are a mix of categorical and numerical values, each of which has an impact of some degree on the price to rent the property. The following is a breakdown of the columns and their respective meanings:

Column	Meaning	Datatype
id	listing ID	int
name	name of the listing	str
host_id	host ID	int
host_name	name of the host	str
neighbourhood_group	location	str
neighbourhood	area	str
latitude	latitude coordinates	float
longitude	longitude coordinates	float
room_type	listing space type	str
price	price in dollars	int
minimum_nights	amount of nights minimum	int
number_of_reviews	number of reviews	int
last_review	latest review	date
reviews_per_month	number of reviews per month	float
calculated_host_listings_count	amount of listing per host	int
availability_365	number of days when listing is available	int

After initial inspection of the dataset, we immediately noticed there were missing values. We edited the data to remove all rows with null values. We also decided to cut down our data to be more aligned with the scope of this project. We randomly selected a subset of 5000 data points in order to ensure the distribution of datapoints and prices were roughly the same for each location.

A distribution of price by neighbourhood before and after we cut down the data can be seen in figures (4.1) and (4.2) below. A display of the datapoints from each neighbourhood group for before and after sampling is also shown in figures (4.3) and (4.4). From this analysis, we can assume that the random sampling preserved the integrity of the data.

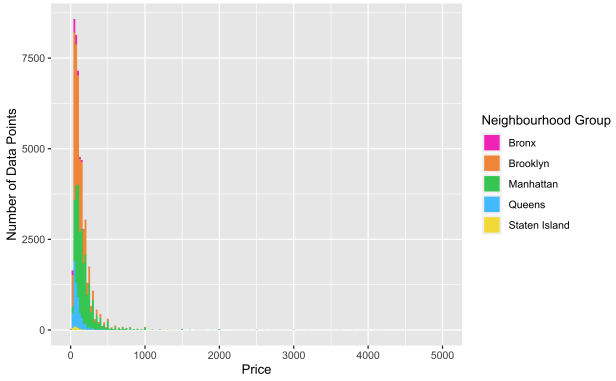


Figure 4.1: Before Random Sampling

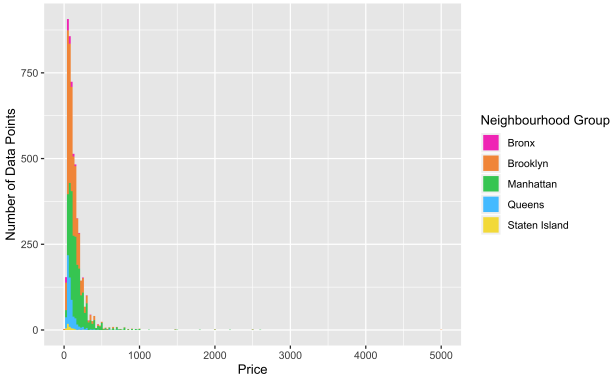


Figure 4.2: After Random Sampling

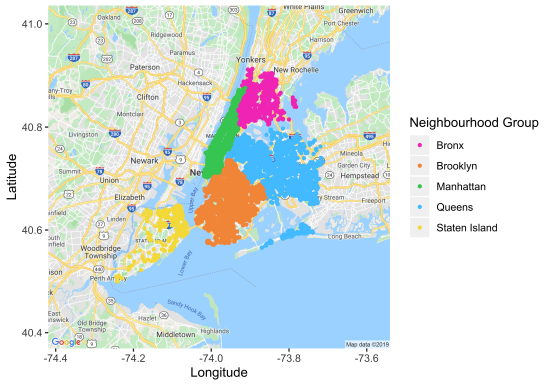


Figure 4.3: Before Random Sampling

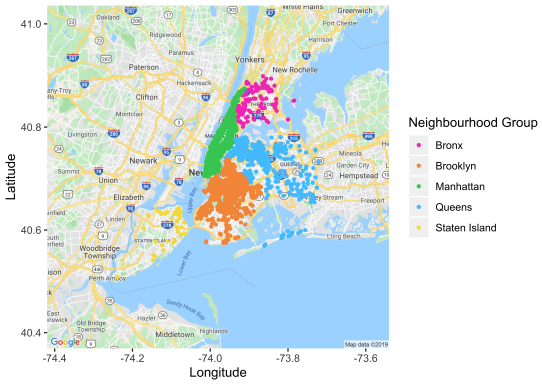


Figure 4.4: After Random Sampling

To ensure readability of the visuals in the rest of the paper, we exclude the few points with prices greater than $1,000. However, the regression analysis does include these points. A closer look at the price distribution can be found in figure (4.5) below:

