zillow by Xiaodan

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1.Define Problem

Given new data to predict its logerror, which is the log of estimated house price minus the log of real sales price.

2.Clean Data

```
#load data
setwd("F:/tiger/zillow")
train<-read.csv('train_property.csv',stringsAsFactors = F)

#remove variables with missing values more than 20%
NA_rate<-colMeans(sapply(train,is.na))
remain_col<-names(train)[which(NA_rate<.2)]
train2<-train[,remain_col]
train2<-train2[,-1]
#remained variables
names(train2)
```

```
##  [1] "parcelid"                     "logerror"
##  [3] "transactiondate"              "bathroomcnt"
##  [5] "bedroomcnt"                   "calculatedbathnbr"
##  [7] "calculatedfinishedsquarefeet" "finishedsquarefeet12"
##  [9] "fips"                         "fullbathcnt"
## [11] "hashottuborspa"               "latitude"
## [13] "longitude"                    "lotsizesquarefeet"
## [15] "propertycountylandusecode"    "propertylandusetypeid"
## [17] "propertyzoningdesc"           "rawcensustractandblock"
## [19] "regionidcity"                 "regionidcounty"
## [21] "regionidzip"                  "roomcnt"
## [23] "yearbuilt"                    "fireplaceflag"
## [25] "structuretaxvaluedollarcnt"   "taxvaluedollarcnt"
## [27] "assessmentyear"               "landtaxvaluedollarcnt"
## [29] "taxamount"                    "taxdelinquencyflag"
## [31] "censustractandblock"
```

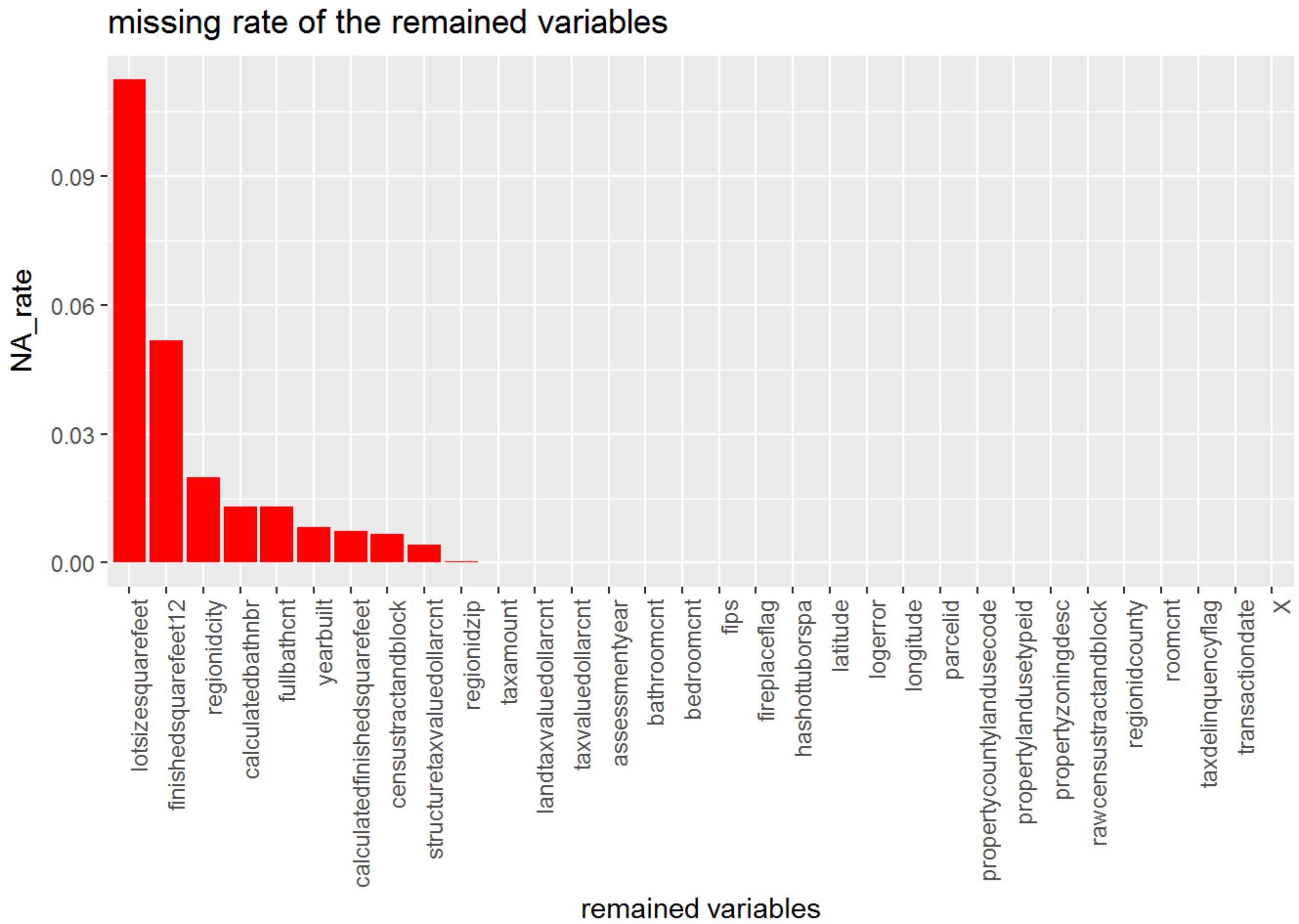
```
head(train2)
```

```
##   parcelid logerror transactiondate bathroomcnt bedroomcnt
## 1 10711738   0.0276      2016-08-02           3          4
## 2 10711755  -0.0182      2016-08-02           3          3
## 3 10711805  -0.1009      2016-05-03           2          3
## 4 10711816  -0.0121      2016-04-05           2          4
## 5 10711858  -0.0481      2016-07-15           2          4
## 6 10711910   0.2897      2016-08-30           2          3
##   calculatedbathnbr calculatedfinishedsquarefeet finishedsquarefeet12 fips
## 1                 3                         2538                 2538 6037
## 2                 3                         1589                 1589 6037
## 3                 2                         2411                 2411 6037
## 4                 2                         2232                 2232 6037
## 5                 2                         1882                 1882 6037
## 6                 2                         1477                 1477 6037
##   fullbathcnt hashottuborspa latitude  longitude lotsizesquarefeet
## 1           3                34220381 -118620802             11012
## 2           3                34222040 -118622240             11010
## 3           2                34220427 -118618549             11723
## 4           2                34222390 -118618631              9002
## 5           2                34222544 -118617961              9002
## 6           2                34221864 -118615739             11285
##   propertycountylandusecode propertylandusetypeid propertyzoningdesc
## 1                      0101                   261             LARE11
## 2                      0101                   261             LARE11
## 3                      0101                   261              LARE9
## 4                      0100                   261              LARE9
## 5                      0101                   261              LARE9
## 6                      0101                   261             LARE11
##   rawcensustractandblock regionidcity regionidcounty regionidzip roomcnt
## 1               60371132        12447           3101       96339       0
## 2               60371132        12447           3101       96339       0
## 3               60371132        12447           3101       96339       0
## 4               60371132        12447           3101       96339       0
## 5               60371132        12447           3101       96339       0
## 6               60371132        12447           3101       96339       0
##   yearbuilt fireplaceflag structuretaxvaluedollarcnt taxvaluedollarcnt
## 1      1978                                   245180            567112
## 2      1959                                   254691            459844
## 3      1973                                   235114            384787
## 4      1973                                   262309            437176
## 5      1973                                   232037            382055
## 6      1960                                    57098             76860
##   assessmentyear landtaxvaluedollarcnt taxamount taxdelinquencyflag
## 1           2015                321932   7219.18
## 2           2015                205153   6901.09
## 3           2015                149673   4876.61
## 4           2015                174867   5560.07
## 5           2015                150018   4878.25
## 6           2015                 19762   1116.46
##   censustractandblock
## 1        6.037113e+13
## 2        6.037113e+13
## 3        6.037113e+13
## 4        6.037113e+13
## 5        6.037113e+13
## 6        6.037113e+13
```

```
#missing rate of the remained variables from the highest to the lowest
miss<-data.frame(var=remain_col,NA_rate=NA_rate[remain_col],row.names = NULL,stringsAsFactors =
 F)
miss<-miss[order(miss$NA_rate,decreasing = T),]
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.4.2
```

```
ggplot(miss,aes(x=reorder(var,-NA_rate),y=NA_rate))+geom_bar(stat='identity',fill='red')+
  labs(x='remained variables',title='missing rate of the remained variables')+
  theme(axis.text.x = element_text(angle=90,hjust=1))
```




```
str(train2)
```

```
## 'data.frame':    90275 obs. of  31 variables:
##  $ parcelid                    : int  10711738 10711755 10711805 10711816 10711858 10711910
 10712086 10712162 10712163 10712195 ...
##  $ logerror                    : num  0.0276 -0.0182 -0.1009 -0.0121 -0.0481 ...
##  $ transactiondate             : chr  "2016-08-02" "2016-08-02" "2016-05-03" "2016-04-05"
 ...
##  $ bathroomcnt                 : num  3 3 2 2 2 2 2 3 3 3 ...
##  $ bedroomcnt                  : int  4 3 3 4 4 3 4 3 4 3 ...
##  $ calculatedbathnbr           : num  3 3 2 2 2 2 2 3 3 3 ...
##  $ calculatedfinishedsquarefeet: int  2538 1589 2411 2232 1882 1477 1850 3193 2421 1678 ...
##  $ finishedsquarefeet12        : int  2538 1589 2411 2232 1882 1477 1850 3193 2421 1678 ...
##  $ fips                        : int  6037 6037 6037 6037 6037 6037 6037 6037 6037 6037 ...
##  $ fullbathcnt                 : int  3 3 2 2 2 2 2 3 3 3 ...
##  $ hashottuborspa              : chr  "" "" "" "" ...
##  $ latitude                    : int  34220381 34222040 34220427 34222390 34222544 34221864
 34226039 34226833 34226843 34223689 ...
##  $ longitude                   : int  -118620802 -118622240 -118618549 -118618631 -118617961
 -118615739 -118618527 -118612917 -118612422 -118612746 ...
##  $ lotsizesquarefeet           : num  11012 11010 11723 9002 9002 ...
##  $ propertycountylandusecode   : chr  "0101" "0101" "0101" "0100" ...
##  $ propertylandusetypeid       : int  261 261 261 261 261 261 261 261 261 261 ...
##  $ propertyzoningdesc          : chr  "LARE11" "LARE11" "LARE9" "LARE9" ...
##  $ rawcensustractandblock      : num  60371132 60371132 60371132 60371132 60371132 ...
##  $ regionidcity                : int  12447 12447 12447 12447 12447 12447 12447 12447 12447
 12447 ...
##  $ regionidcounty              : int  3101 3101 3101 3101 3101 3101 3101 3101 3101 3101 ...
##  $ regionidzip                 : int  96339 96339 96339 96339 96339 96339 96339 96339 96339
 96339 ...
##  $ roomcnt                     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ yearbuilt                   : int  1978 1959 1973 1973 1973 1960 1974 1964 1962 1961 ...
##  $ fireplaceflag               : chr  "" "" "" "" ...
##  $ structuretaxvaluedollarcnt  : num  245180 254691 235114 262309 232037 ...
##  $ taxvaluedollarcnt           : num  567112 459844 384787 437176 382055 ...
##  $ assessmentyear              : int  2015 2015 2015 2015 2015 2015 2015 2015 2015 2015 ...
##  $ landtaxvaluedollarcnt       : num  321932 205153 149673 174867 150018 ...
##  $ taxamount                   : num  7219 6901 4877 5560 4878 ...
##  $ taxdelinquencyflag          : chr  "" "" "" "" ...
##  $ censustractandblock         : num  6.04e+13 6.04e+13 6.04e+13 6.04e+13 6.04e+13 ...
```

3.Explore data

The original train dataset has 90275 observations and 61 variables. After removing data with missing rate more than 20%, 31 variables are remained.

Among these 31 variables, 18 are continuous variables. Except the outcome variablE logerror, the other 17 variables can be grouped into 5 categories.

