Case Study 2

```
dat <- read.csv("AB_NYC_2019.csv", header = TRUE)

# Split numbers and strings:
col_str <- c("name", "host_name", "neighbourhood_group", "neighbourhood", "room_type",
             "last_review")
col_num <- names(dat)[!names(dat) %in% col_str]

# Find column with missing values
colnames(dat)[colSums(is.na(dat)) > 0] # reviews_per_month has NAs
```

```
## [1] "reviews_per_month"
```

```
summary(dat$number_of_reviews[which(is.na(dat$reviews_per_month))])
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0       0       0       0       0
```

```
sum(dat$last_review[which(is.na(dat$reviews_per_month))]!="")
```

```
## [1] 0
```

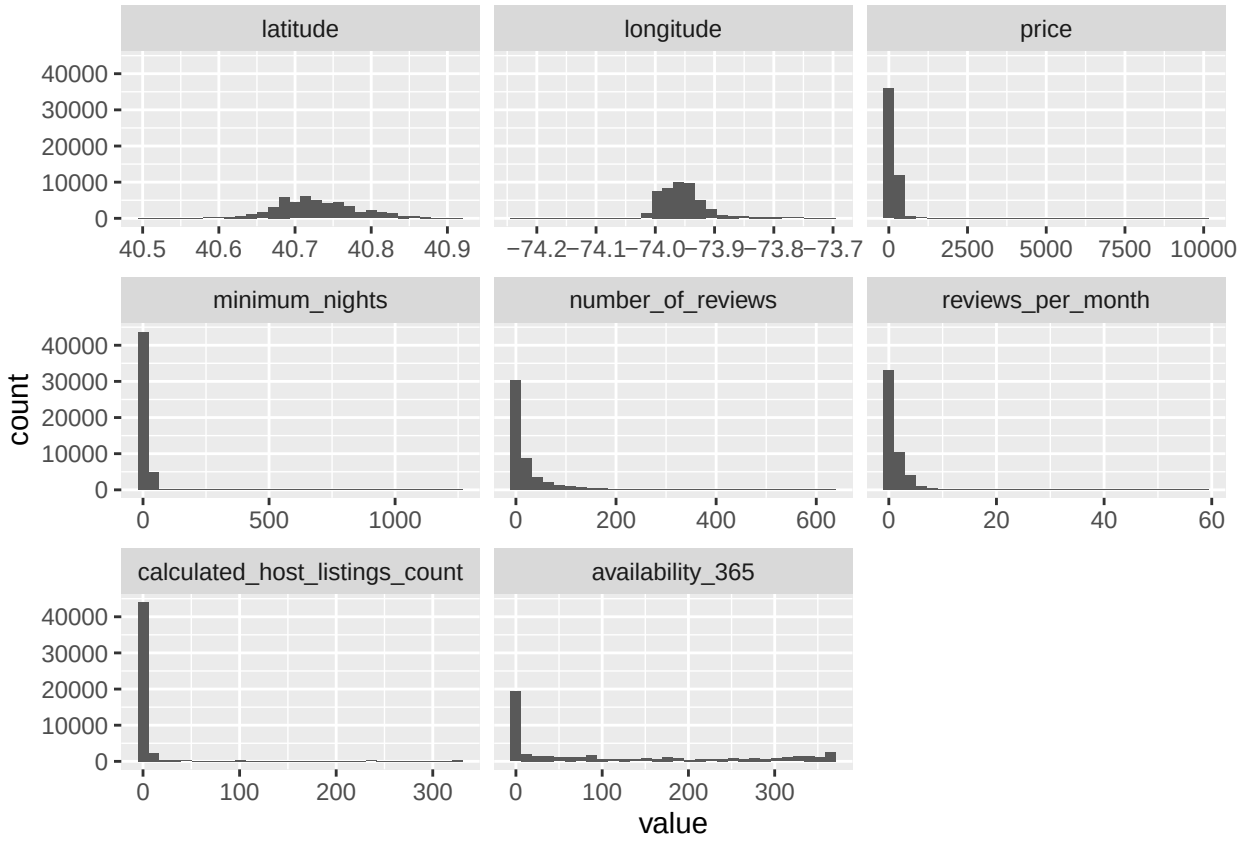
```
# all missing values in reviews_per_month correspond to 0 in number_of_reviews and blank in last_review
# fill in "reviews_per_month" with 0
dat$reviews_per_month[which(is.na(dat$reviews_per_month))] <- 0

# str(dat)

# Drop useless columns
drops <- c("id", "host_name", "host_id")
dat <- dat[ , !(names(dat) %in% drops)]

# log transform price
dat <- dat %>%
      mutate(log_price = ifelse(price == 0, log(price + 5), log(price)))

# Check unique values
# unique(dat$neighbourhood_group)
# unique(dat$neighbourhood)
# unique(dat$room_type)
```

```
# EDA
# Histograms for numeric variables
d <- melt(dat[, names(dat) %in% col_num])
```

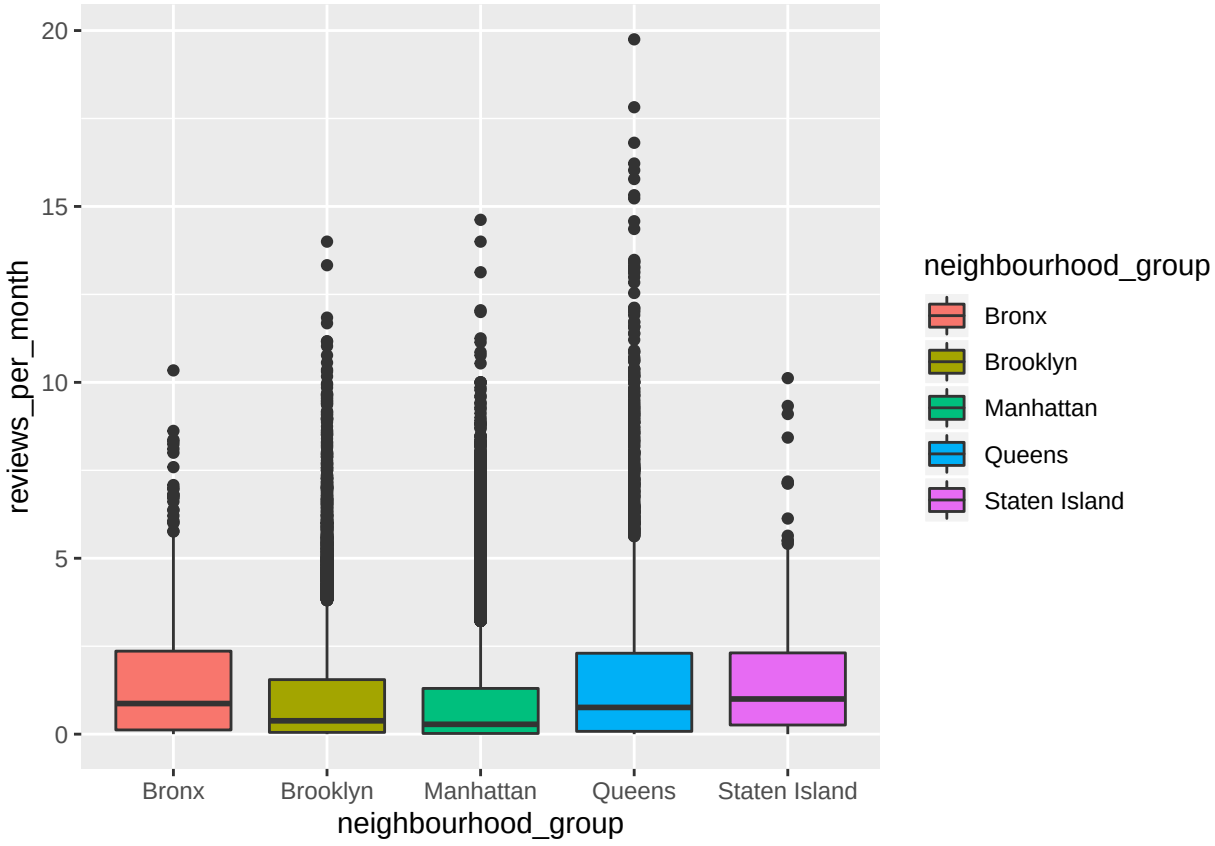
```
## No id variables; using all as measure variables
```

```
ggplot(d,aes(x = value)) +
    facet_wrap(~variable,scales = "free_x") +
    geom_histogram()
```