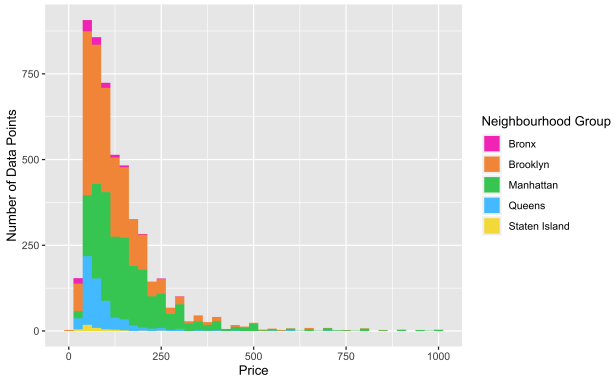


Figure 4.5: Histogram of Prices - Closer Look

The numerical-valued attributes can be directly represented by variables, but we needed to map each of the categorical values to dummy variables. These include neighborhood_group, neighborhood, and room_type. We dropped the id, name, host_id, host_name, and last_review columns because they have no categorical or numerical meaning for our analysis. We also cut out the latitude and longitude variables because location is already represented by the dummy variables.

4.2 Variables

Now that we have a reduced dataset, we would like to check for any potential multicollinearity among our independent variables. Multicollinearity is when one independent variable can predict another with a fair degree of accuracy. Strong interactions between variables can be an indicator of any potential multicollinearity. Multicollinearity can be measured in a multitude of ways, one

being correlation coefficients.

Below, in figure (4.6), the correlation matrix for all numerical variables is shown:

Figure 4.6: Correlation Plot By Neighbourhood Group

The plot shows no coefficients larger than 0.5, which indicates that none of our independent variables are correlated. As a result, we proceed by keeping all variables for further analysis.

4.3 A Closer Look

Prices to stay at an Airbnb in New York can vary wildly by borough. In figure (4.7) below, a map of Airbnb prices by location can be found:

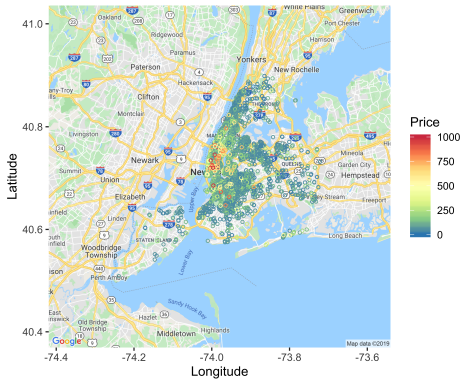


Figure 4.7: Prices By Location

As you can see, Manhattan is clearly the most expensive borough. Considering the density of theaters, restaurants, and other visitor attractions in Manhattan, it doesn't come as too much of a

shock that it leads the pack in terms of Airbnb price. In our appendix (8), we have a graph breaking out price to each of the five boroughs.

Similarly, we can look at New York in terms of availability. Below, figure (4.8) shows the frequency of available rental properties throughout the city.