1. room count related variables: bathroomcnt, bedroomcnt, caculatedbathnbr, fullbathcnt, roomcnt
2. house size related variables: calculatedfinishedsquarefeet, finishedsquarefeet12, lotsizesquarefeet
3. house location related: longitute, latitute

4)house value related: taxvaluedollarcnt, landtaxvaluedollarcnt, taxamount,structuretaxvaluedollarcnt

5. date related: yearbuilt, transactiondate , assessmentyear

There are 13 categorical variables: 1) parcelid

2. house adress related: fips, regionidcity, regionidcounty, regionidzip
3. house feature related: hashottuborspa, fireplaceflag
4. property use variable: propertycountylandusecode, propertyzoningdesc, propertylandusetypeid
5. tax : taxdelinquencyflag
6. census track and block variables: censustractandblock and rawcensustractandblock

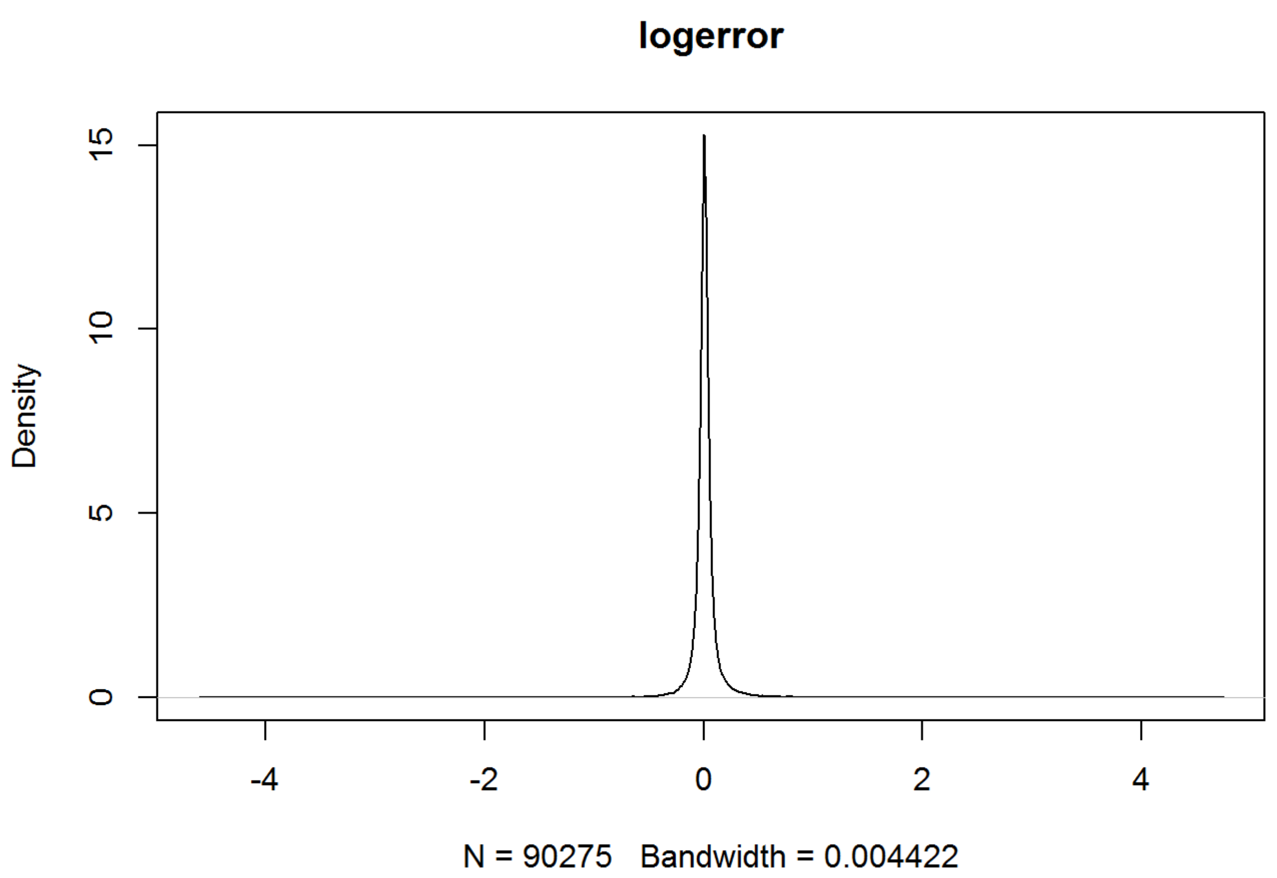
3.1 Univariate analysis

3.11 the outcome variable: logerror

```
summary(train2$logerror)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
## -4.60500 -0.02530  0.00600  0.01146  0.03920  4.73700
```

```
plot(density(train2$logerror),main='logerror')
```



Findings: in general, the logerror between estimated house price and the actual sale price is very small

3.12 Continuous variable

Roomcount related

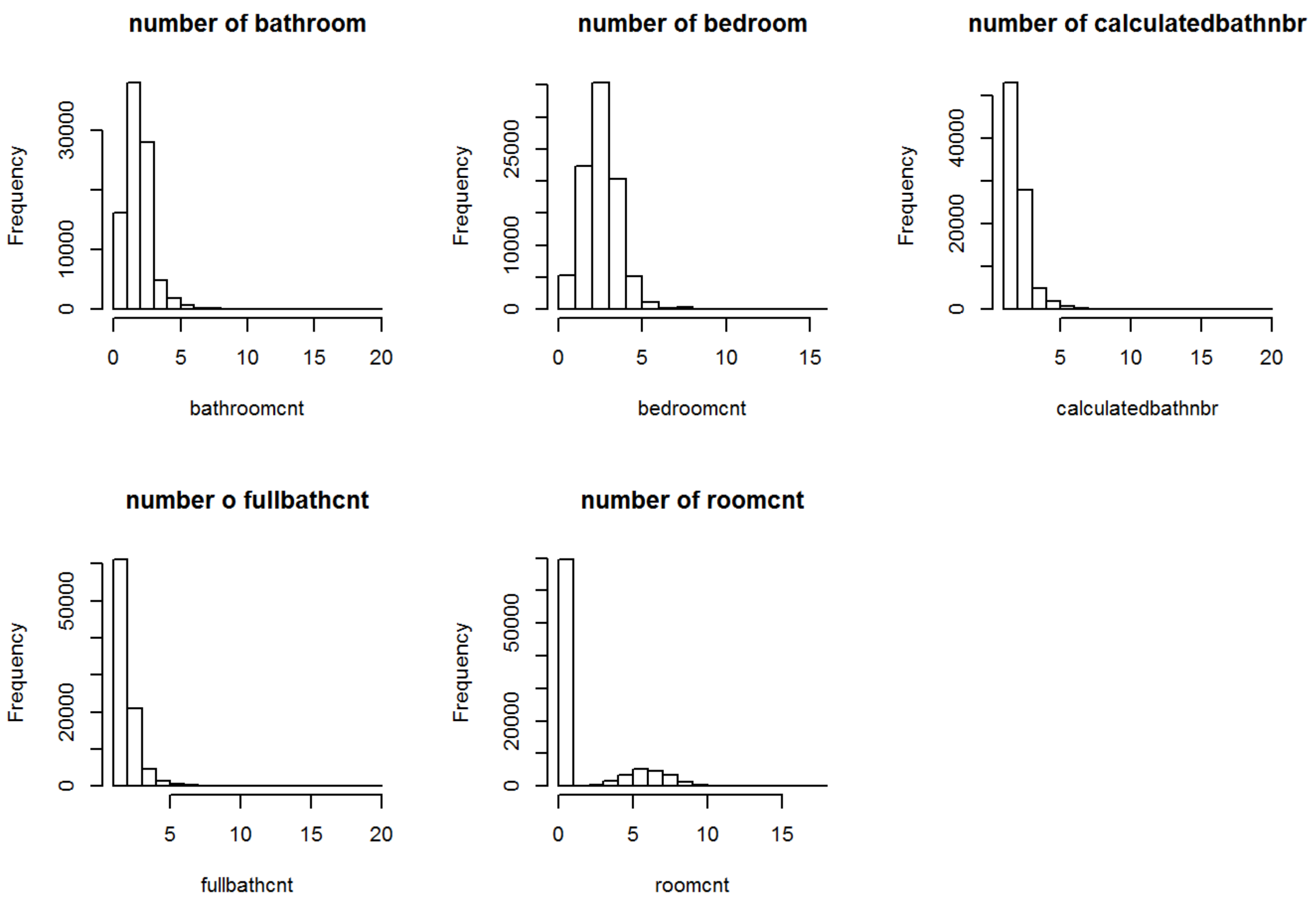
```
names(train2)
```

```
##  [1] "parcelid"                     "logerror"
##  [3] "transactiondate"              "bathroomcnt"
##  [5] "bedroomcnt"                   "calculatedbathnbr"
##  [7] "calculatedfinishedsquarefeet" "finishedsquarefeet12"
##  [9] "fips"                         "fullbathcnt"
## [11] "hashottuborspa"               "latitude"
## [13] "longitude"                    "lotsizesquarefeet"
## [15] "propertycountylandusecode"    "propertylandusetypeid"
## [17] "propertyzoningdesc"           "rawcensustractandblock"
## [19] "regionidcity"                 "regionidcounty"
## [21] "regionidzip"                  "roomcnt"
## [23] "yearbuilt"                    "fireplaceflag"
## [25] "structuretaxvaluedollarcnt"   "taxvaluedollarcnt"
## [27] "assessmentyear"               "landtaxvaluedollarcnt"
## [29] "taxamount"                    "taxdelinquencyflag"
## [31] "censustractandblock"
```

```
summary(train2[,c(4,5,6,10,22)])
```

```
##   bathroomcnt       bedroomcnt     calculatedbathnbr  fullbathcnt
##  Min.   : 0.000   Min.   : 0.000   Min.   : 1.000    Min.   : 1.000
##  1st Qu.: 2.000   1st Qu.: 2.000   1st Qu.: 2.000    1st Qu.: 2.000
##  Median : 2.000   Median : 3.000   Median : 2.000    Median : 2.000
##  Mean   : 2.279   Mean   : 3.032   Mean   : 2.309    Mean   : 2.241
##  3rd Qu.: 3.000   3rd Qu.: 4.000   3rd Qu.: 3.000    3rd Qu.: 3.000
##  Max.   :20.000   Max.   :16.000   Max.   :20.000    Max.   :20.000
##                                    NA's   :1182      NA's   :1182
##     roomcnt
##  Min.   : 0.000
##  1st Qu.: 0.000
##  Median : 0.000
##  Mean   : 1.479
##  3rd Qu.: 0.000
##  Max.   :18.000
##
```

```
par(mfrow=c(2,3))
hist(train2[,4],xlab='bathroomcnt',main='number of bathroom')
hist(train2[,5],xlab='bedroomcnt',main='number of bedroom')
hist(train2[,6],xlab='calculatedbathnbr',main='number of calculatedbathnbr')
hist(train2[,10],xlab='fullbathcnt',main='number o fullbathcnt')
hist(train2[,22],xlab='roomcnt',main='number of roomcnt')
```



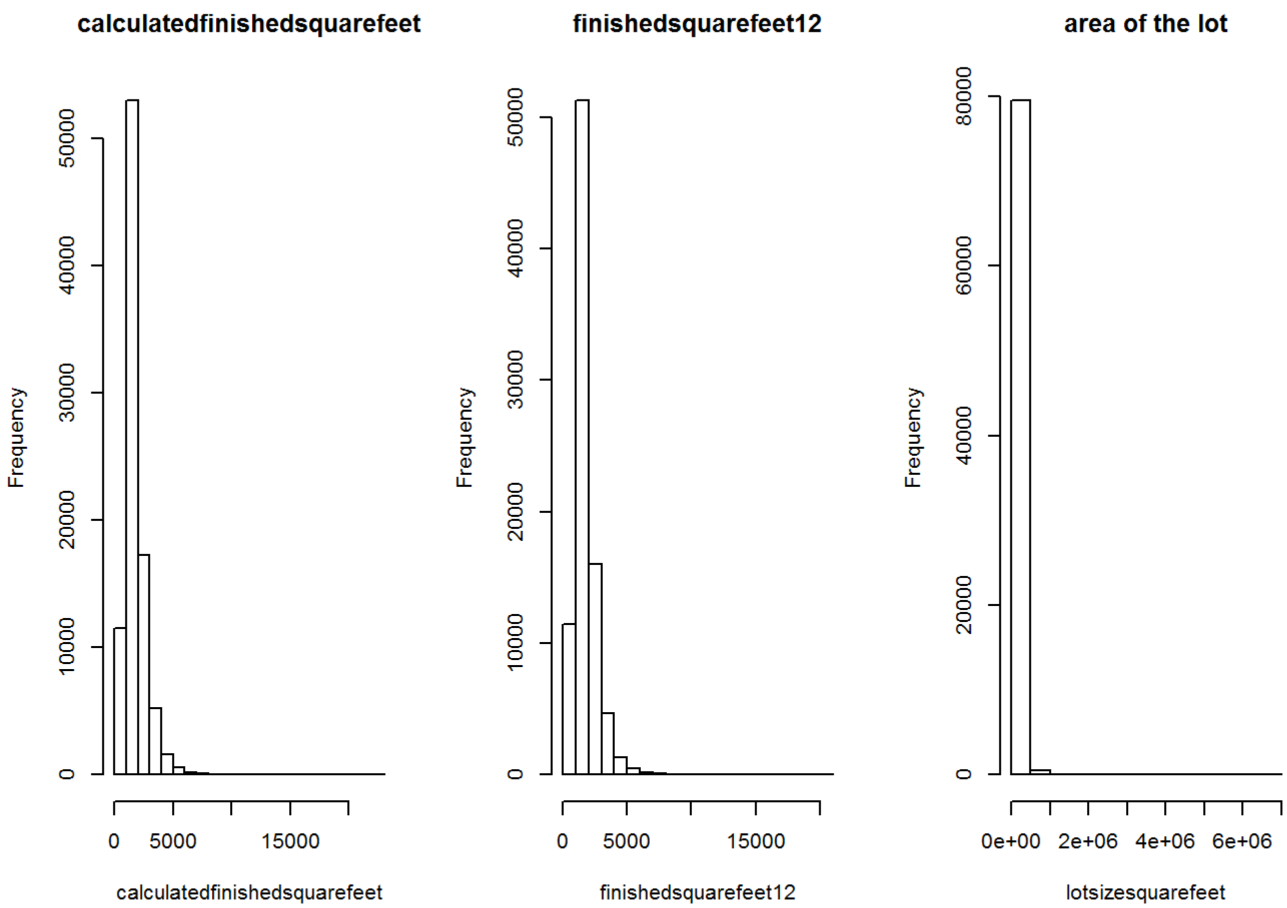
Findings: 1) the distribution of bathroom and bedroom are positively skewed 2) most houses have less than 5 bedroom and bathrooms 3) apart from some houses with only one room, a lot of houses have 5~8 rooms in total 4) bathroomcnt, bedroomcnt and roomcnt have better data quality cuz they do not have NAs