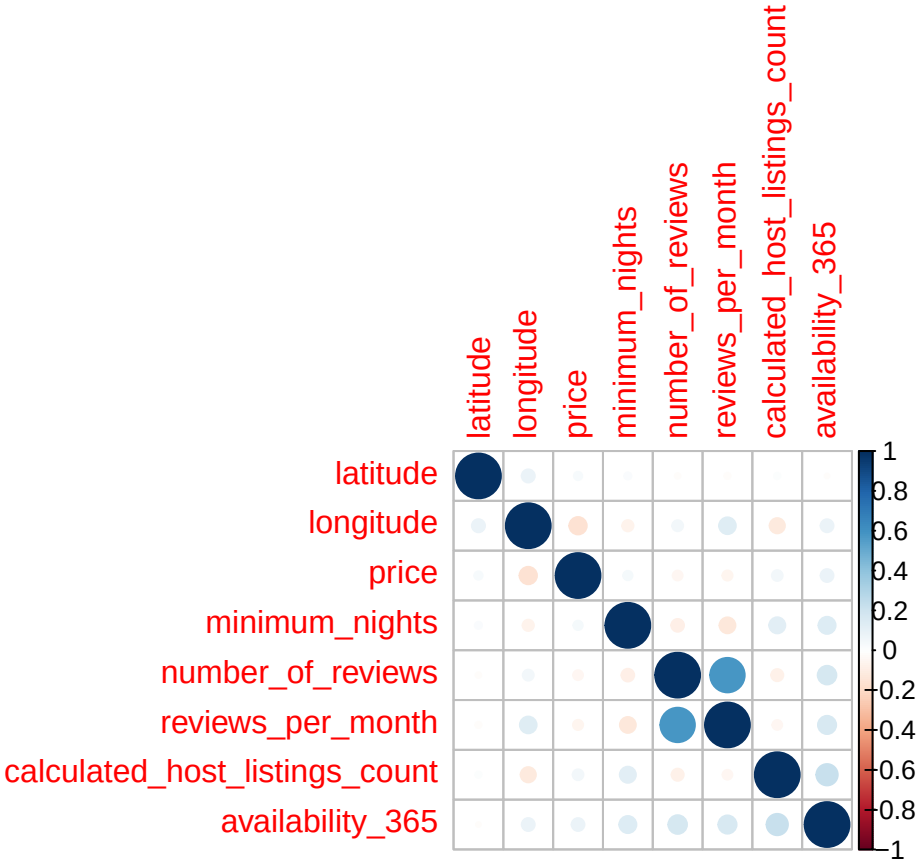
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```
# Boxplots (remove extreme values to see distribution)
ggplot(dat[dat$reviews_per_month<=20,], aes(x=neighbourhood_group, y=reviews_per_month,
                                    fill=neighbourhood_group)) + geom_boxplot()
```




```
# Manhattan: highest price, fewest reviews

# Correlation plot
corrplot(cor(dat[, names(dat) %in% col_num]))
```




```
# only number_of_reviews & reviews_per_month have high correlation: expected

# Check if all listings under one host_id are in the same borough # but neighbourhood??
# table_host_borough <- table(dat$host_id, dat$neighbourhood_group)
# dat$host_id[which(apply(as.matrix(table_host_borough), 1, function(x) sum(x!=0))!=1)]