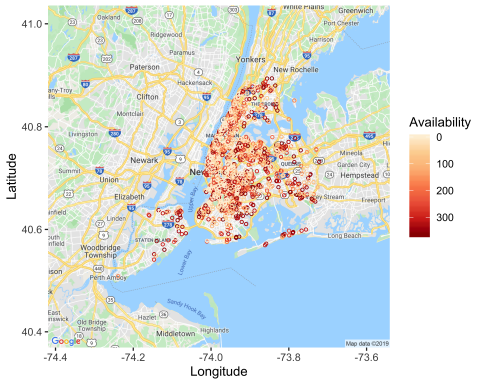


Figure 4.8: Availability By Location

The figure shows that Manhattan and Brooklyn are the most dense areas in terms of openings. These are the two most densely populated areas of the city, so it shouldn't come as a surprise that they lead the way in terms of Airbnb rental property openings.

Furthermore, we can break the city out by the type of rental openings. Specifically, we look at openings where the entire apartment/house can be rented, openings where a private room can be rented, and openings where a shared room can be rented. The figures below summarize our findings:

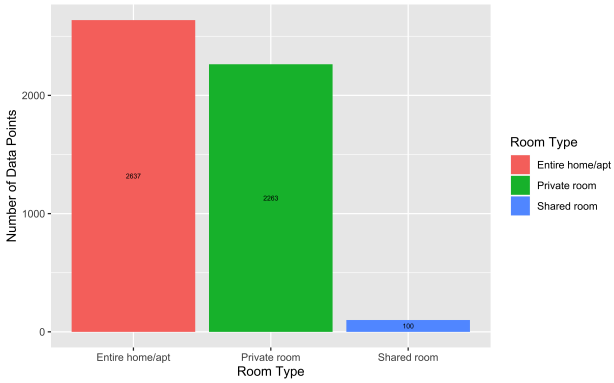


Figure 4.9: Counts of Room Types

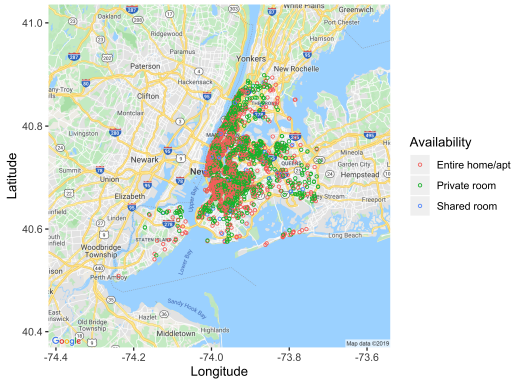


Figure 4.10: Map of Room Types

Very few property owners rent out a shared room, which is likely due to the fact that most people would prefer to have their own space when possible. Manhattan has a higher concentration of entire properties available for rent, which would make sense when considering the high cost of a very small space in the city. There simply isn't room for someone to live in their home and also rent out space to a guest.

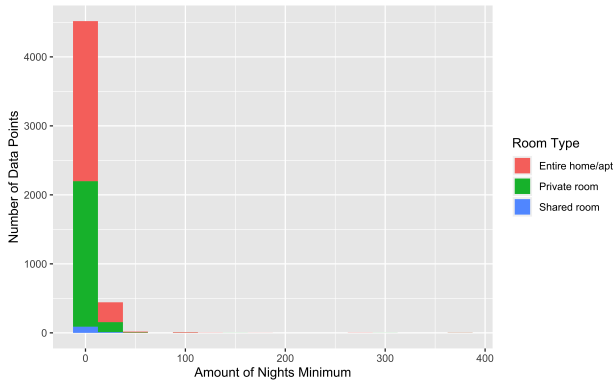


Figure 4.11: Histogram of Minimum Nights By Room Type

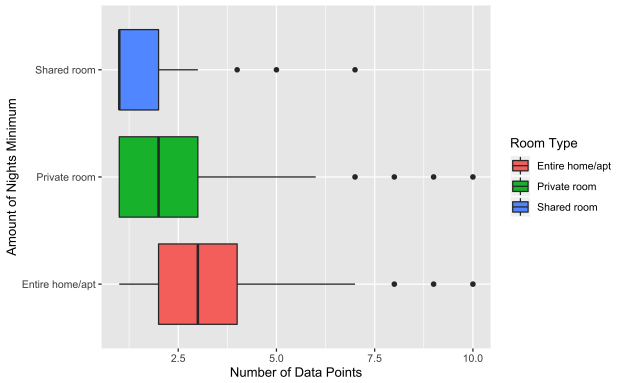


Figure 4.12: Box Plot of Minimum Nights By Room Type

5 Regression Analysis

We break up our analysis into two sections. The first is the creation of a base model that includes all variables, and the second is the determination of a best model through regression analysis. The R implementations and outputs of the models from both of these parts can be referenced in the appendix (8).