House size related

```
summary(train2[,c(7,8,14)])
```

```
##  calculatedfinishedsquarefeet finishedsquarefeet12 lotsizesquarefeet
##  Min.   :    2                Min.   :    2        Min.   :    167
##  1st Qu.: 1184                1st Qu.: 1172        1st Qu.:   5703
##  Median : 1540                Median : 1518        Median :   7200
##  Mean   : 1773                Mean   : 1745        Mean   :  29110
##  3rd Qu.: 2095                3rd Qu.: 2056        3rd Qu.:  11686
##  Max.   :22741                Max.   :20013        Max.   :6971010
##  NA's   :661                  NA's   :4679         NA's   :10150
```

```
par(mfrow=c(1,3))
hist(train2[,7],xlab='calculatedfinishedsquarefeet',main='calculatedfinishedsquarefeet')
hist(train2[,8],xlab='finishedsquarefeet12',main='finishedsquarefeet12')
hist(train2[,14],xlab='lotsizesquarefeet',main='area of the lot')
```



House location related variables

```
summary(train2[,c(12,13)])
```

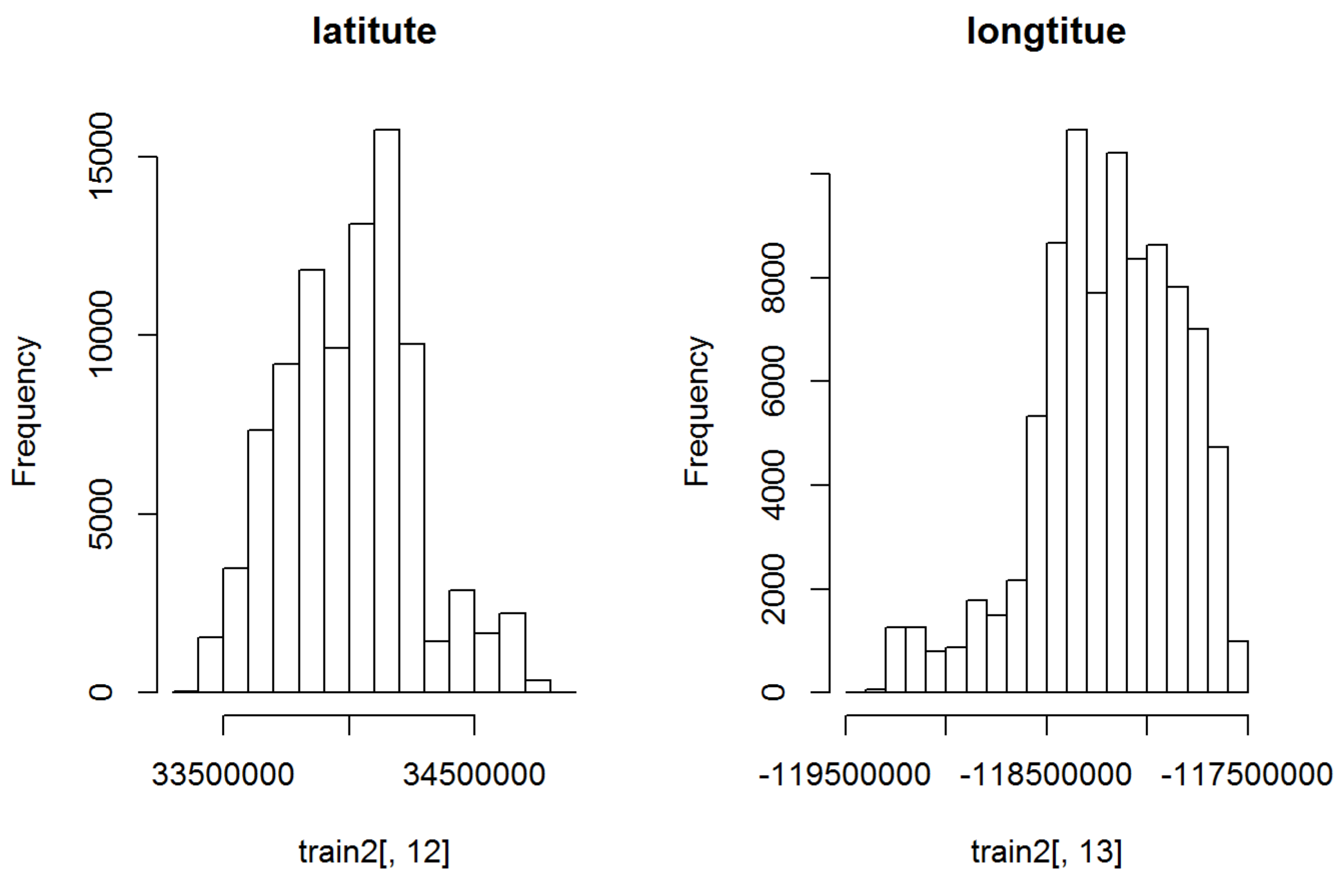
```
##     latitude          longitude
##  Min.   :33339295   Min.   :-119447865
##  1st Qu.:33811538   1st Qu.:-118411692
##  Median :34021500   Median :-118173431
##  Mean   :34005411   Mean   :-118198868
##  3rd Qu.:34172742   3rd Qu.:-117921588
##  Max.   :34816009   Max.   :-117554924
```

```
par(mfrow=c(1,2))
hist(train2[,12],main='latitute')
```

```
## Warning in n * h: 整数上溢产生了NA
```

```
hist(train2[,13],main='longtitue')
```

```
## Warning in n * h: 整数上溢产生了NA
```

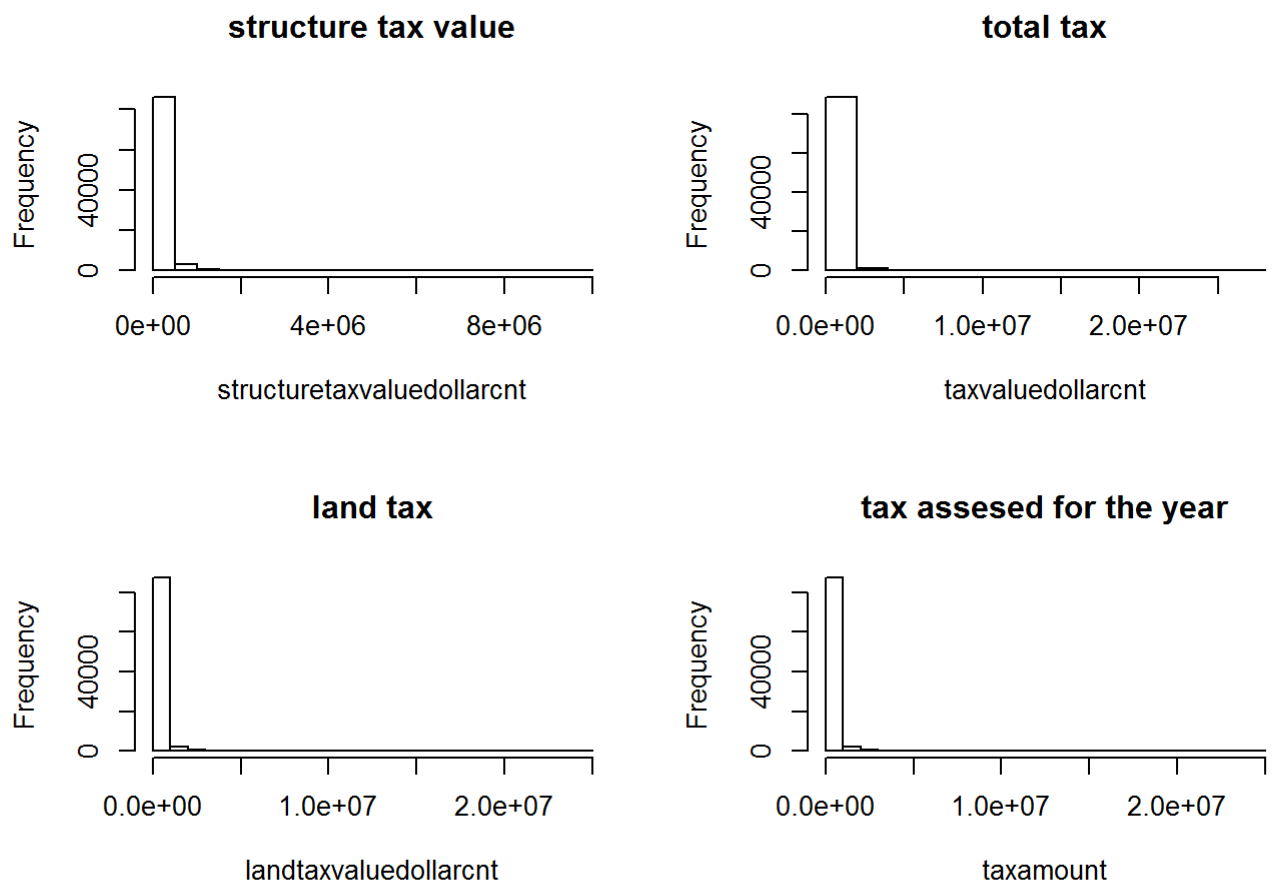


House value related variables

```
summary(train2[,c(25,26,28,29)])
```

```
##  structuretaxvaluedollarcnt taxvaluedollarcnt  landtaxvaluedollarcnt
##  Min.   :    100            Min.   :       22  Min.   :       22
##  1st Qu.:  81245            1st Qu.:   199023  1st Qu.:    82228
##  Median : 132000            Median :   342872  Median :   192970
##  Mean   : 180093            Mean   :   457673  Mean   :   278335
##  3rd Qu.: 210534            3rd Qu.:   540589  3rd Qu.:   345420
##  Max.   :9948100            Max.   :27750000   Max.   :24500000
##  NA's   :380                NA's   :1          NA's   :1
##    taxamount
##  Min.   :    49.1
##  1st Qu.:  2872.8
##  Median :  4542.8
##  Mean   :  5984.0
##  3rd Qu.:  6901.1
##  Max.   :321936.1
##  NA's   :6
```

```
par(mfrow=c(2,2))
hist(train2[,25],xlab='structuretaxvaluedollarcnt',main='structure tax value')
hist(train2[,26],xlab='taxvaluedollarcnt',main='total tax')
hist(train2[,28],xlab='landtaxvaluedollarcnt',main='land tax')
hist(train2[,28],xlab='taxamount',main='tax assesed for the year')
```