xtabs( ~ neighbourhood + neighbourhood_group, data = dat)
```

```
##                              neighbourhood_group
## neighbourhood                 Bronx Brooklyn Manhattan Queens Staten Island
##   Allerton                       42        0         0      0             0
##   Arden Heights                   0        0         0      0             4
##   Arrochar                        0        0         0      0            21
##   Arverne                         0        0         0     77             0
##   Astoria                         0        0         0    900             0
##   Bath Beach                      0       17         0      0             0
##   Battery Park City               0        0        70      0             0
##   Bay Ridge                       0      141         0      0             0
##   Bay Terrace                     0        0         0      6             0
##   Bay Terrace, Staten Island      0        0         0      0             2
##   Baychester                      7        0         0      0             0
##   Bayside                         0        0         0     39             0
##   Bayswater                       0        0         0     17             0
##   Bedford-Stuyvesant              0     3714         0      0             0
##   Belle Harbor                    0        0         0      8             0
##   Bellerose                       0        0         0     14             0
```

##	Belmont	24	0	0	0	0
##	Bensonhurst	0	75	0	0	0
##	Bergen Beach	0	10	0	0	0
##	Boerum Hill	0	177	0	0	0
##	Borough Park	0	136	0	0	0
##	Breezy Point	0	0	0	3	0
##	Briarwood	0	0	0	56	0
##	Brighton Beach	0	75	0	0	0
##	Bronxdale	19	0	0	0	0
##	Brooklyn Heights	0	154	0	0	0
##	Brownsville	0	61	0	0	0
##	Bull's Head	0	0	0	0	6
##	Bushwick	0	2465	0	0	0
##	Cambria Heights	0	0	0	26	0
##	Canarsie	0	147	0	0	0
##	Carroll Gardens	0	233	0	0	0
##	Castle Hill	9	0	0	0	0
##	Castleton Corners	0	0	0	0	4
##	Chelsea	0	0	1113	0	0
##	Chinatown	0	0	368	0	0
##	City Island	18	0	0	0	0
##	Civic Center	0	0	52	0	0
##	Claremont Village	28	0	0	0	0
##	Clason Point	21	0	0	0	0
##	Clifton	0	0	0	0	15
##	Clinton Hill	0	572	0	0	0
##	Co-op City	2	0	0	0	0
##	Cobble Hill	0	99	0	0	0
##	College Point	0	0	0	19	0
##	Columbia St	0	42	0	0	0
##	Concord	0	0	0	0	26
##	Concourse	50	0	0	0	0
##	Concourse Village	32	0	0	0	0
##	Coney Island	0	17	0	0	0
##	Corona	0	0	0	64	0
##	Crown Heights	0	1564	0	0	0
##	Cypress Hills	0	135	0	0	0
##	Ditmars Steinway	0	0	0	309	0
##	Dongan Hills	0	0	0	0	7
##	Douglaston	0	0	0	8	0
##	Downtown Brooklyn	0	83	0	0	0
##	DUMBO	0	36	0	0	0
##	Dyker Heights	0	12	0	0	0
##	East Elmhurst	0	0	0	185	0
##	East Flatbush	0	500	0	0	0
##	East Harlem	0	0	1117	0	0
##	East Morrisania	10	0	0	0	0
##	East New York	0	218	0	0	0
##	East Village	0	0	1853	0	0
##	Eastchester	13	0	0	0	0
##	Edenwald	13	0	0	0	0
##	Edgemere	0	0	0	11	0
##	Elmhurst	0	0	0	237	0
##	Eltingville	0	0	0	0	3

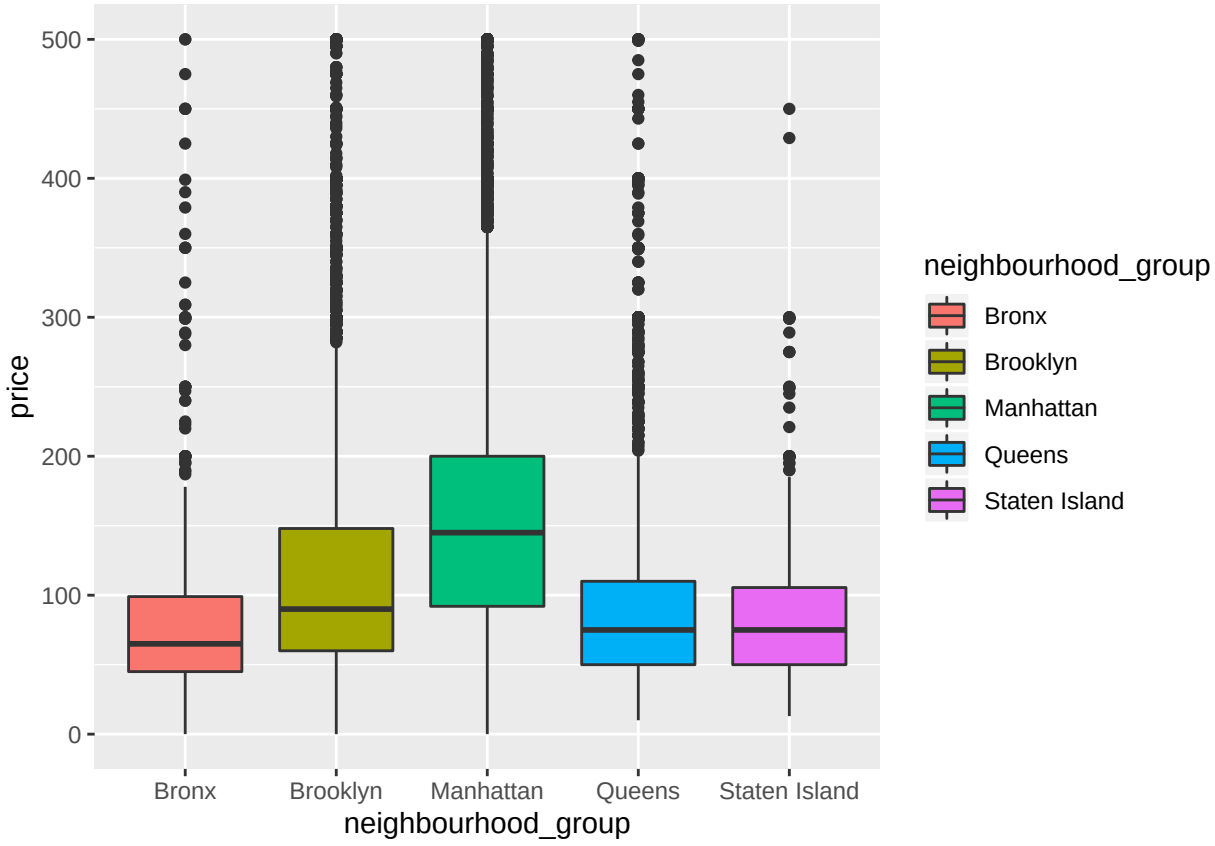
```
##   Emerson Hill                0        0        0      0             5
##   Far Rockaway                0        0        0     29             0
##   Fieldston                  12        0        0      0             0
##   Financial District          0        0      744      0             0
##   Flatbush                    0      621        0      0             0
##   Flatiron District           0        0       80      0             0
##   Flatlands                   0       83        0      0             0
##   Flushing                    0        0        0    426             0
##   Fordham                    63        0        0      0             0
##   Forest Hills                0        0        0    144             0
##   Fort Greene                 0      489        0      0             0
##   Fort Hamilton               0       55        0      0             0
##   Fort Wadsworth              0        0        0      0             1
##   Fresh Meadows               0        0        0     32             0
##   Glendale                    0        0        0     54             0
##   Gowanus                     0      247        0      0             0
##   Gramercy                    0        0      338      0             0
##   Graniteville                0        0        0      0             3
##   Grant City                  0        0        0      0             6
##   Gravesend                   0       68        0      0             0
##   Great Kills                 0        0        0      0            10
##   Greenpoint                  0     1115        0      0             0
##   Greenwich Village           0        0      392      0             0
##   Grymes Hill                 0        0        0      0             7
##   Harlem                      0        0     2658      0             0
##   Hell's Kitchen              0        0     1958      0             0
##   Highbridge                 27        0        0      0             0
##   Hollis                      0        0        0     14             0
##   Holliswood                  0        0        0      4             0
##   Howard Beach                0        0        0     20             0
##   Howland Hook                0        0        0      0             2
##   Huguenot                    0        0        0      0             3
##   Hunts Point                18        0        0      0             0
##   Inwood                      0        0      252      0             0
##   Jackson Heights             0        0        0    186             0
##   Jamaica                     0        0        0    231             0
##   Jamaica Estates             0        0        0     19             0
##   Jamaica Hills               0        0        0      8             0
##   Kensington                  0      175        0      0             0
##   Kew Gardens                 0        0        0     32             0
##   Kew Gardens Hills           0        0        0     26             0
##   Kingsbridge                70        0        0      0             0
##   Kips Bay                    0        0      470      0             0
##   Laurelton                   0        0        0     18             0
##   Lighthouse Hill             0        0        0      0             2
##   Little Italy                0        0      121      0             0
##   Little Neck                 0        0        0      5             0
##   Long Island City            0        0        0    537             0
##   Longwood                   62        0        0      0             0
##   Lower East Side             0        0      911      0             0
##   Manhattan Beach             0        8        0      0             0
##   Marble Hill                 0        0       12      0             0
##   Mariners Harbor             0        0        0      0             8
##   Maspeth                     0        0        0    110             0
```

```
##   Melrose                    10        0        0      0             0
##   Middle Village              0        0        0     31             0
##   Midland Beach               0        0        0      0             6
##   Midtown                     0        0     1545      0             0
##   Midwood                     0      109        0      0             0
##   Mill Basin                  0        4        0      0             0
##   Morningside Heights         0        0      346      0             0
##   Morris Heights             17        0        0      0             0
##   Morris Park                15        0        0      0             0
##   Morrisania                 18        0        0      0             0
##   Mott Haven                 60        0        0      0             0
##   Mount Eden                  6        0        0      0             0
##   Mount Hope                 20        0        0      0             0
##   Murray Hill                 0        0      485      0             0
##   Navy Yard                   0       14        0      0             0
##   Neponsit                    0        0        0      3             0
##   New Brighton                0        0        0      0             5
##   New Dorp                    0        0        0      0             1
##   New Dorp Beach              0        0        0      0             5
##   New Springville             0        0        0      0             8
##   NoHo                        0        0       78      0             0
##   Nolita                      0        0      253      0             0
##   North Riverdale            10        0        0      0             0
##   Norwood                    31        0        0      0             0
##   Oakwood                     0        0        0      0             5
##   Olinville                   4        0        0      0             0
##   Ozone Park                  0        0        0     62             0
##   Park Slope                  0      506        0      0             0
##   Parkchester                39        0        0      0             0
##   Pelham Bay                 17        0        0      0             0
##   Pelham Gardens             28        0        0      0             0
##   Port Morris                46        0        0      0             0
##   Port Richmond               0        0        0      0             9
##   Prince's Bay                0        0        0      0             4
##   Prospect Heights            0      357        0      0             0
##   Prospect-Lefferts Gardens   0      535        0      0             0
##   Queens Village              0        0        0     60             0
##   Randall Manor               0        0        0      0            19
##   Red Hook                    0       79        0      0             0
##   Rego Park                   0        0        0    106             0
##   Richmond Hill               0        0        0     94             0
##   Richmondtown                0        0        0      0             1
##   Ridgewood                   0        0        0    423             0
##   Riverdale                  11        0        0      0             0
##   Rockaway Beach              0        0        0     56             0
##   Roosevelt Island            0        0       77      0             0
##   Rosebank                    0        0        0      0             7
##   Rosedale                    0        0        0     59             0
##   Rossville                   0        0        0      0             1
##   Schuylerville              13        0        0      0             0
##   Sea Gate                    0        7        0      0             0
##   Sheepshead Bay              0      164        0      0             0
##   Shore Acres                 0        0        0      0             7
##   Silver Lake                 0        0        0      0             2
```