5.1 Part 1 Analysis: Base Model

We began our analysis with a model containing all of our variables. We will refer to this model as our base model and use it as a benchmark for comparison to other models tested.

Independent tests were run on this model to identify relationships between all independent variables. We define the set of all independent variables as V where $V = \{$ number_of_reviews, minimum_nights, reviews_per_month, calculated_host_listings_count, availability_365, shared_room_dummy, staten_dummy, brooklyn_dummy, queens_dummy, bronx_dummy, private_room_dummy $\}$. Our base model is the following:

$$\text{Base Model: } price = \beta_0 + \beta_i X_i \;\; \forall i \in V \tag{5.1}$$

The summary of this base model in figure (5.1) reveals that all variables tested are significant except for reviews_per_month and calculated_host_listings_count. All other variables have p-values significantly less than 0.05. The analysis can also be found on page 14 of the appendix (8).

```
lm(formula = price ~ number_of_reviews + minimum_nights + reviews_per_month +
    calculated_host_listings_count + availability_365 + shared_room_dummy +
    staten_dummy + brooklyn_dummy + queens_dummy + bronx_dummy +
    private_room_dummy, data = project_data_sample)

Residuals:
   Min     1Q Median     3Q    Max
-191.7  -53.5  -15.1   19.1 4876.5

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                    213.86270    4.22492  50.619  < 2e-16 ***
number_of_reviews               -0.20184    0.04956  -4.072 4.73e-05 ***
minimum_nights                  -0.64761    0.13913  -4.655 3.33e-06 ***
reviews_per_month               -1.40665    1.41241  -0.996    0.319
calculated_host_listings_count  -0.03833    0.08366  -0.458    0.647
availability_365                 0.19493    0.01632  11.946  < 2e-16 ***
shared_room_dummy             -135.87966   14.41519  -9.426  < 2e-16 ***
staten_dummy                  -107.97891   21.32911  -5.063 4.29e-07 ***
brooklyn_dummy                 -46.55858    4.36708 -10.661  < 2e-16 ***
queens_dummy                   -66.63348    6.77516  -9.835  < 2e-16 ***
bronx_dummy                    -84.93433   13.99659  -6.068 1.39e-09 ***
private_room_dummy            -108.38674    4.11035 -26.369  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 140.9 on 4988 degrees of freedom
Multiple R-squared:  0.1877, Adjusted R-squared:  0.1859
F-statistic: 104.8 on 11 and 4988 DF,  p-value: < 2.2e-16
```

Figure 5.1: Base Model Summary

We also ran a VIF test to look for any potential multicollinearity. All of the VIF factors hovered around 1, meaning that once again no significant multicollinearity was detected. This further indicates that the variables in our model are independent of one another. Additionally, we performed outlier tests including Cooks Distance measure (CooksD) and Studentized Deleted Residuals (SDR). These outlier results can be referenced in the appendix (8).