####Date variables

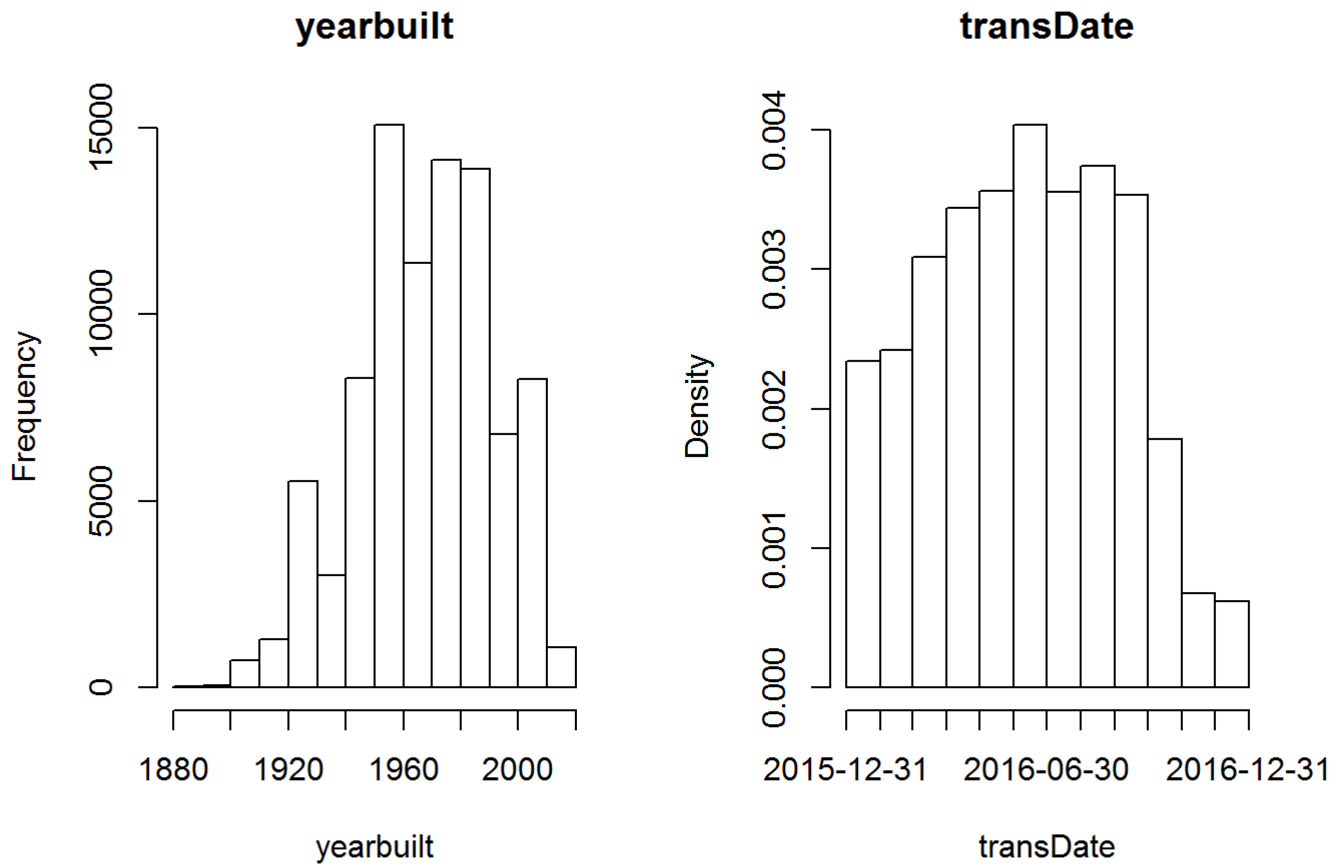
```
#convert transactiondate from character to date format and create a new variable transdate to s
tore it
train2$transDate<-as.Date(train2$transactiondate,'%Y-%m-%d')
summary(train2[,c(23,27,32)])
```

```
##    yearbuilt    assessmentyear   transDate
##  Min.   :1885   Min.   :2015   Min.   :2016-01-01
##  1st Qu.:1953   1st Qu.:2015   1st Qu.:2016-04-05
##  Median :1970   Median :2015   Median :2016-06-14
##  Mean   :1969   Mean   :2015   Mean   :2016-06-11
##  3rd Qu.:1987   3rd Qu.:2015   3rd Qu.:2016-08-19
##  Max.   :2015   Max.   :2015   Max.   :2016-12-30
##  NA's   :756
```

```
str(train2[,c(23,27,32)])
```

```
## 'data.frame':    90275 obs. of  3 variables:
##  $ yearbuilt     : int  1978 1959 1973 1973 1973 1960 1974 1964 1962 1961 ...
##  $ assessmentyear: int  2015 2015 2015 2015 2015 2015 2015 2015 2015 2015 ...
##  $ transDate     : Date, format: "2016-08-02" "2016-08-02" ...
```

```
par(mfrow=c(1,2))
hist(train2[,23],xlab='yearbuilt',main='yearbuilt')
hist(train2[,32],xlab='transDate',main='transDate',breaks='months')
```



3.1.3categorical variables

House adress related variables

```
#fips distribution
table(train2$fips)/nrow(train2)
```

```
##
##       6037       6059       6111
## 0.64883966 0.27144835 0.07971199
```

```
#6037 for LA county, 6059 for Orange county and 6111 for ventura
```

```
#city distribution
#table(train2$regionidcity)

#county distribution
#table(train2$regionidcounty)

#zip
#table(train2$regionidzip)
```

House feature variable

```
table(train2$hashottuborspa)/nrow(train2)
```

```
##
##                  true
## 0.97380227 0.02619773
```

```
table(train2$fireplaceflag)/nrow(train2)
```

```
##
##                    true
## 0.997540847 0.002459153
```

Findings: very few houses have fireplace or spa tub

propertyuse variable

```
table(train2$propertycountylandusecode)
```

```
##
##           0   010  0100  0101  0102  0103  0104  0108  0109  010C  010D
##     1     1     1 30846  7435     3   100   348    46    27 10264  2209
##  010E  010F  010G  010H  010M  010V  0110  0111  0114  012C  012D  012E
##  2286    28    80    72    59   201     4     1     1   523     4     7
##  0130  0131  01DC  01DD  01HC  0200  0201  020G  020M  0210  0300  0301
##     1     1   251     1   148  2153    43     4     1     1   578     1
##  0303  030G  0400  0401  040A  040V  0700  070D     1  100V  1011  1012
##     1     2   747     4     1     6    54     7  2915     5     2     2
##  1014   105  1110  1111  1112  1116  1117  1128  1129  1200  1210   122
##    32     4  1117  3883     5    11    46   356  1643     1    47 15383
##  1222  1310  1321  1333   135  1410  1420  1421  1432  1720  1722   200
##    28     4     7     1    35    13     1     2     2     7     1     1
##    34    38  6050    73  8800    96
##  5946   106     1    11     1   104
```

```
#table(train2$propertyzoningdesc)
```

tax related

```
table(train2$taxdelinquencyflag)/nrow(train2)
```

```
##
##                     Y
## 0.98024924 0.01975076
```

Findings:2% of the houses have tax delinquency

3.2 Bivariate analysis

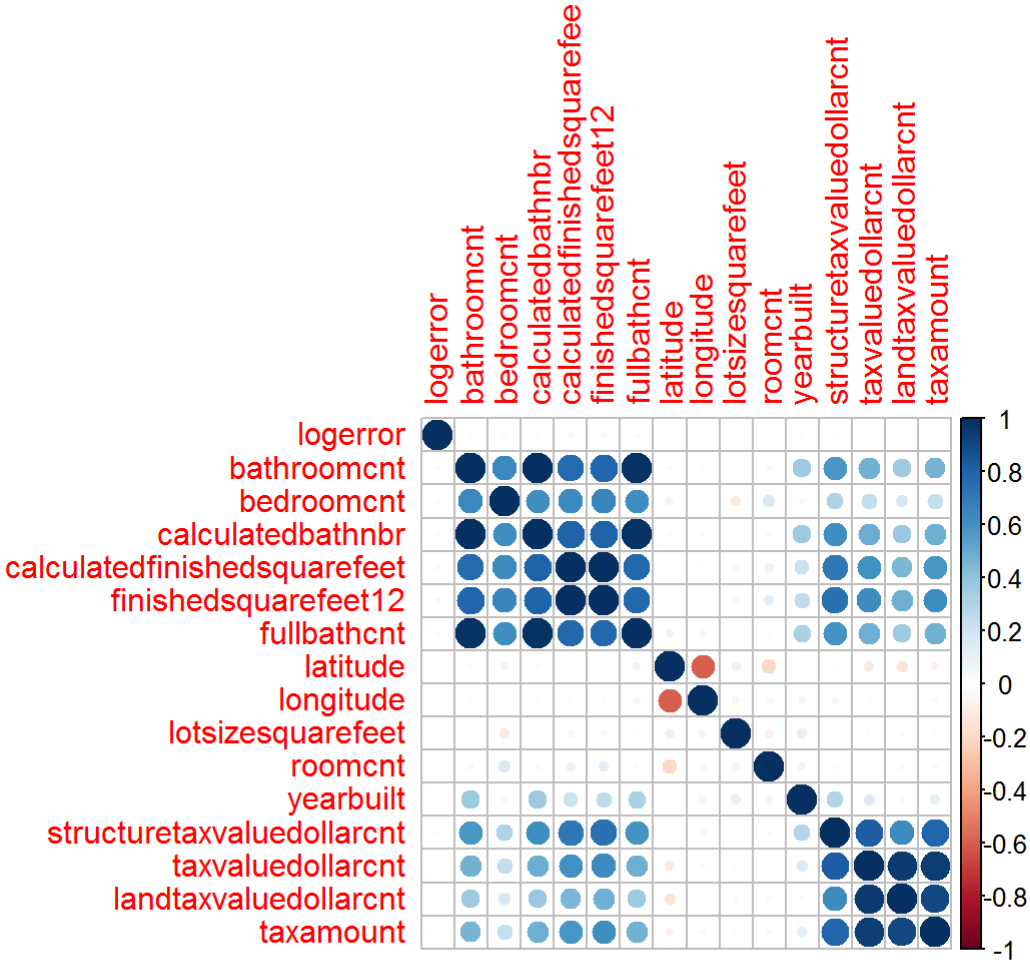
3.2.1 continuous vs outcome

```
corr<-cor(train2[,c(2,4:8,10,12:14,22,23,25,26,28,29)],use='pairwise.complete.obs')
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 3.4.3
```

```
## corrplot 0.84 loaded
```

```
corrplot(corr)
```

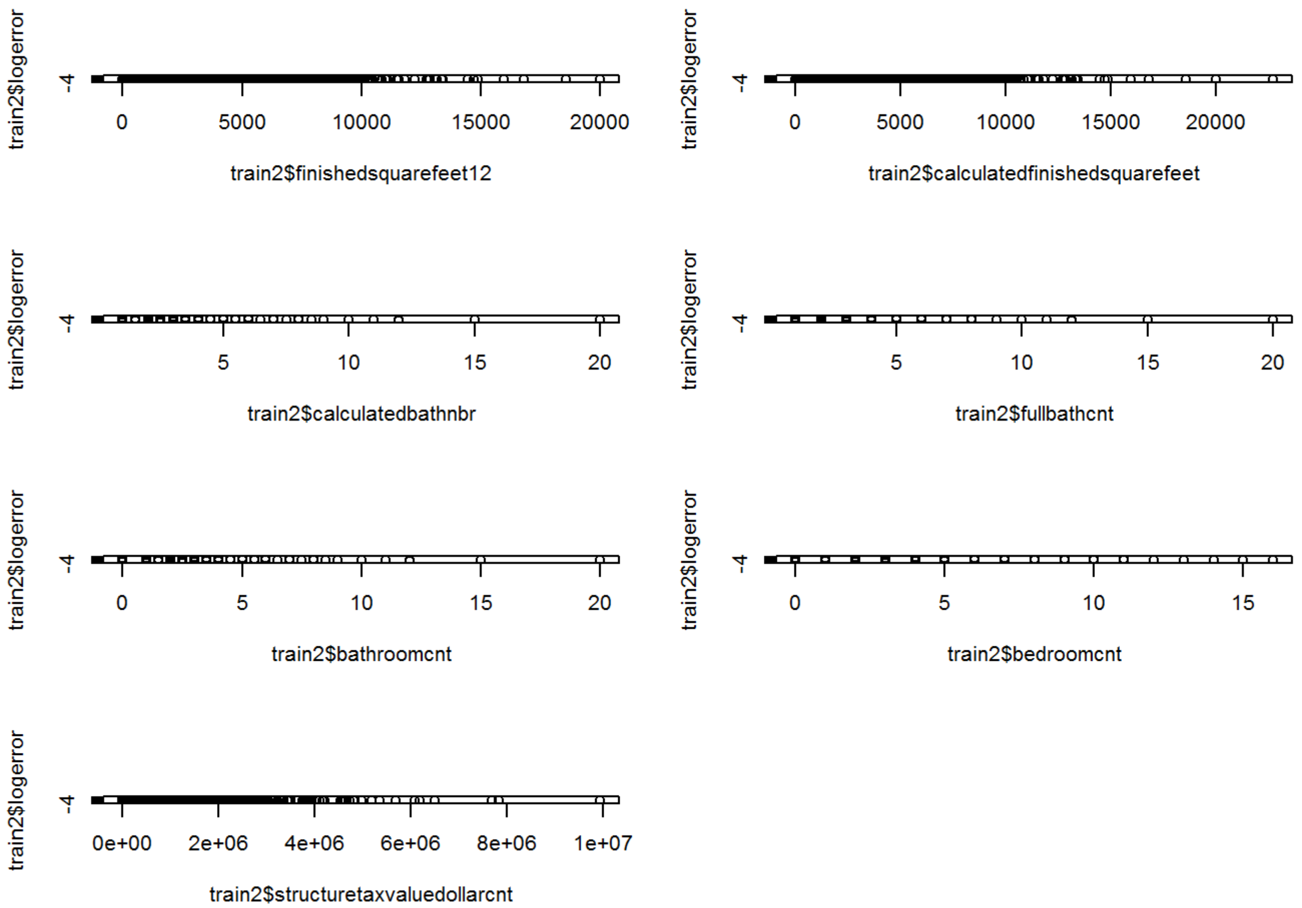



```
cor_logerror<-sort(corr[,1],decreasing = T)
cor_logerror
```

```
##                     logerror          finishedsquarefeet12
##                  1.000000000                   0.041922367
## calculatedfinishedsquarefeet             calculatedbathnbr
##                  0.038784069                   0.029447685
##                  fullbathcnt                   bathroomcnt
##                  0.028845122                   0.027889287
##                   bedroomcnt    structuretaxvaluedollarcnt
##                  0.025467090                   0.022084970
##                    yearbuilt             taxvaluedollarcnt
##                  0.017312211                   0.006507999
##                      roomcnt                      latitude
##                  0.005759796                   0.004915466
##            lotsizesquarefeet         landtaxvaluedollarcnt
##                  0.004835250                  -0.003051035
##                    longitude                     taxamount
##                 -0.003432217                  -0.006671116
```

```
#corelations are all soooo weak
```

```
#show corelation between each variable and the logerror
par(mfrow=c(4,2))
plot(train2$finishedsquarefeet12,train2$logerror)
plot(train2$calculatedfinishedsquarefeet,train2$logerror)
plot(train2$calculatedbathnbr,train2$logerror)
plot(train2$fullbathcnt,train2$logerror)
plot(train2$bathroomcnt,train2$logerror)
plot(train2$bedroomcnt,train2$logerror)
plot(train2$structuretaxvaluedollarcnt,train2$logerror)
```