```
##   SoHo                          0        0       358      0             0
##   Soundview                    15        0         0      0             0
##   South Beach                   0        0         0      0             8
##   South Ozone Park              0        0         0     40             0
##   South Slope                   0      284         0      0             0
##   Springfield Gardens           0        0         0     85             0
##   Spuyten Duyvil                4        0         0      0             0
##   St. Albans                    0        0         0     76             0
##   St. George                    0        0         0      0            48
##   Stapleton                     0        0         0      0            27
##   Stuyvesant Town               0        0        37      0             0
##   Sunnyside                     0        0         0    363             0
##   Sunset Park                   0      390         0      0             0
##   Theater District              0        0       288      0             0
##   Throgs Neck                  24        0         0      0             0
##   Todt Hill                     0        0         0      0             4
##   Tompkinsville                 0        0         0      0            42
##   Tottenville                   0        0         0      0             7
##   Tremont                      11        0         0      0             0
##   Tribeca                       0        0       177      0             0
##   Two Bridges                   0        0        72      0             0
##   Unionport                     7        0         0      0             0
##   University Heights           21        0         0      0             0
##   Upper East Side               0        0      1798      0             0
##   Upper West Side               0        0      1971      0             0
##   Van Nest                     11        0         0      0             0
##   Vinegar Hill                  0       34         0      0             0
##   Wakefield                    50        0         0      0             0
##   Washington Heights            0        0       899      0             0
##   West Brighton                 0        0         0      0            18
##   West Farms                    2        0         0      0             0
##   West Village                  0        0       768      0             0
##   Westchester Square           10        0         0      0             0
##   Westerleigh                   0        0         0      0             2
##   Whitestone                    0        0         0     11             0
##   Williamsbridge               40        0         0      0             0
##   Williamsburg                  0     3920         0      0             0
##   Willowbrook                   0        0         0      0             1
##   Windsor Terrace               0      157         0      0             0
##   Woodhaven                     0        0         0     88             0
##   Woodlawn                     11        0         0      0             0
##   Woodrow                       0        0         0      0             1
##   Woodside                      0        0         0    235             0
```

```
# neighbourhood_group & neighbourhood are nested
```

```
# Boxplots - price by borough (remove extreme values)
ggplot(dat[dat$price<=500,], aes(x=neighbourhood_group, y=price,
                                 fill=neighbourhood_group)) + geom_boxplot()
```



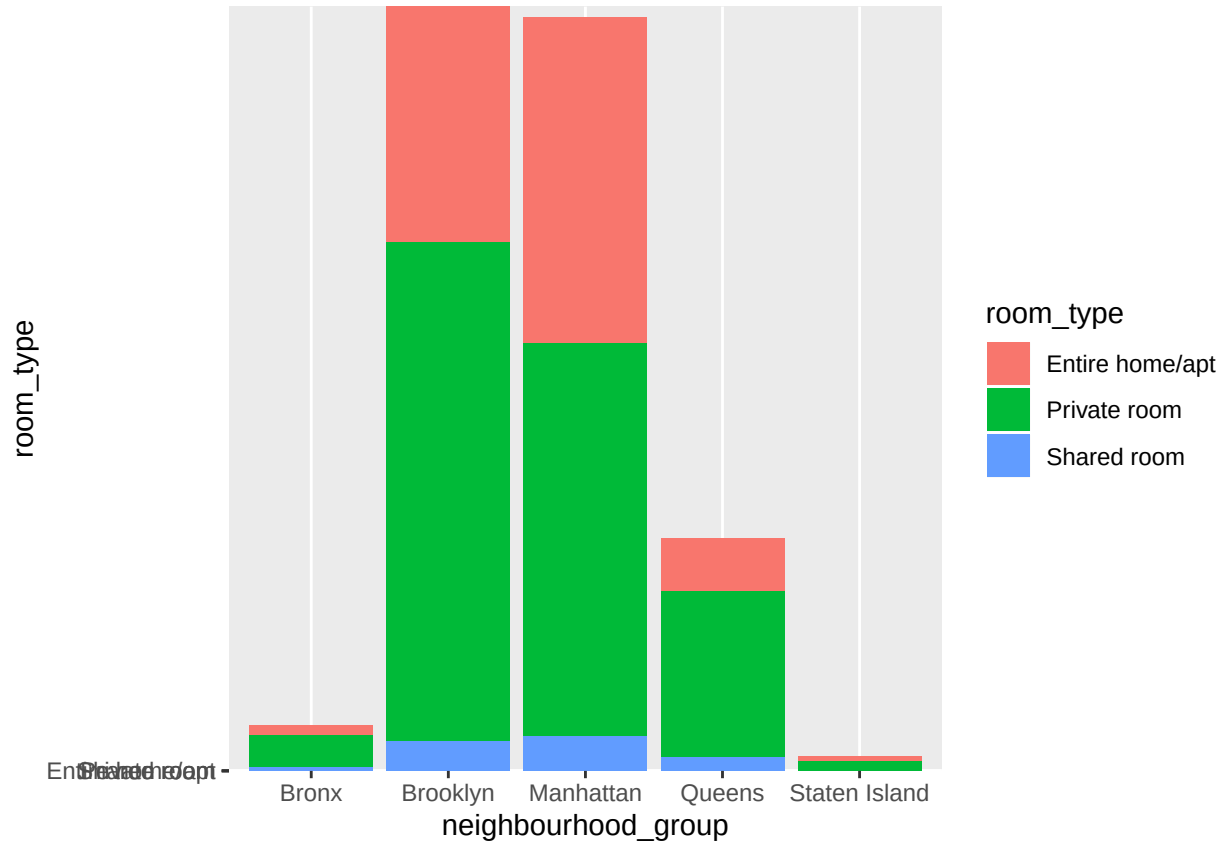

```
anova(lm(price~neighbourhood,data=dat))
```

```
## Analysis of Variance Table
##
## Response: price
##                  Df     Sum Sq Mean Sq F value    Pr(>F)
## neighbourhood   220  189750135  862501  15.961 < 2.2e-16 ***
## Residuals     48674 2630163656   54036
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