The normal probability plots of residuals can be seen in the figure below:

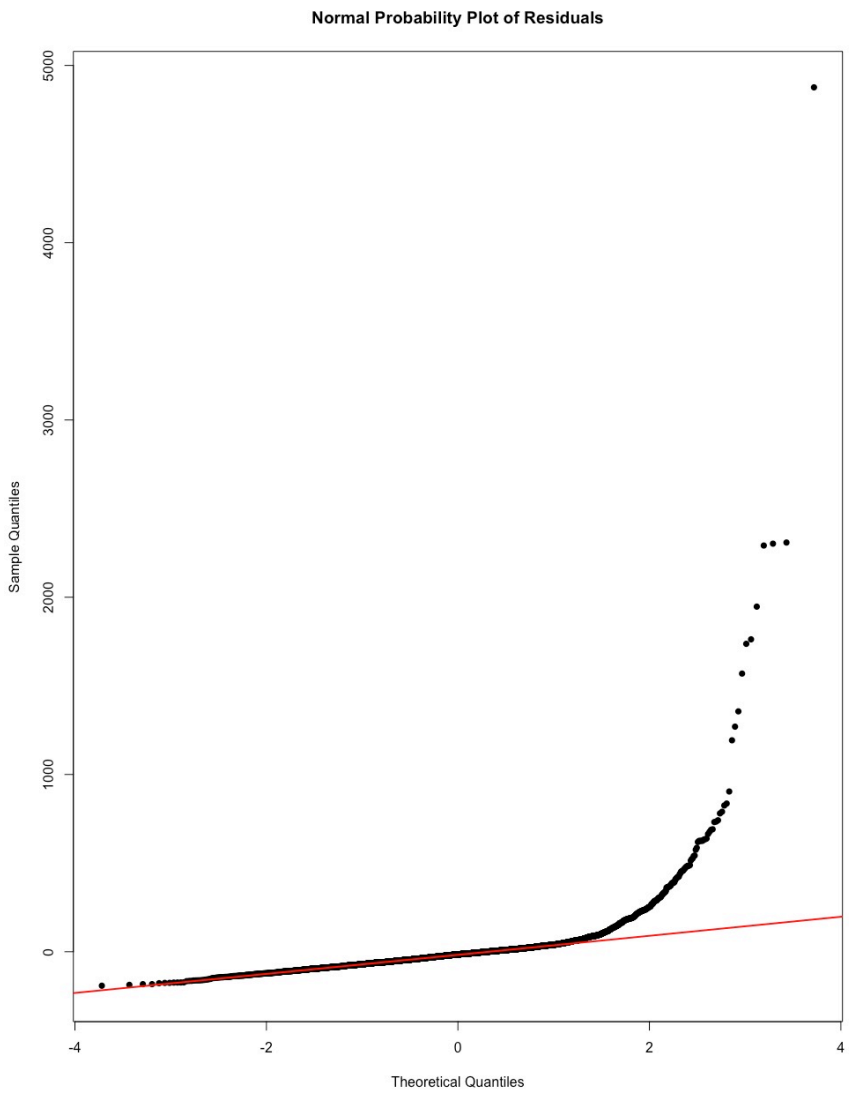
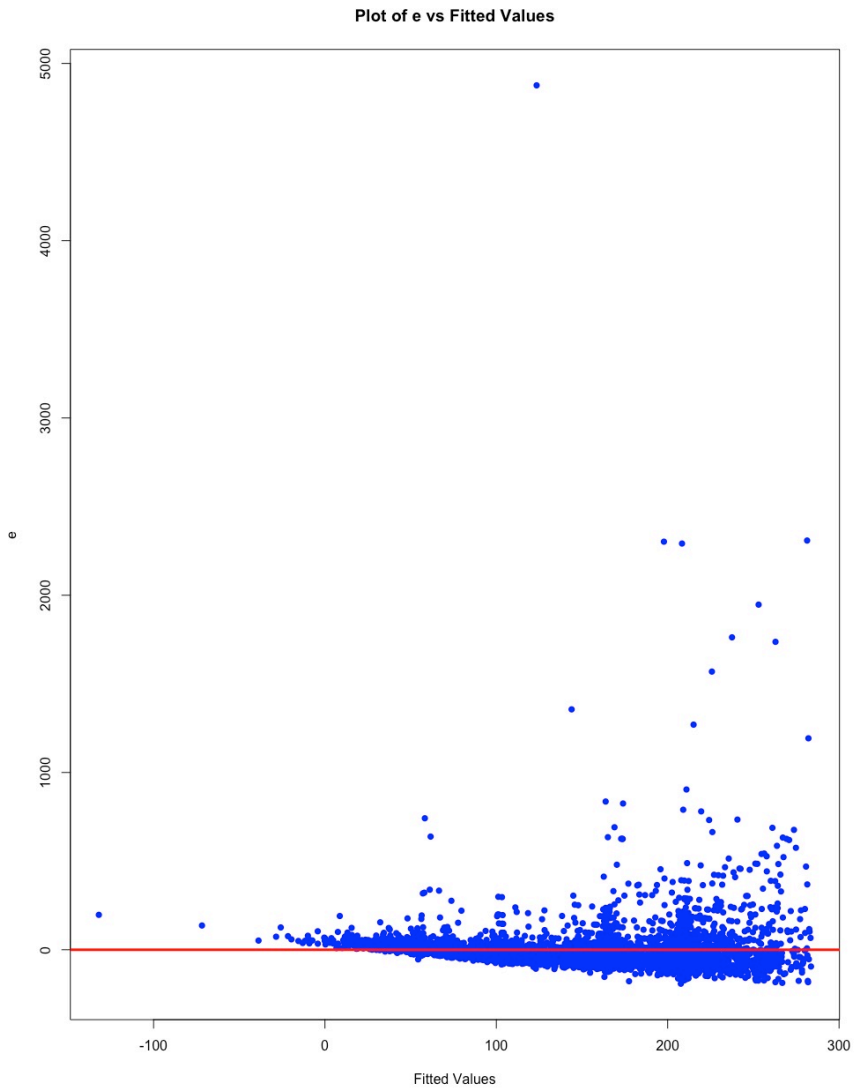