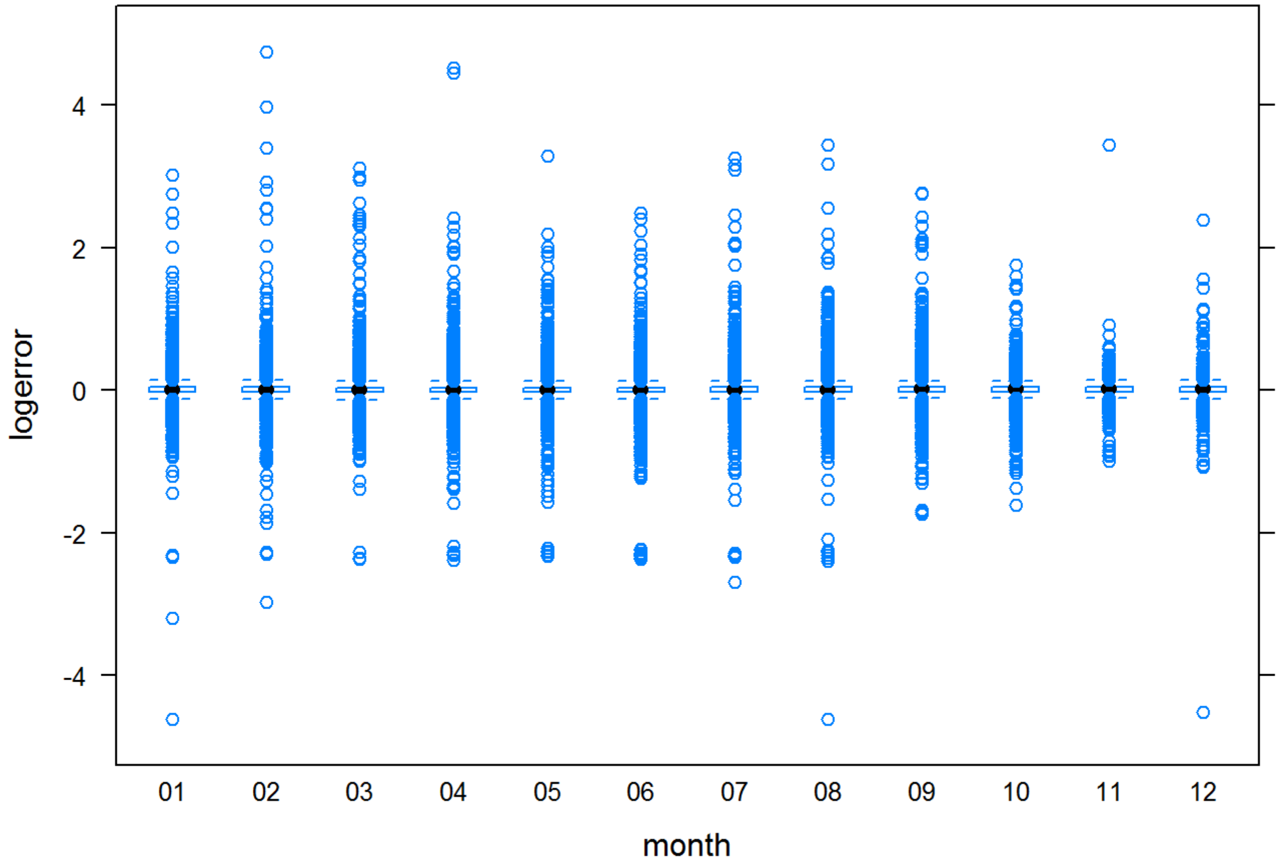
the points are randomly scattered and indicates the corelation is weak

correlation between the transDate and the logerror

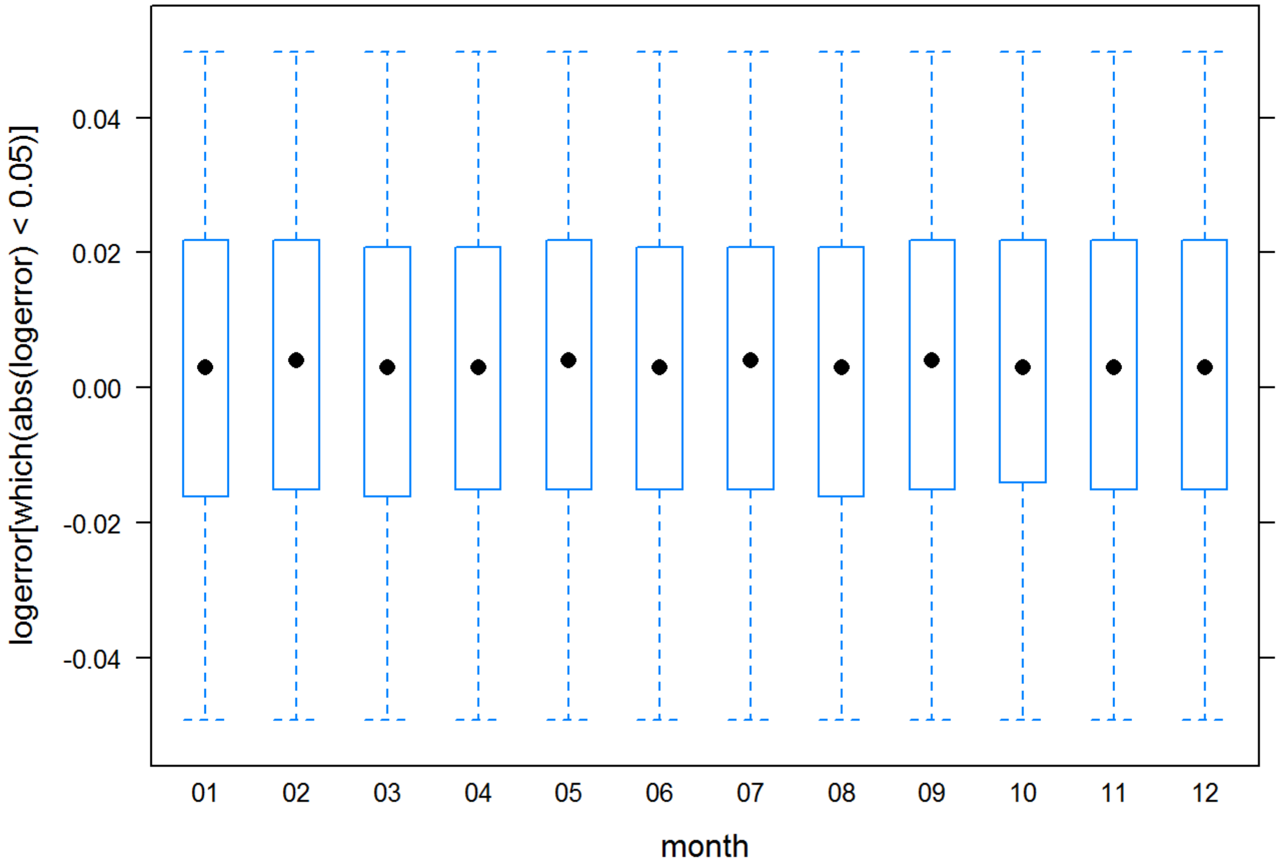
```
library(lattice)
```

```
## Warning: package 'lattice' was built under R version 3.4.3
```

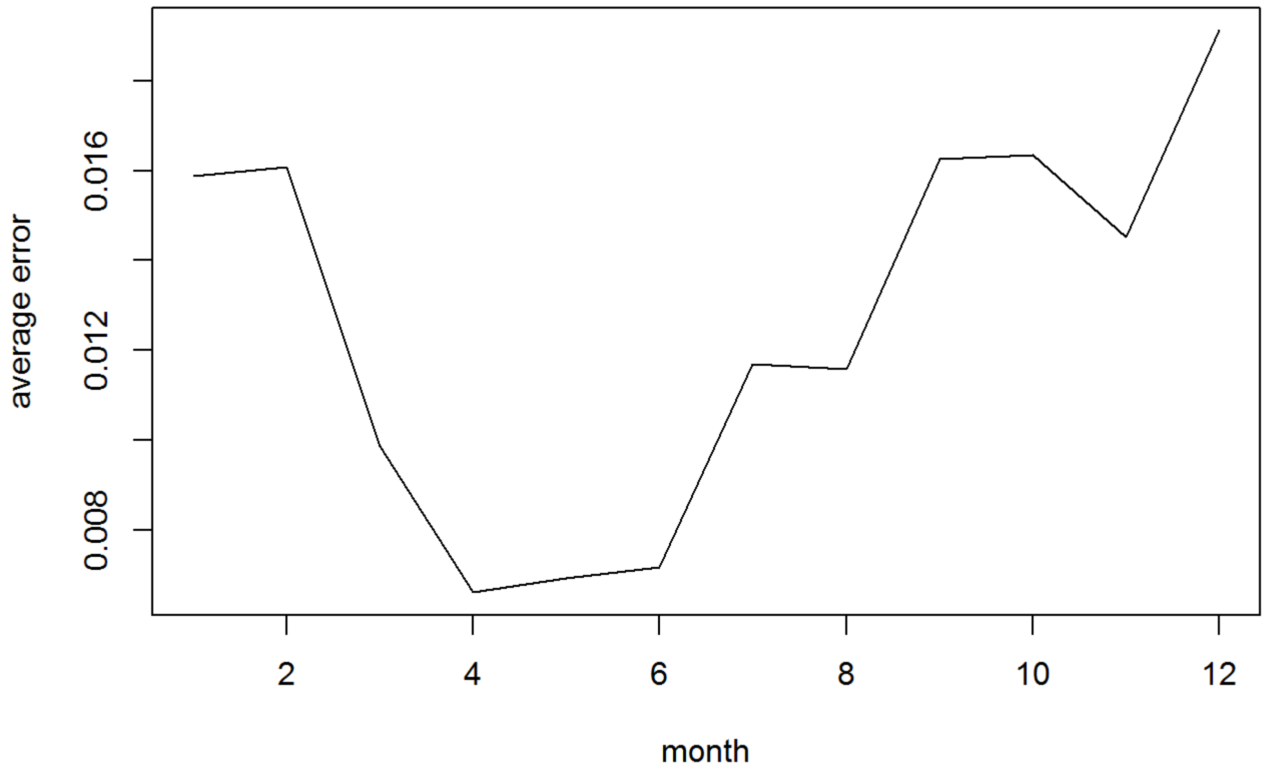
```
train2$transMonth<-sapply(strsplit(train2$transactiondate,'-'),function(x) x[2])
bwplot(logerror~transMonth,data=train2,xlab='month')
```




```
bwplot(logerror[which(abs(logerror)<0.05)]~transMonth,data=train2,xlab='month')
```



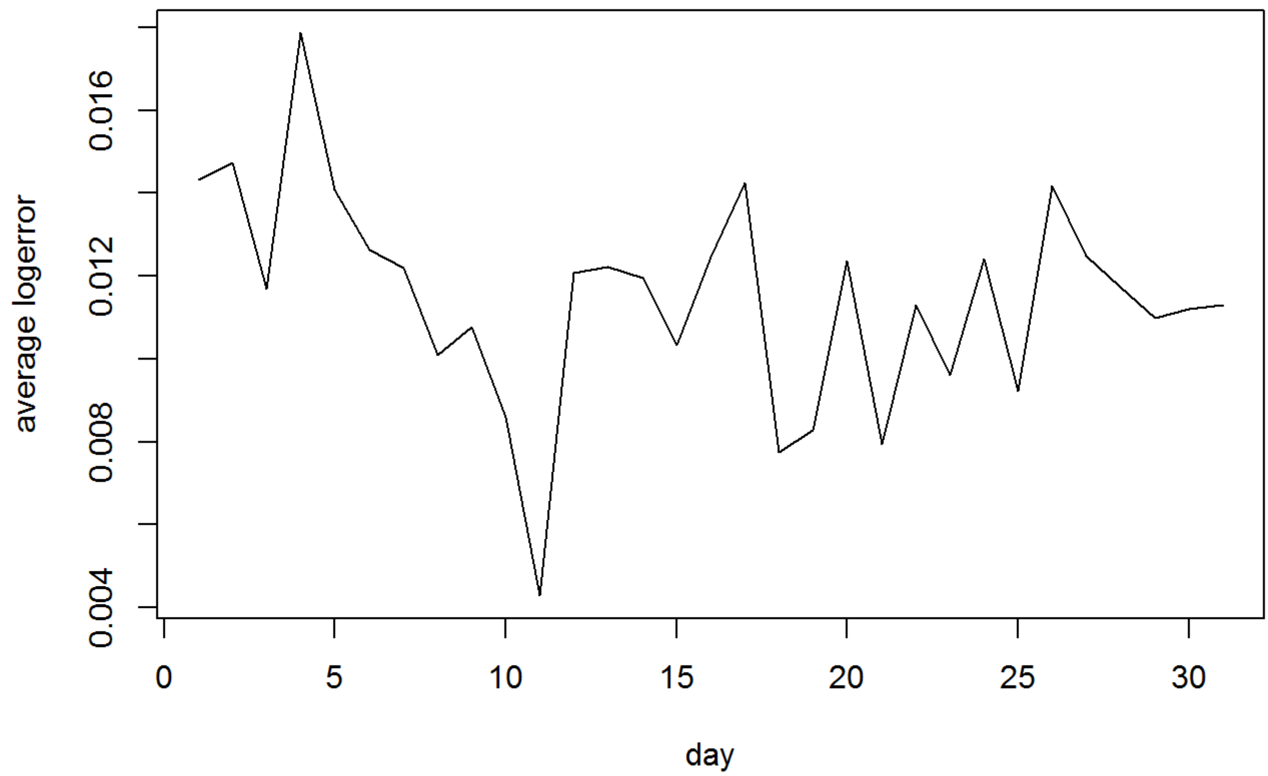
```
err.month<-by(train2,train2$transMonth,function(x){return(mean(x$logerror))})
plot(names(err.month),err.month,type='l',xlab='month',ylab='average error')
```