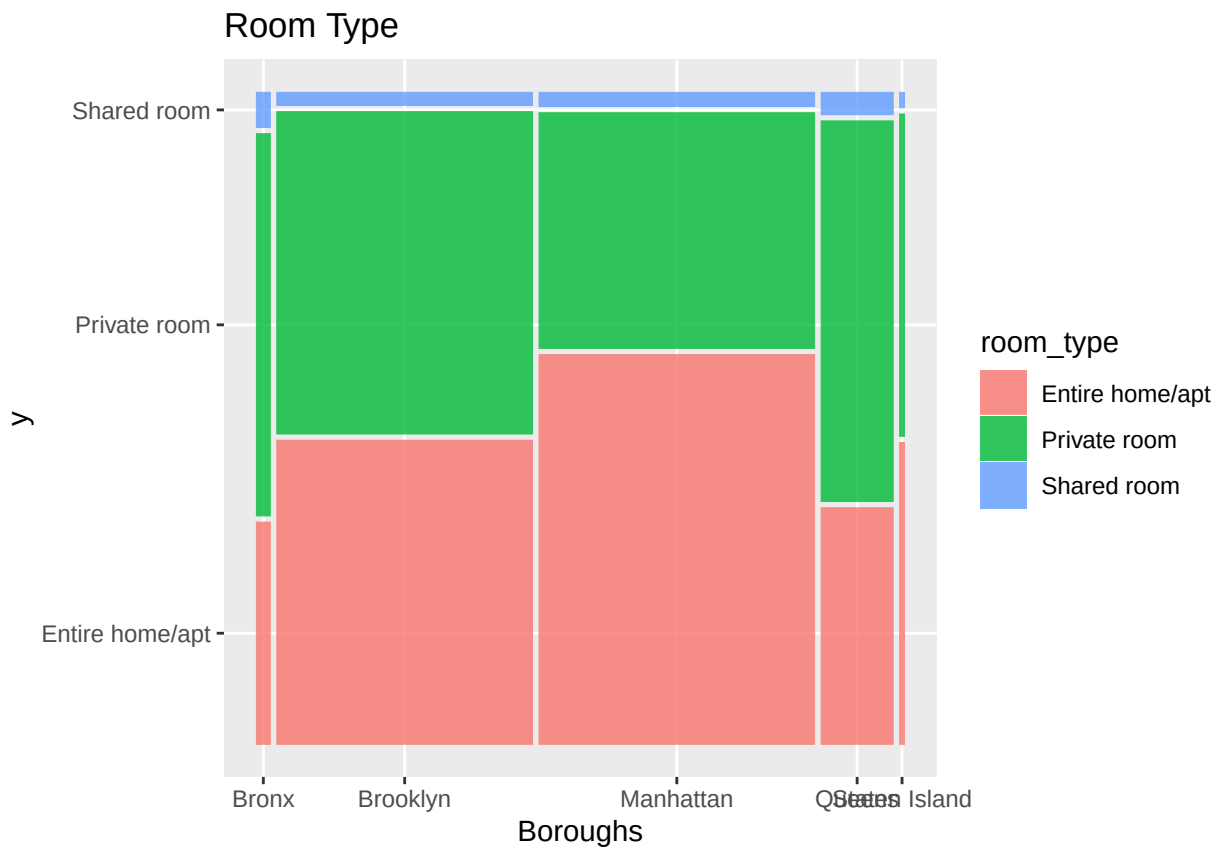
```
anova(lm(price~neighbourhood_group,data=dat))
```

```
## Analysis of Variance Table
##
## Response: price
##                        Df     Sum Sq  Mean Sq F value    Pr(>F)
## neighbourhood_group     4   79590956 19897739  354.99 < 2.2e-16 ***
## Residuals           48890 2740322834    56051
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

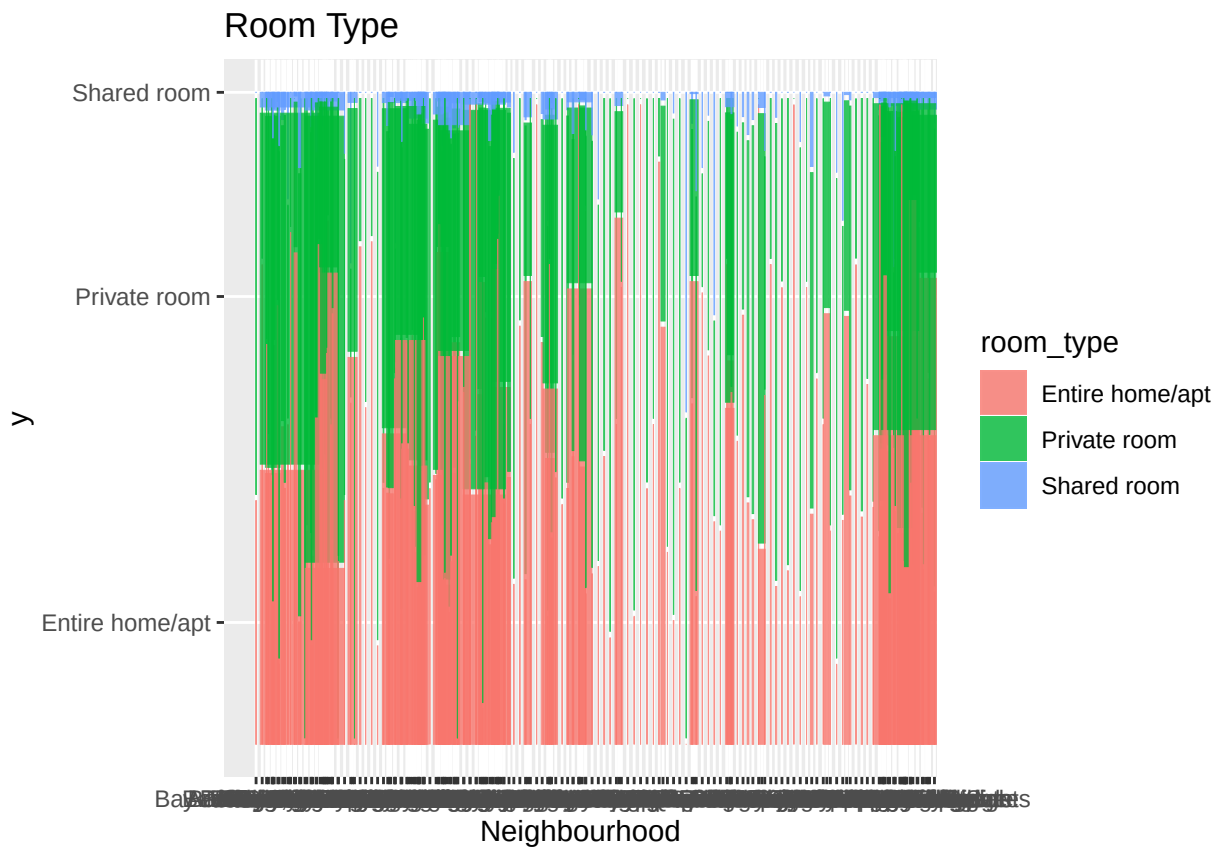
```
# Barplots & Mosaic plot - room type by borough
ggplot(data=dat, aes(x = neighbourhood_group, y = room_type, fill = room_type)) +
  geom_bar(stat="identity")
```



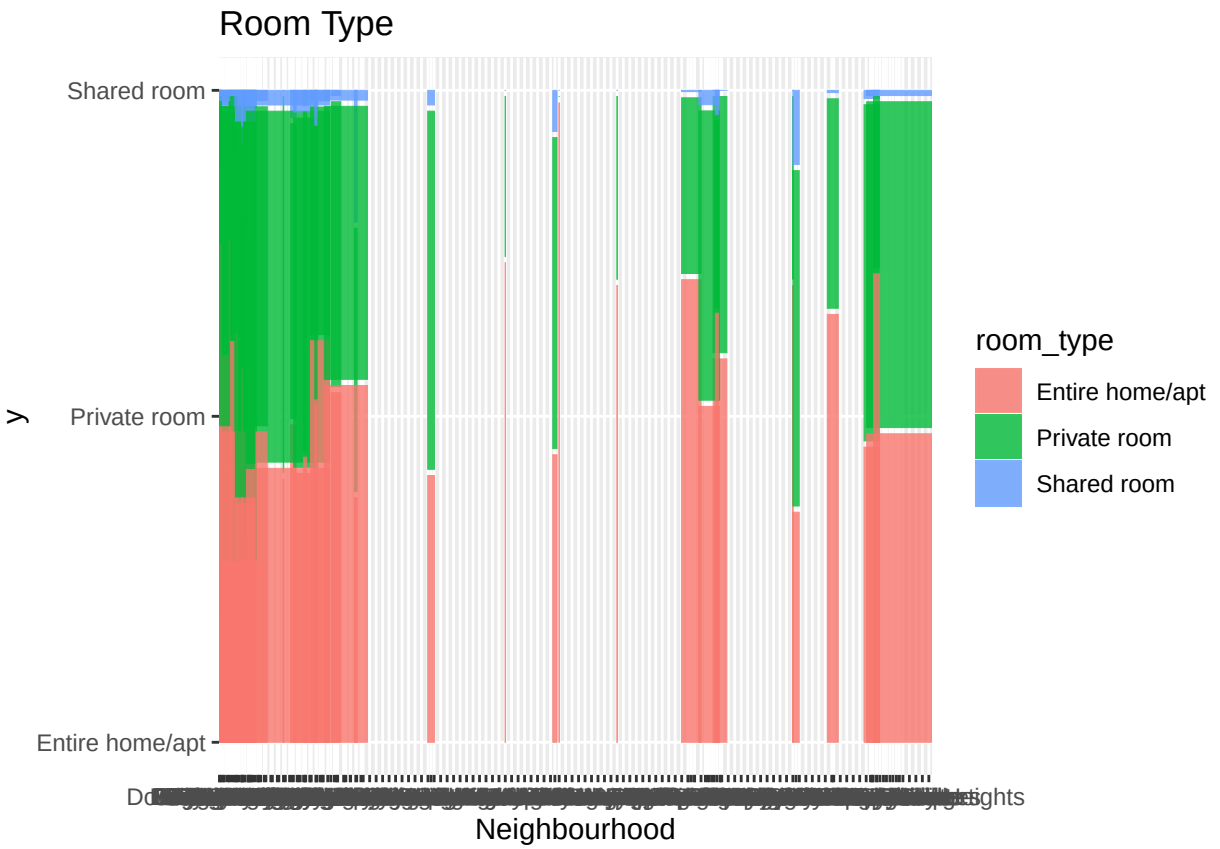