Figure 5.2: Normal Probability Plots of Residuals

The plot of residual error vs fitted values:



vs fitted $_BASE.jpeg$

Figure 5.3: Error vs. Fitted Values

5.2 Part 2 Analysis: Best Model

In order to determine the best model, we performed stepwise elimination in both directions. The lowest AIC corresponds to the best model. This resulted in the following best model:

We define the set variables for the best base model as V_{best} where $V_{\text{best}} = \{$ private_room_dummy, availability_365, shared_room_dummy, brooklyn_dummy, bronx_dummy, number_of_reviews, minimum_nights, queens_dummy, staten_dummy $\}$. Our best model is the following:

$$\text{Best Model: } price = \beta_0 + \beta_i X_i \;\; \forall i \in V_{\text{best}} \tag{5.2}$$

The summary of this base model in figure (5.4) reveals that all variables tested are significant. All variables have p-values significantly less than 0.05. The analysis can also be found on page 26 of the appendix (8).

```
lm(formula = price ~ private_room_dummy + availability_365 +
    shared_room_dummy + brooklyn_dummy + bronx_dummy + number_of_reviews +
    minimum_nights + queens_dummy + staten_dummy)

Residuals:
   Min     1Q Median     3Q    Max
-192.3  -53.6  -15.0   19.1 4878.4

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         212.55929    4.05706  52.392  < 2e-16 ***
private_room_dummy -108.39142    4.10207 -26.424  < 2e-16 ***
availability_365      0.19200    0.01592  12.061  < 2e-16 ***
shared_room_dummy  -135.72689   14.41210  -9.418  < 2e-16 ***
brooklyn_dummy      -46.21379    4.34315 -10.641  < 2e-16 ***
bronx_dummy         -85.16244   13.97069  -6.096 1.17e-09 ***
number_of_reviews    -0.22470    0.04266  -5.267 1.44e-07 ***
minimum_nights       -0.63347    0.13795  -4.592 4.50e-06 ***
queens_dummy        -67.19520    6.71403 -10.008  < 2e-16 ***
staten_dummy       -107.82482   21.31308  -5.059 4.36e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 140.9 on 4990 degrees of freedom
Multiple R-squared:  0.1875,    Adjusted R-squared:  0.186
F-statistic: 127.9 on 9 and 4990 DF,  p-value: < 2.2e-16
```