Findings: distributon of logerror is similar, but average logerror differs in the month of april, may, june

transaction day with logerror

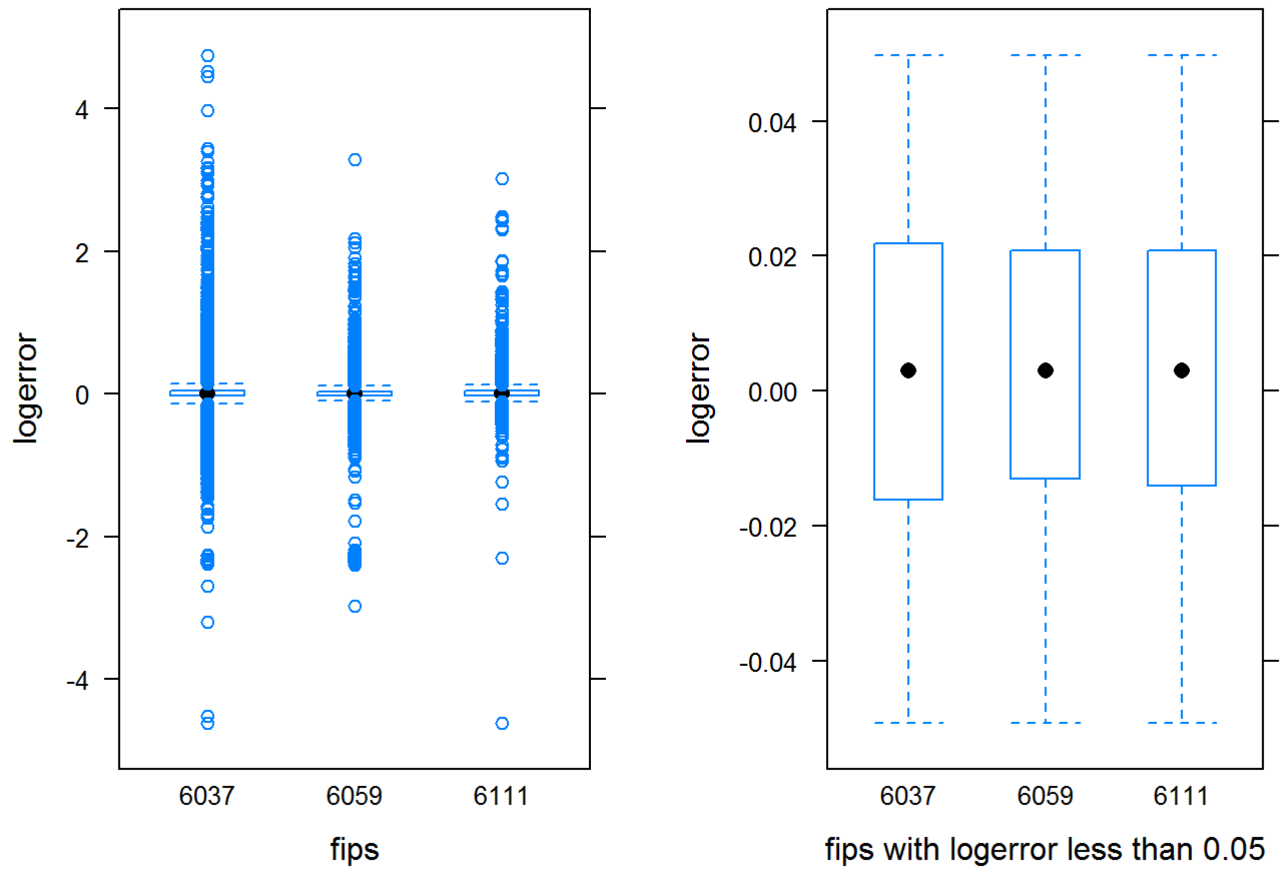
```
train2$transDay<-sapply(strsplit(train2$transactiondate,'-'),function(x) x[3])
err.day<-by(train2,train2$transDay,function(x){return(mean(x$logerror))})
plot(names(err.day),err.day,type='l',xlab='day',ylab='average logerror')
```



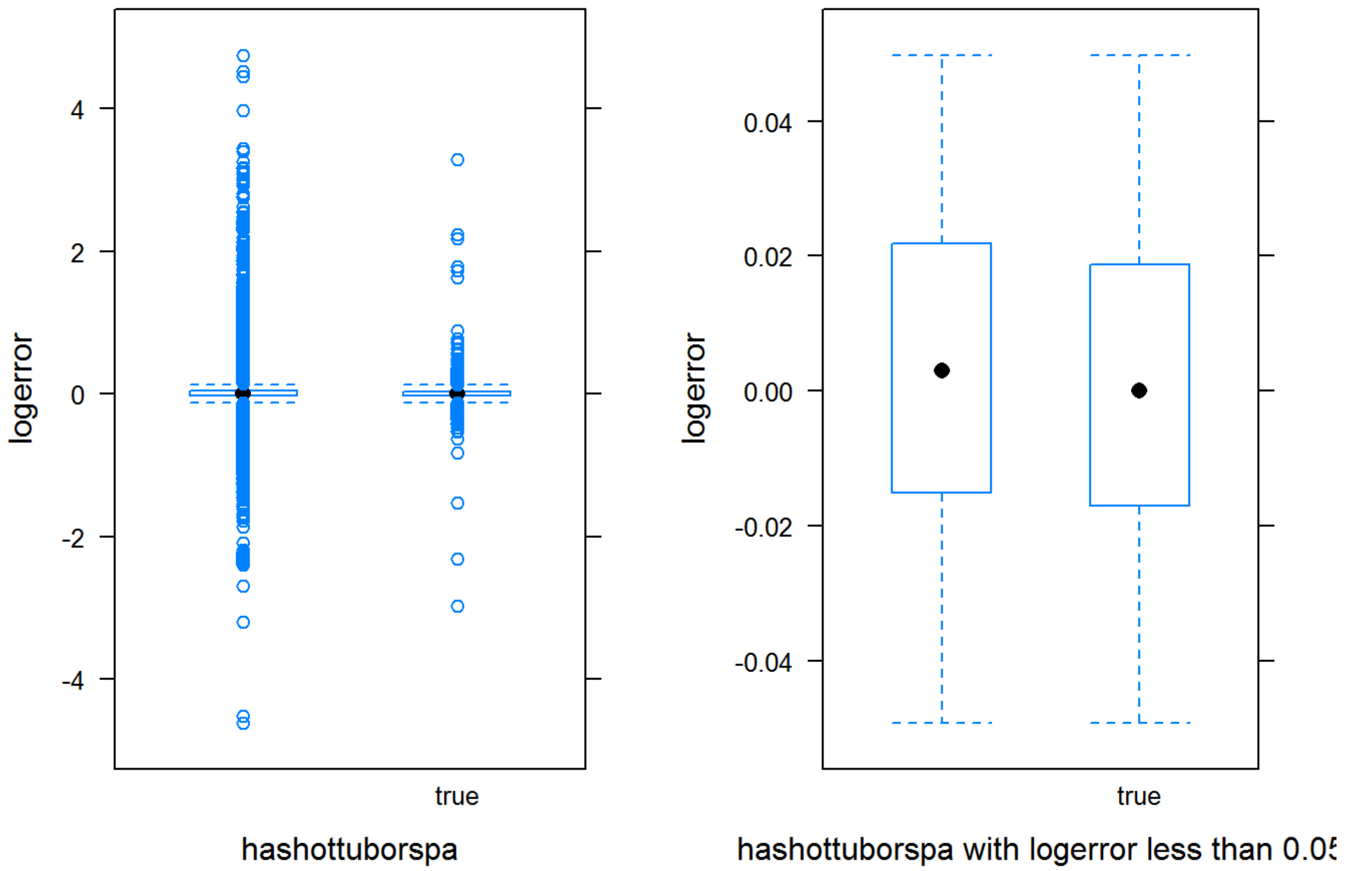
3.2.2categorical variables vs outcome

For categorical variables , I would explore the relationship between the logerror and the fips, hashottuborspa,fireplaceflag,propertylanusetypeid, taxdelinquency

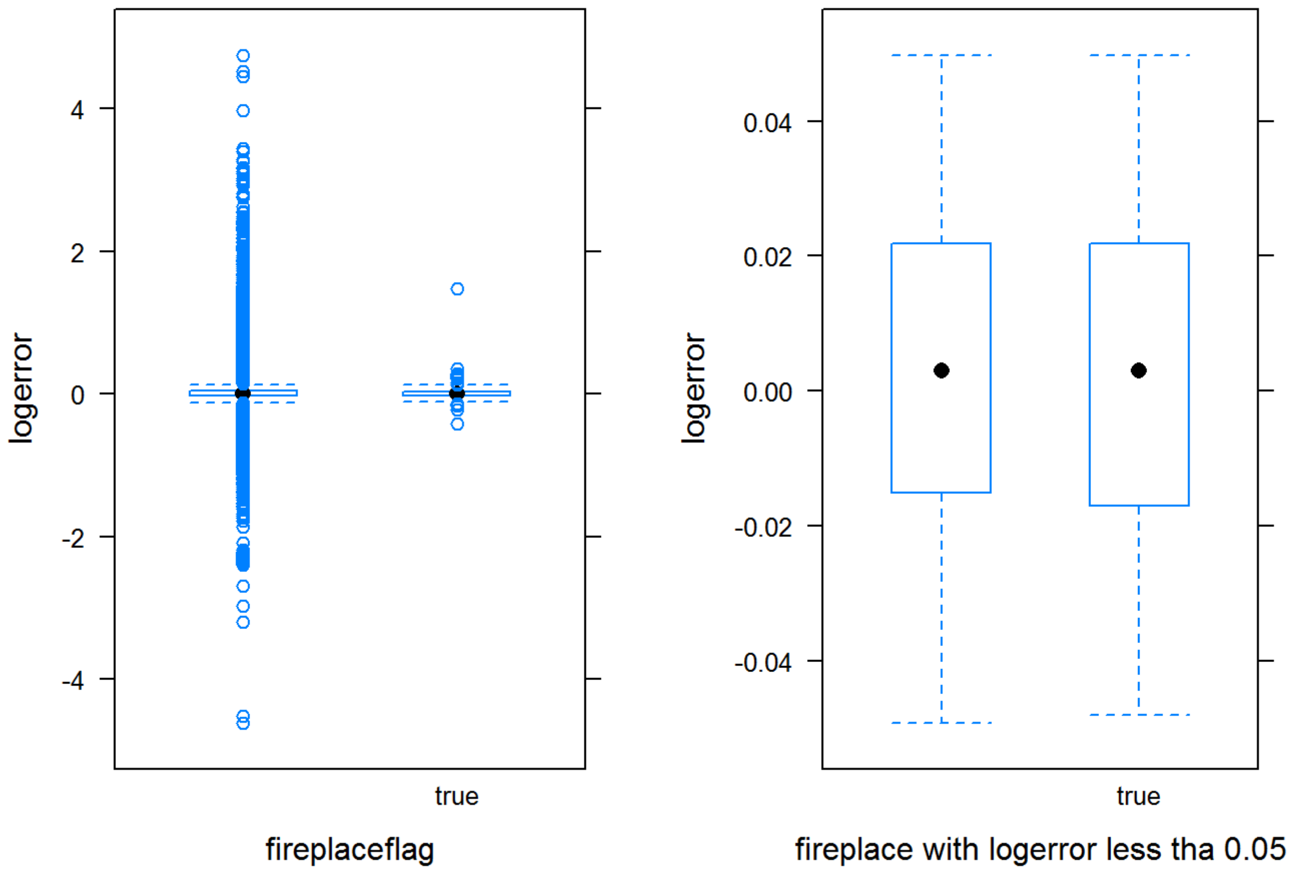
```
library(lattice)
library(gridExtra)
fipsPlot1<-bwplot(logerror~as.character(fips),data=train2,xlab='fips')
fipsPlot2<-bwplot(logerror~as.character(fips),data=subset(train2,abs(logerror)<.05),
                  xlab='fips with logerror less than 0.05')
grid.arrange(fipsPlot1,fipsPlot2,ncol=2)
```