```
# boroughs
ggplot(data = dat) +
  geom_mosaic(aes(x = product(room_type, neighbourhood_group), fill=room_type), na.rm=TRUE) +
  labs(x="Boroughs", title='Room Type')
```



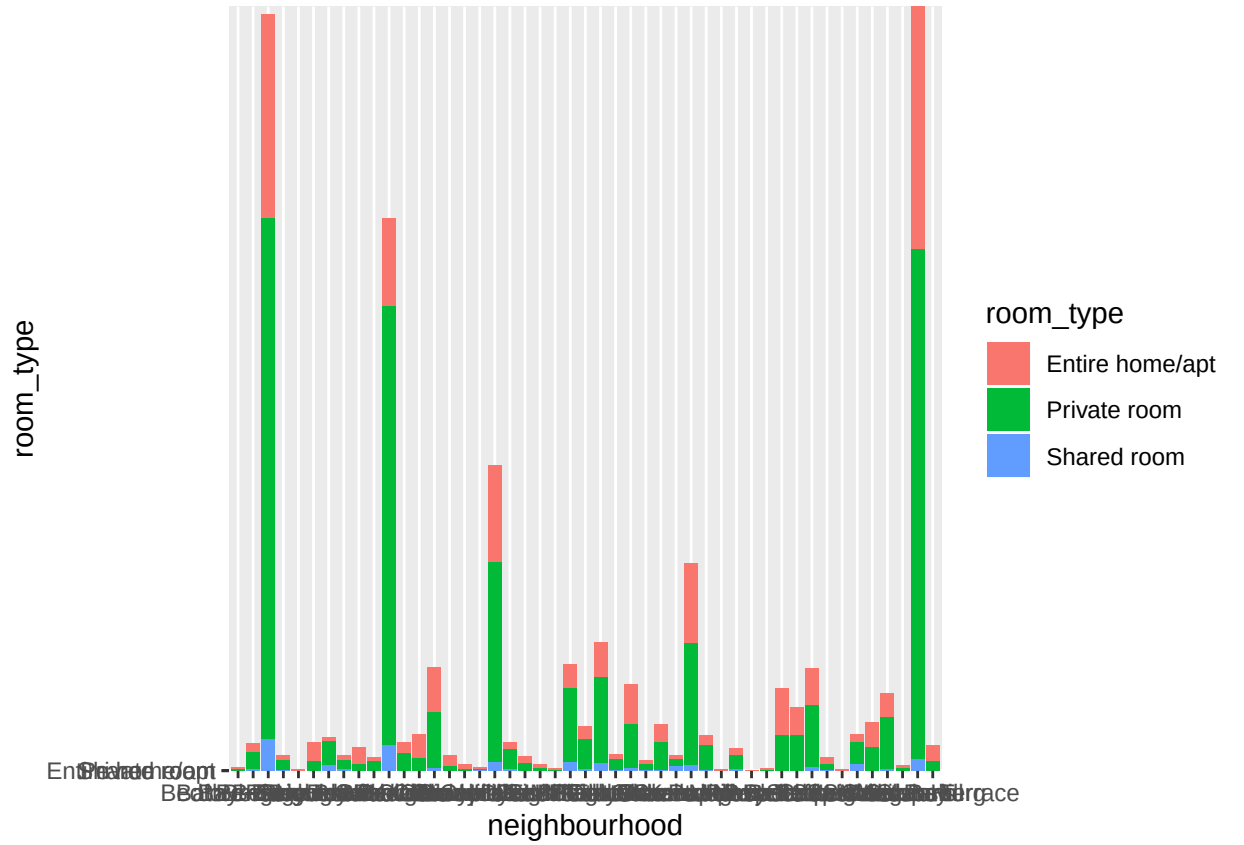

```
# all neighbourhood -> difficult to see
ggplot(data = dat) +
  geom_mosaic(aes(x = product(room_type, neighbourhood), fill=room_type), na.rm=TRUE) +
  labs(x="Neighbourhood", title='Room Type')
```




```
# plot by boroughs
ggplot(data = dat %>%
         filter(neighbourhood_group=="Brooklyn")) +
  geom_mosaic(aes(x = product(room_type, neighbourhood), fill=room_type), na.rm=TRUE) +
  labs(x="Neighbourhood", title='Room Type')
```



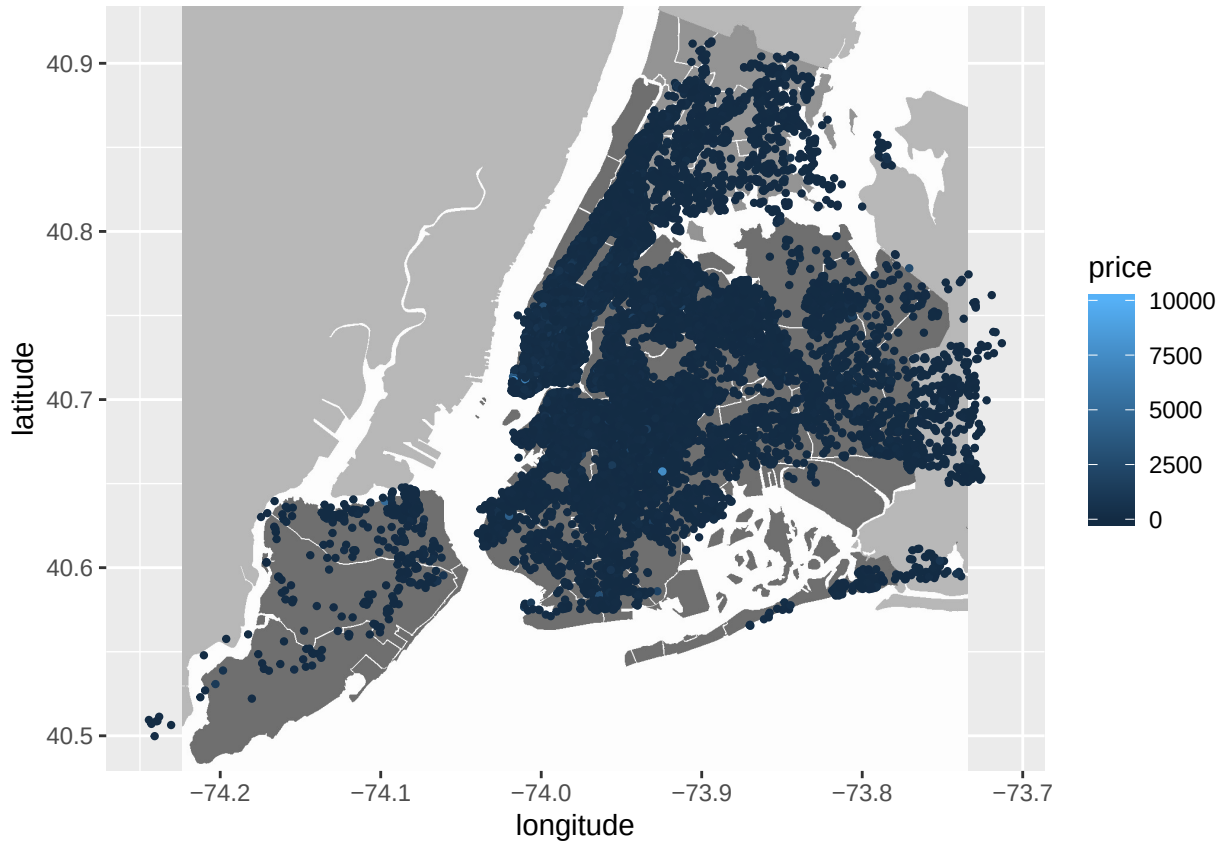

```
ggplot(data = dat %>%
         filter(neighbourhood_group=="Brooklyn"),
       aes(x = neighbourhood, y = room_type, fill = room_type)) +
       geom_bar(stat="identity")
```




```
library(magick)
```

```
## Linking to ImageMagick 6.9.9.39
## Enabled features: cairo, fontconfig, freetype, lcms, pango, rsvg, webp
## Disabled features: fftw, ghostscript, x11
```

```
library(grid)
img <- image_read("New_York_City_.png")
g <- rasterGrob(img)

ggplot() +
  annotation_custom(g) +
  geom_point(data = dat, mapping = aes(x = longitude, y = latitude, colour = price),size=0.8)
```