Figure 5.4: Best Model Summary

The normal probability plots of residuals can be seen in the figure below:

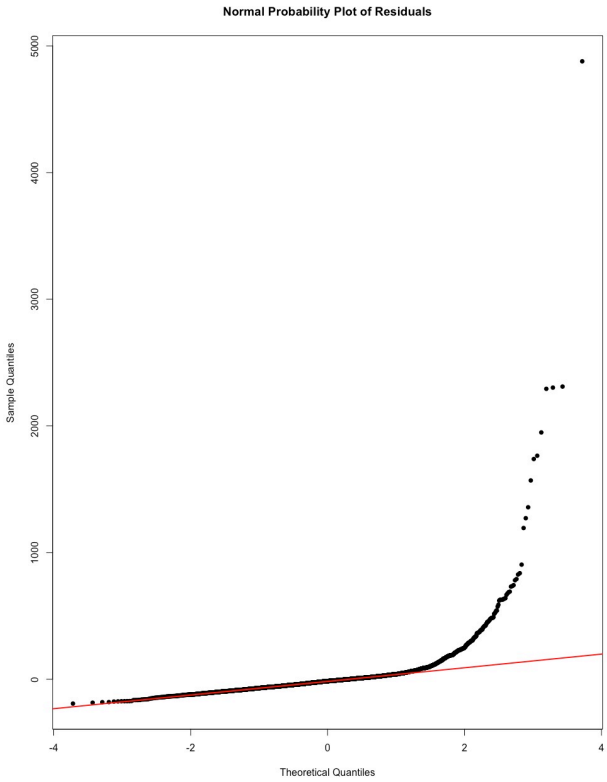


Figure 5.5: Normal Probability Plots of Residuals

Looking at the coefficient values and the p-values from the model, the location with the most significant correlation is clearly Manhattan. The data for Manhattan shows a positive correlation between demand and price, indicating that prices tend to be the highest in that borough. The trend for the Bronx and Staten Island locations is that demand decreases as price increases, which represents the fact that people will not stay in these locations if the rental property is not a relatively cheap option. In reality, this is an accurate indicator of how consumers will choose a place to stay, and also of the quality of the average rental property at each location. To find the best overall model, a stepwise elimination analysis was run which resulted in the best model using only the most significant variables.

6 Conclusion

Airbnb is a business that is successful because of its versatility of locations and services that are provided to guests as well as the ease of being a host. These two sides of the business have the same goal, price. Whether it be to search out the lower price as a consumer or to make the most of a location as you host, Airbnb has a variety of variables that adjust price, and throughout the report we have discussed the variables' interaction with price using regression and data analysis.

Our analysis has real-world appeal to both ends of the Airbnb market. It appeals to potential renters because they want to determine which Airbnb rental property is the best deal in a given city. Quantifying the factors that increase the price of a destination can help renters choose a destination that aligns with their top preferences while also not breaking the bank. After all, having an affordable yet also comfortable and convenient place to stay for a vacation or work trip can almost singlehandedly make a trip successful.

Our findings also have appeal to potential hosts. While hosts seek to maximize profit, they can struggle to know what price range will achieve that goal. By understanding which factors influence the optimal price of renting their space, hosts can set a price for their property which maximizes their returns.

Our final recommendation to a potential client would be fairly simple. Airbnb users can have wildly different needs and desires, so it is hard to give a lot of concrete advice. Instead, we recommend that users make an informed decision using data and their personal desires before taking a trip to New York. As an example, if you are seeking to be very near the tourist attractions in the city but willing to spend money, Manhattan is probably the place for you to stay. The other neighbourhoods each have positives and negatives as well, and any potential New York tourist should understand them all before choosing their temporary home away from home.

7 References

Dataset: https://www.kaggle.com/dgomonov/new-york-city-airbnb-open-data

8 Appendix

8.1 R Code and Outputs