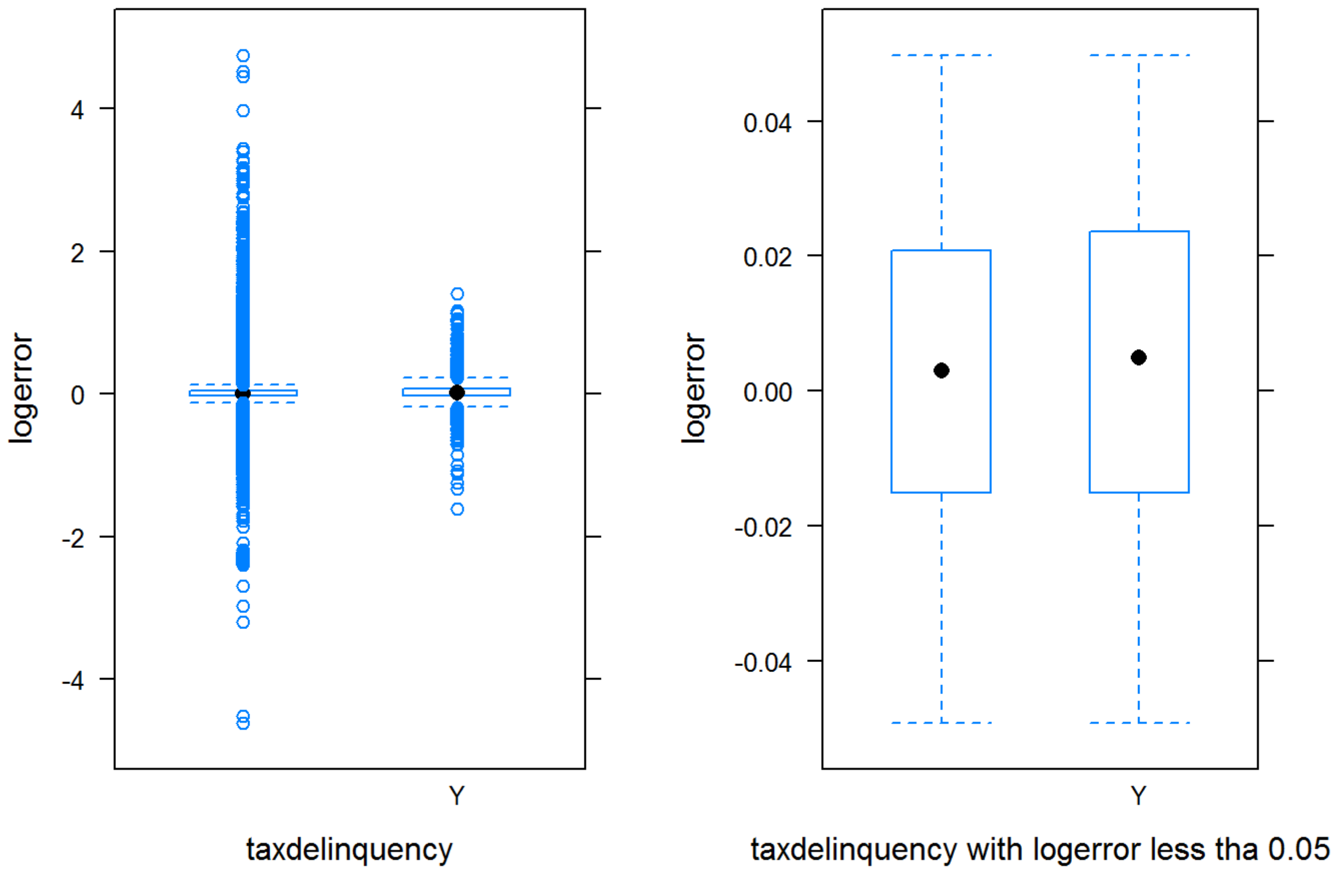

```
spaPlot1<-bwplot(logerror~hashottuborspa,data=train2,xlab='hashottuborspa')
spaPlot2<-bwplot(logerror~hashottuborspa,data=subset(train2,abs(logerror)<.05),
                  xlab='hashottuborspa with logerror less than 0.05')
grid.arrange(spaPlot1,spaPlot2,ncol=2)
```



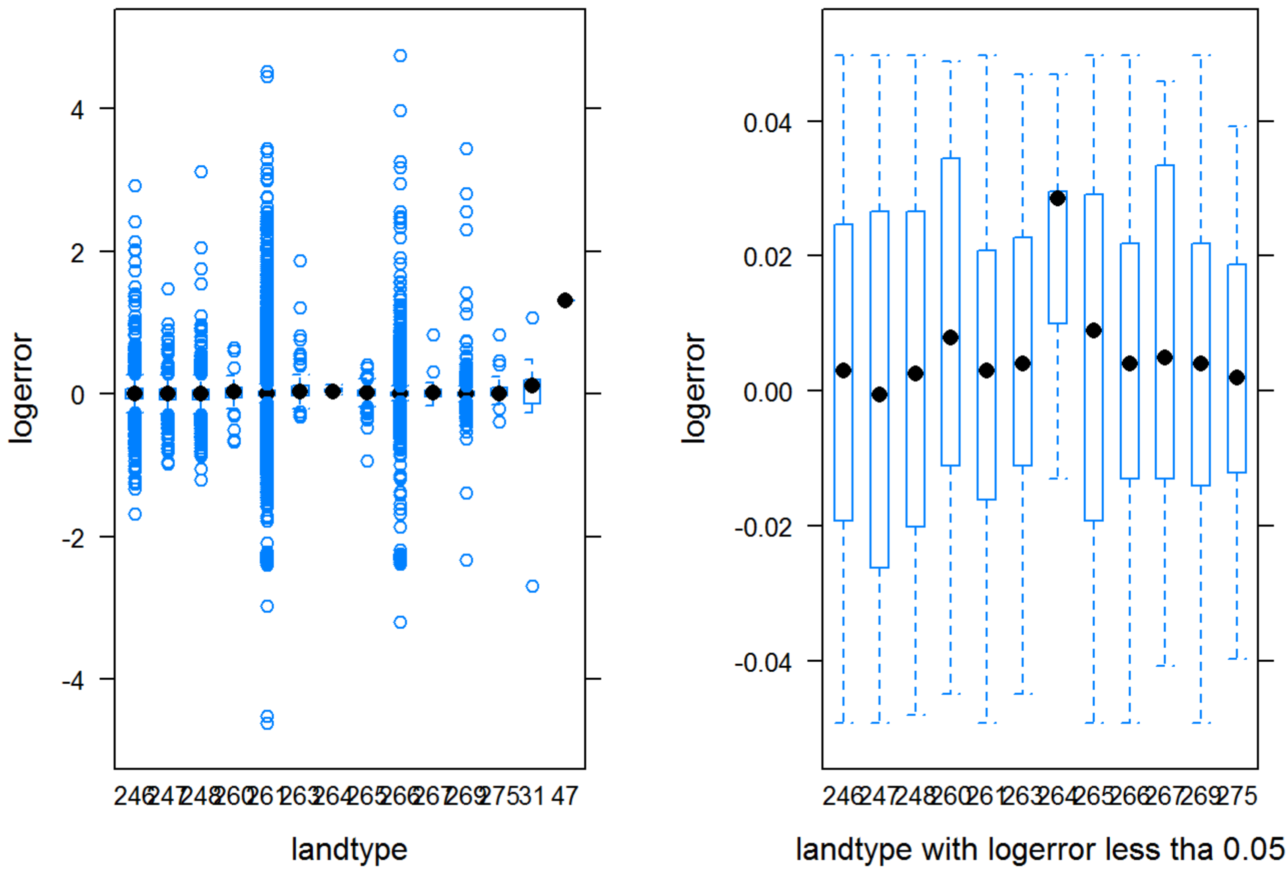

```
firePlot1<-bwplot(logerror~fireplaceflag,data=train2,xlab='fireplaceflag')
firePlot2<-bwplot(logerror~fireplaceflag,data=subset(train2,abs(logerror)<.05),
                                                     xlab='fireplace with logerror less tha 0.0
5')
grid.arrange(firePlot1,firePlot2,ncol=2)
```




```
taxPlot1<-bwplot(logerror~taxdelinquencyflag,data=train2,xlab='taxdelinquency')
taxPlot2<-bwplot(logerror~taxdelinquencyflag,data=subset(train2,abs(logerror)<.05),
                              xlab='taxdelinquency with logerror less tha 0.05')
grid.arrange(taxPlot1,taxPlot2,ncol=2)
```




```
landPlot1<-bwplot(logerror~as.character(propertylandusetypeid),data=train2,xlab='landtype')
landPlot2<-bwplot(logerror~as.character(propertylandusetypeid),data=subset(train2,abs(logerror)
<.05),
                              xlab='landtype with logerror less tha 0.05')
grid.arrange(landPlot1,landPlot2,ncol=2)
```




```
anova(with(train2,lm(logerror~as.character(fips))))
```

```
## Analysis of Variance Table
##
## Response: logerror
##                       Df  Sum Sq  Mean Sq F value   Pr(>F)
## as.character(fips)     2    0.27 0.136935  5.2781 0.005104 **
## Residuals          90272 2342.01 0.025944
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(with(train2,lm(logerror~as.character(propertylandusetypeid))))
```

```
## Analysis of Variance Table
##
## Response: logerror
##                                         Df Sum Sq  Mean Sq F value
## as.character(propertylandusetypeid)     13    2.8 0.215373  8.3094
## Residuals                            90261 2339.5 0.025919
##                                         Pr(>F)
## as.character(propertylandusetypeid) < 2.2e-16 ***
## Residuals
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(with(train2,lm(logerror~hashottuborspa)))
```

```
## Analysis of Variance Table
##
## Response: logerror
##                   Df  Sum Sq  Mean Sq F value Pr(>F)
## hashottuborspa     1    0.06 0.062835  2.4218 0.1197
## Residuals      90273 2342.22 0.025946
```

```
anova(with(train2,lm(logerror~fireplaceflag)))
```

```
## Analysis of Variance Table
##
## Response: logerror
##                  Df Sum Sq   Mean Sq F value Pr(>F)
## fireplaceflag     1    0.0 0.0032303  0.1245 0.7242
## Residuals     90273 2342.3 0.0259466
```

```
anova(with(train2,lm(logerror~taxdelinquencyflag)))
```

```
## Analysis of Variance Table
##
## Response: logerror
##                       Df  Sum Sq Mean Sq F value    Pr(>F)
## taxdelinquencyflag     1    0.84 0.83984   32.38 1.272e-08 ***
## Residuals          90273 2341.44 0.02594
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Findings: taxdelinquence, fips and propertylandusetypeid really matters

3.2.3 create new variables

number of houses sold by city

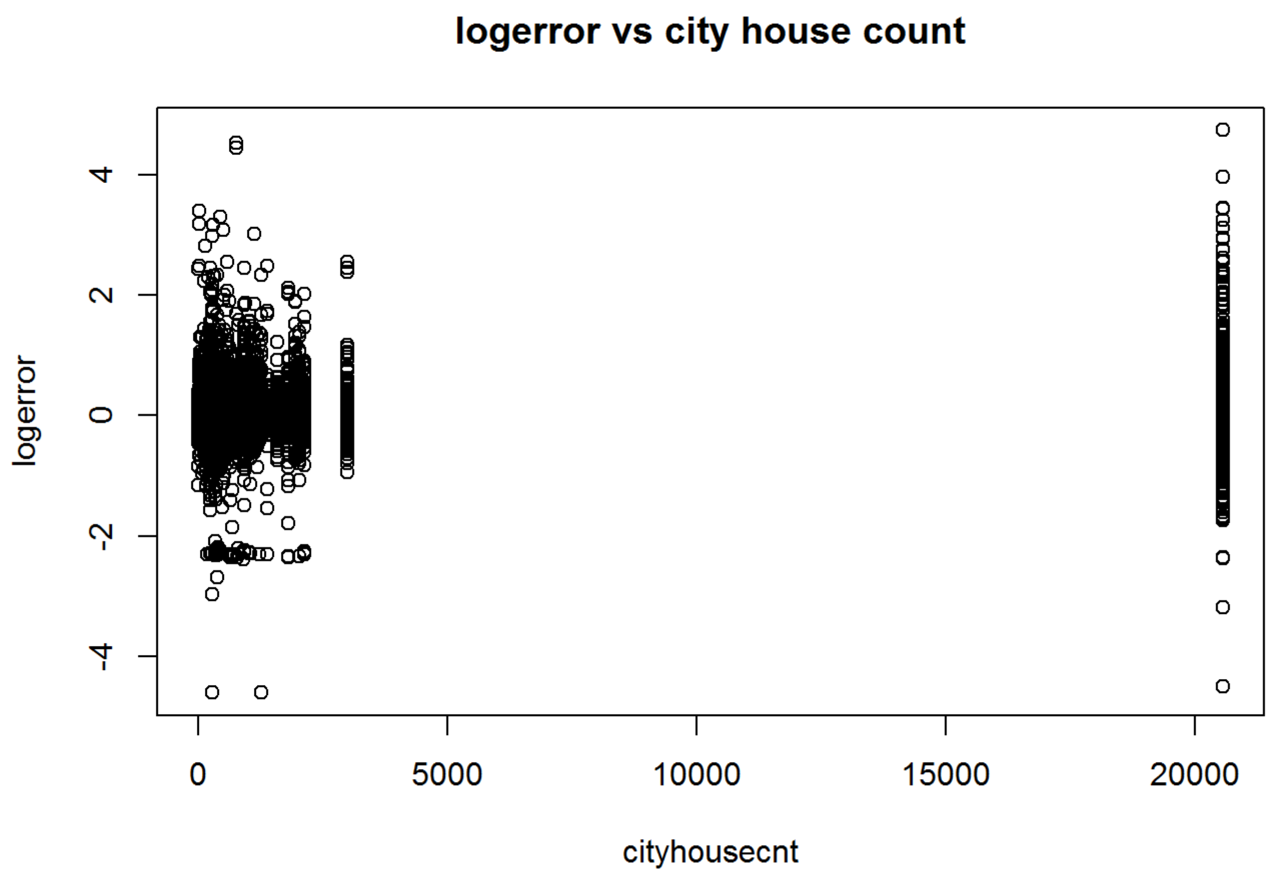
```
#calculate the number of houses sold by city
library(plyr)
```