```
#ggmap
```

```
availability <- dat$availability_365==0
last_review_year <- as.numeric(substr(dat$last_review, start = 1, stop = 4))
review_per_month <- dat$reviews_per_month
# table(last_review_year, availability)
# table(review_per_month, availability)
```

```
lm_1 <- lmer(log_price ~ latitude + longitude + room_type + reviews_per_month +
                         calculated_host_listings_count + availability_365 +
                         (1 | neighbourhood_group) + (1 | neighbourhood), data = dat,
                         REML=TRUE)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
summary(lm_1)
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: log_price ~ latitude + longitude + room_type + reviews_per_month +
```

```
##     calculated_host_listings_count + availability_365 + (1 |
##     neighbourhood_group) + (1 | neighbourhood)
##    Data: dat
##
## REML criterion at convergence: 66794
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -7.7388 -0.6166 -0.1089  0.4695 10.7041
##
## Random effects:
##  Groups              Name        Variance Std.Dev.
##  neighbourhood       (Intercept) 0.04578  0.2140
##  neighbourhood_group (Intercept) 0.20555  0.4534
##  Residual                        0.22666  0.4761
## Number of obs: 48895, groups:  neighbourhood, 221; neighbourhood_group, 5
##
## Fixed effects:
##                                 Estimate Std. Error         df  t value
## (Intercept)                    -2.196e+02  2.131e+01  8.950e+02  -10.306
## latitude                       -4.098e-01  2.746e-01  6.356e+02   -1.492
## longitude                      -3.261e+00  2.364e-01  1.131e+03  -13.794
## room_typePrivate room          -7.063e-01  4.611e-03  4.882e+04 -153.186
## room_typeShared room           -1.082e+00  1.456e-02  4.885e+04  -74.271
## reviews_per_month              -1.116e-02  1.411e-03  4.884e+04   -7.904
## calculated_host_listings_count -6.268e-04  7.623e-05  4.884e+04   -8.223
## availability_365                7.140e-04  1.756e-05  4.878e+04   40.654
##                                Pr(>|t|)
## (Intercept)                     < 2e-16 ***
## latitude                          0.136
## longitude                       < 2e-16 ***
## room_typePrivate room           < 2e-16 ***
## room_typeShared room            < 2e-16 ***
## reviews_per_month              2.76e-15 ***
## calculated_host_listings_count  < 2e-16 ***
## availability_365                < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) latitd longtd rm_tPr rm_tSr rvws__ clc___
## latitude    -0.574
## longitude    0.852 -0.060
## rm_typPrvtr -0.010 -0.029 -0.031
## rm_typShrdr -0.007 -0.003 -0.010  0.161
## rvws_pr_mnt -0.039  0.018 -0.036  0.007  0.021
## clcltd_hs__  0.004  0.008  0.011  0.066  0.030  0.074
## avlblty_365 -0.035  0.019 -0.030 -0.005 -0.051 -0.148 -0.212
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```
anova(lm_1) # test fixed effect
```

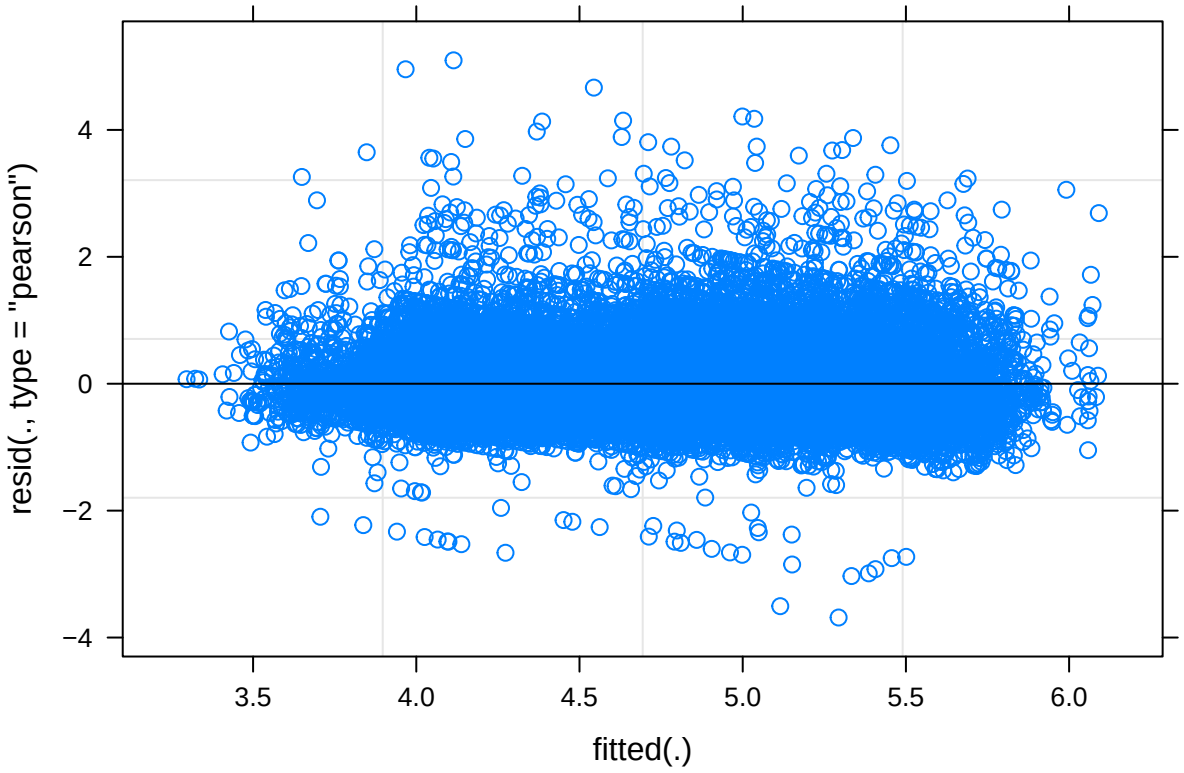
```
## Type III Analysis of Variance Table with Satterthwaite's method
```

```
##                                 Sum Sq Mean Sq NumDF DenDF    F value    Pr(>F)
## latitude                           0.5    0.50     1   636     2.2273    0.1361
## longitude                         43.1   43.13     1  1131   190.2773 < 2.2e-16
## room_type                       5892.0 2946.00     2 48837 12997.5413 < 2.2e-16
## reviews_per_month                 14.2   14.16     1 48842    62.4705 2.761e-15
## calculated_host_listings_count    15.3   15.32     1 48836    67.6126 < 2.2e-16
## availability_365                 374.6  374.60     1 48785  1652.7086 < 2.2e-16
##
## latitude
## longitude                       ***
## room_type                       ***
## reviews_per_month               ***
## calculated_host_listings_count ***
## availability_365                ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
rand(lm_1) # test random effect
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## ANOVA-like table for random-effects: Single term deletions
##
## Model:
## log_price ~ latitude + longitude + room_type + reviews_per_month +
##     calculated_host_listings_count + availability_365 + (1 |
##     neighbourhood_group) + (1 | neighbourhood)
##                            npar logLik   AIC    LRT Df Pr(>Chisq)
## <none>                       11 -33397 66816
## (1 | neighbourhood_group)   10 -33490 67000  186.2  1  < 2.2e-16 ***
## (1 | neighbourhood)         10 -35647 71315 4500.6  1  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