```
## Warning: package 'plyr' was built under R version 3.4.3
```

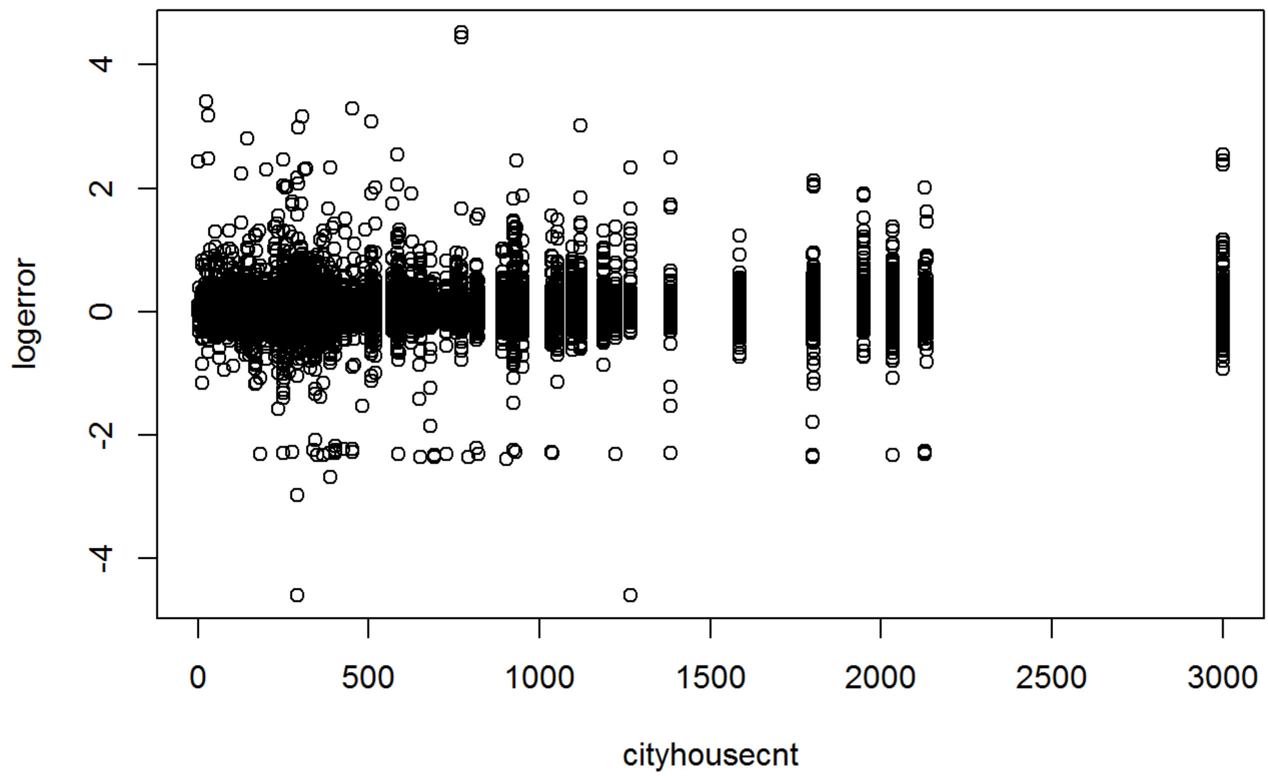
```
house.city<-ddply(train2,.(regionidcity),summarise,cityhousecnt=length(regionidcity))

train3<-merge(train2,house.city,by='regionidcity',all.x=T)

with(train3,plot(cityhousecnt,logerror,main='logerror vs city house count' ))
```




```
train3_sub<-train3[train3$cityhousecnt != max(train3$cityhousecnt),]
with(train3_sub,plot(cityhousecnt,logerror))
```

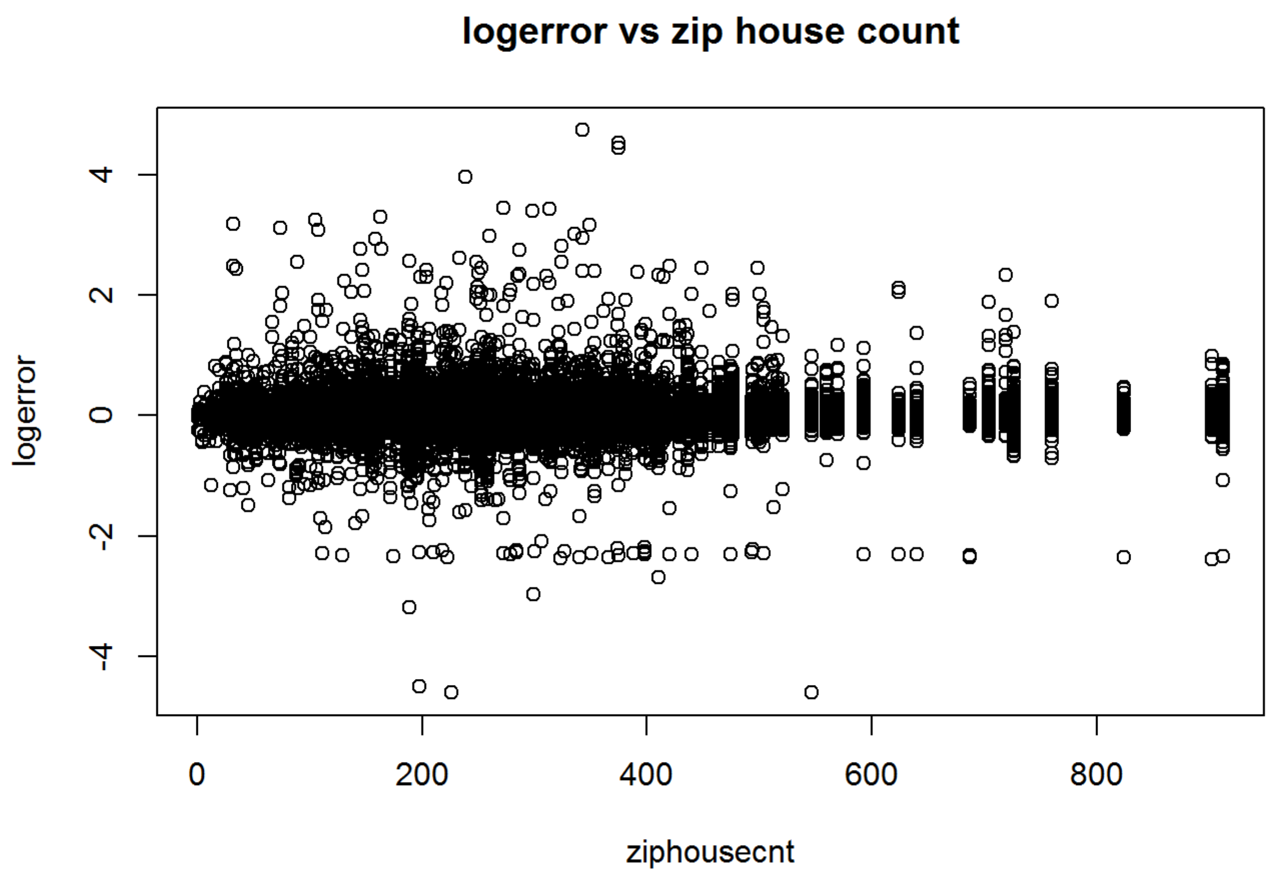


####number of house sold by zip

```
house.zip<-ddply(train2,.(regionidzip),summarise,ziphousecnt=length(regionidzip))

train4<-merge(train2,house.zip,by='regionidzip',all.x=T)

with(train4,plot(ziphousecnt,logerror,main='logerror vs zip house count' ))
```



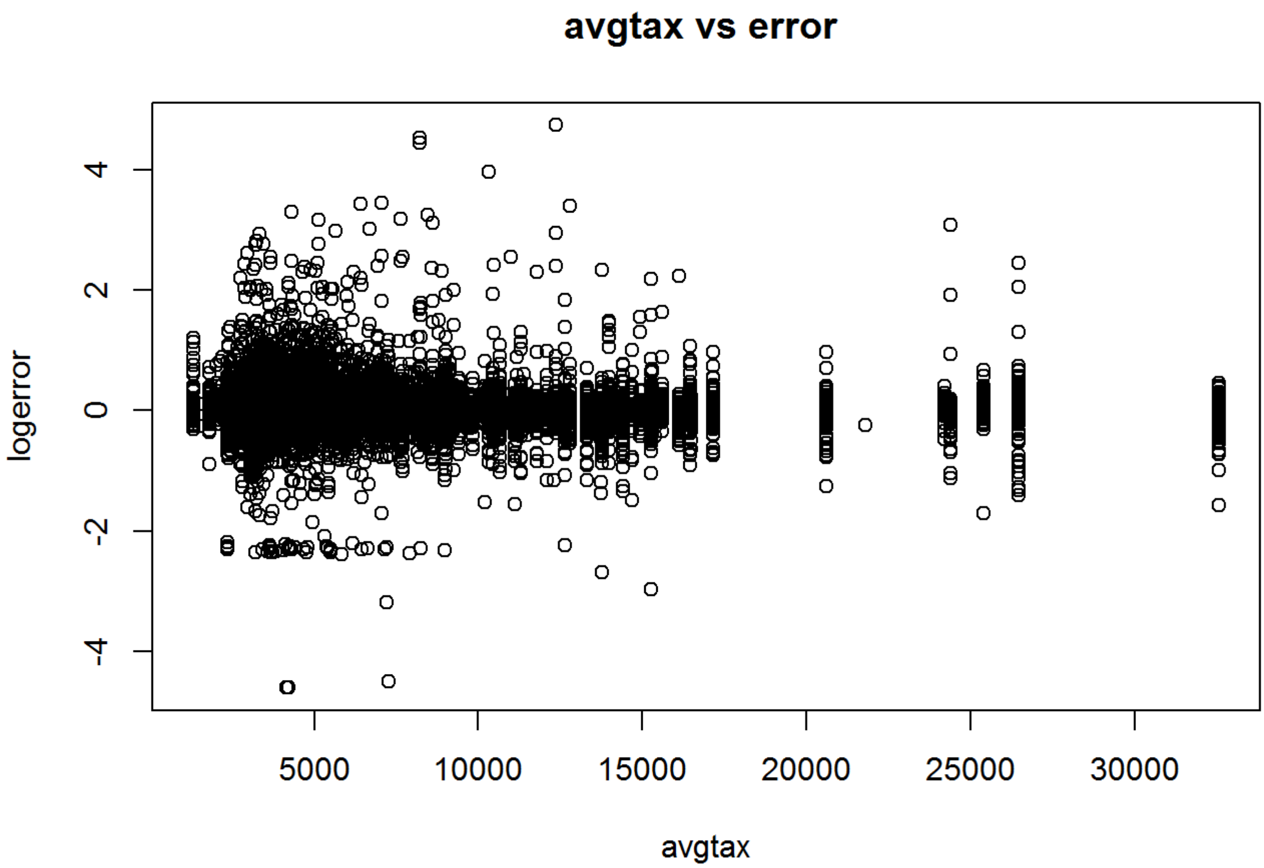

```
cor(train4$ziphousecnt,train$logerror)
```

```
## [1] 0.0002476373
```

community quality

```
price.zip<-ddply(train4,.(regionidzip),summarize,avgtax=mean(taxamount,na.rm = T))
train5<-merge(train4,price.zip,by='regionidzip',all.x=T)

with(train5,plot(avgtax,logerror,main='avgtax vs error ' ))
```


avgtax vs error
logerror
avgtax
-4
-2
0
2
4
5000
10000
15000
20000
25000
30000