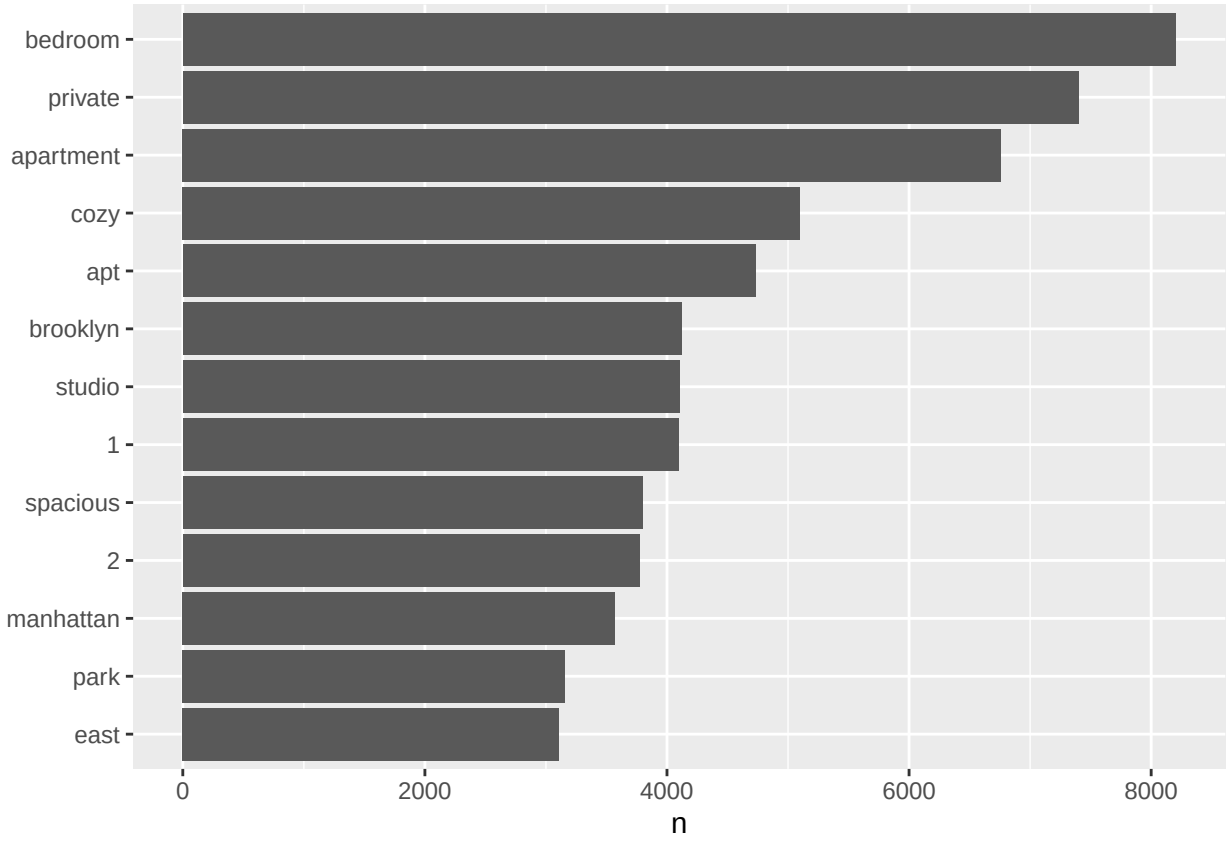
```
plot(lm_1) # residual plot
```




```
library(tidytext)
data(stop_words)

dat$name <- as.character(dat$name)
name_df <- tibble(line = 1:nrow(dat), dat$name)

tokens <- name_df %>%
          unnest_tokens(word, dat$name) %>%
          anti_join(stop_words)
```

```
## Joining, by = "word"
```

```
tokens %>%
      count(word, sort = TRUE) %>%
      filter(n > 3000) %>%
      mutate(word = reorder(word, n)) %>%
      ggplot(aes(word, n)) +
      geom_col() +
      xlab(NULL) +
      coord_flip()
```




```
# library(caret)
# set.seed(1)
# train_index <- sample(1:nrow(dat), 0.9 * nrow(dat))
# dat_train <- dat[train_index, ]
# dat_test <- dat[-train_index, ]
# # fit a random forest model (using ranger)
# rf_fit <- train(log_price ~ latitude + longitude + room_type + reviews_per_month +
#                           calculated_host_listings_count + availability_365 +
#                           neighbourhood_group + neighbourhood, data = dat_train,
#                           method = "ranger")
# rf_fit
# rf_pred <- predict(rf_fit, dat_test)
# dat_VarImp = varImp(rf_fit)

library(randomForest)
```

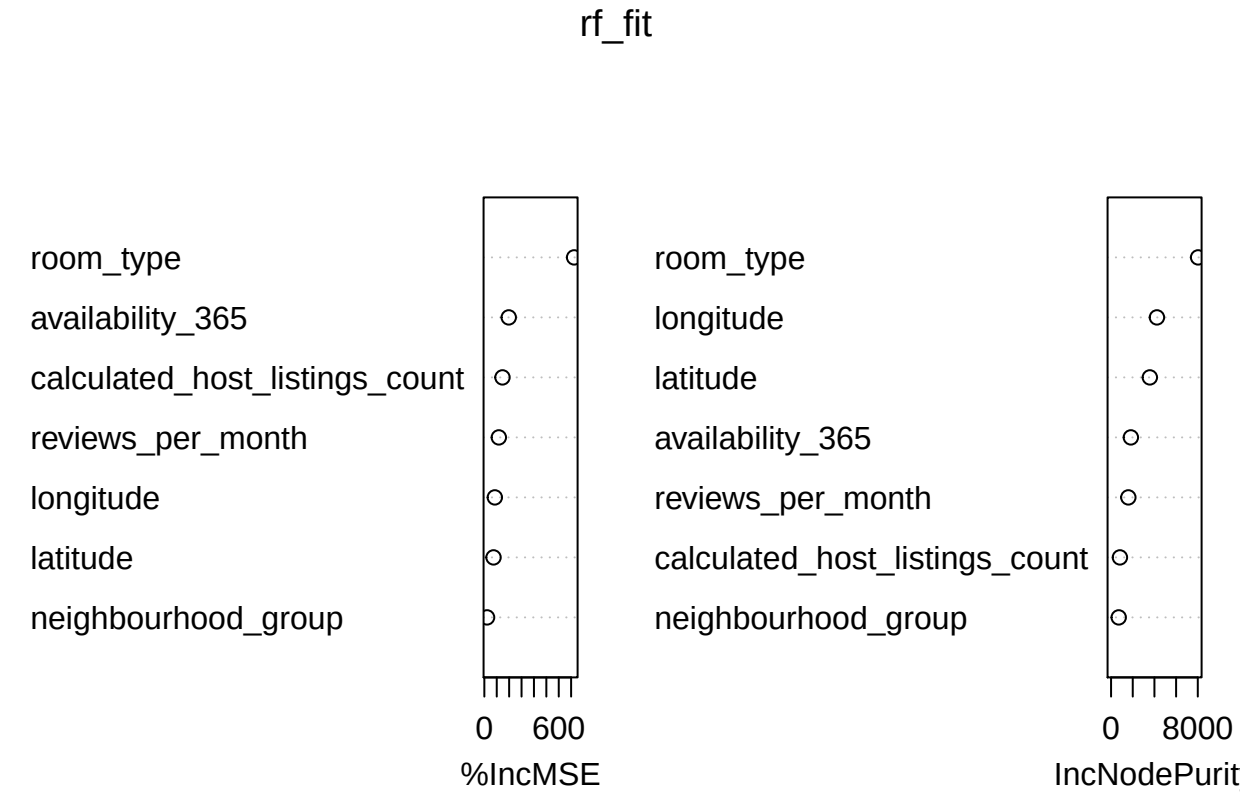
```
## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:dplyr':
##
##     combine
```

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

```
set.seed(1)
train_index <- sample(1:nrow(dat), 0.9 * nrow(dat))
dat_train <- dat[train_index, ]
dat_test <- dat[-train_index, ]
# fit a random forest model
rf_fit <- randomForest(log_price ~ latitude + longitude + room_type + reviews_per_month +
                         calculated_host_listings_count + availability_365 +
                         neighbourhood_group, data = dat_train,
                         ntree = 500, mtry = 6,
                         importance = TRUE) # cannot use neighbourhood: # levels > 53
importance(rf_fit)
```

```
##                                  %IncMSE IncNodePurity
## latitude                        74.08658     3575.9157
## longitude                       84.49337     4230.5005
## room_type                      724.07856     8030.9396
## reviews_per_month              116.70760     1594.1227
## calculated_host_listings_count 146.23027      816.5953
## availability_365               196.84354     1825.2299
## neighbourhood_group             21.93242      705.7680
```

```
varImpPlot(rf_fit)
```



```r
rf_pred <- predict(rf_fit, dat_test)
plot(dat_test$log_price, rf_pred)
abline(0,1,col="red")
```