Zillow_EDA

```
library(tabplot)
library(lattice)
setwd("D:/data_camp/zillow_project")
train <- read.csv("train_property.csv",stringsAsFactors = FALSE)
```

1. Data cleaning

We found there are some missing values, let us take a look.

```
num.NA  <- sort(colSums(sapply(train,is.na)))
num.NA.perc <- num.NA/dim(train)[1]
```

We can see a lot features have a large portion of missing value, however, before we decided to delete some of these features, let us take a look at whether the missing proportion of each row might influence log value. We do that because we want to make sure that the percentage of missing value in each row do not have influence on logerror.

```
row.NA.perc <- rowSums(sapply(train,is.na))/dim(train)[2]
log.error <- train$logerror
cor(log.error,row.NA.perc)
```

```
## [1] -0.005944324
```

We can see the corrlation is all most 0. So for now, let us delete these features that has more than 80% missing value

```
delete.thredshold <- 0.2
remain.rows <- names(num.NA)[num.NA.perc < delete.thredshold]
train <- train[ , remain.rows]
print(paste(ncol(train)/ncol(train),"of the features are not deleted"))
```

```
## [1] "1 of the features are not deleted"
```

Done! We cleaned up the NA part for now.

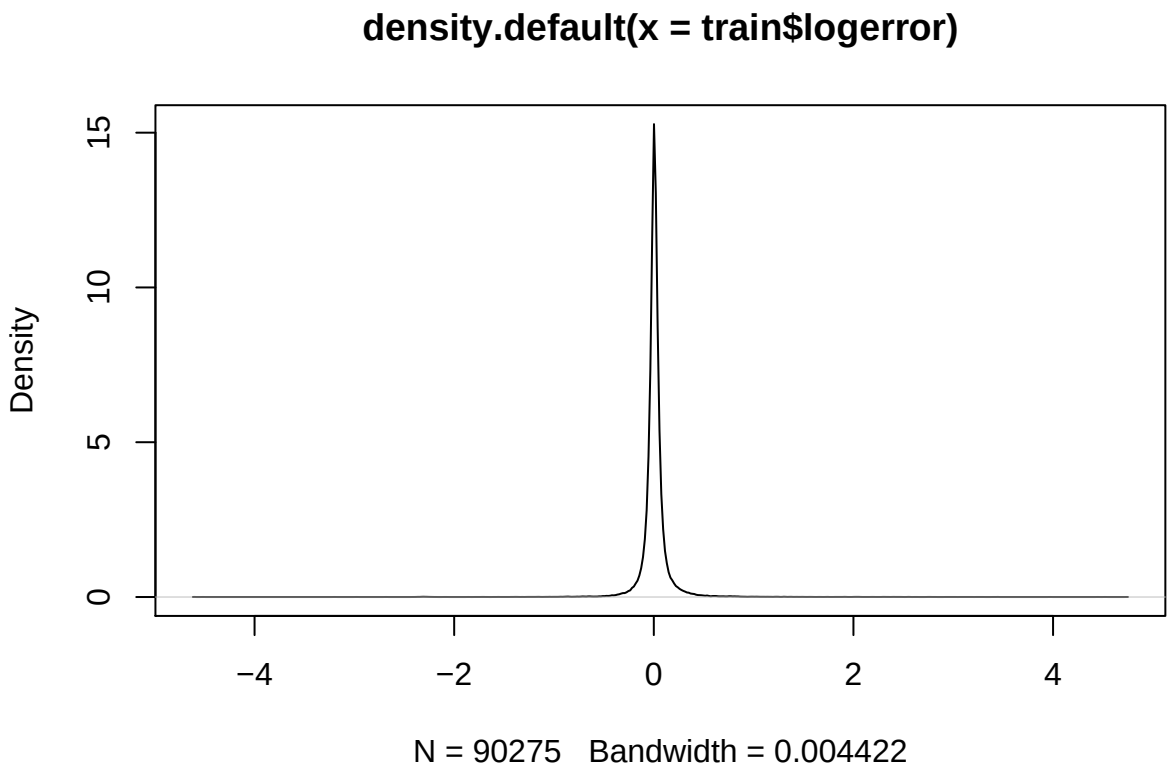
The other thing we have to do is to set some of the feature to character for further exploration

```
train[, c('fips', 'propertylandusetypeid', 'rawcensustractandblock', 'regionidcounty', 'assessmentyear'
  as.character(train[, c('fips', 'propertylandusetypeid', 'rawcensustractandblock', 'regionidcounty', '
```

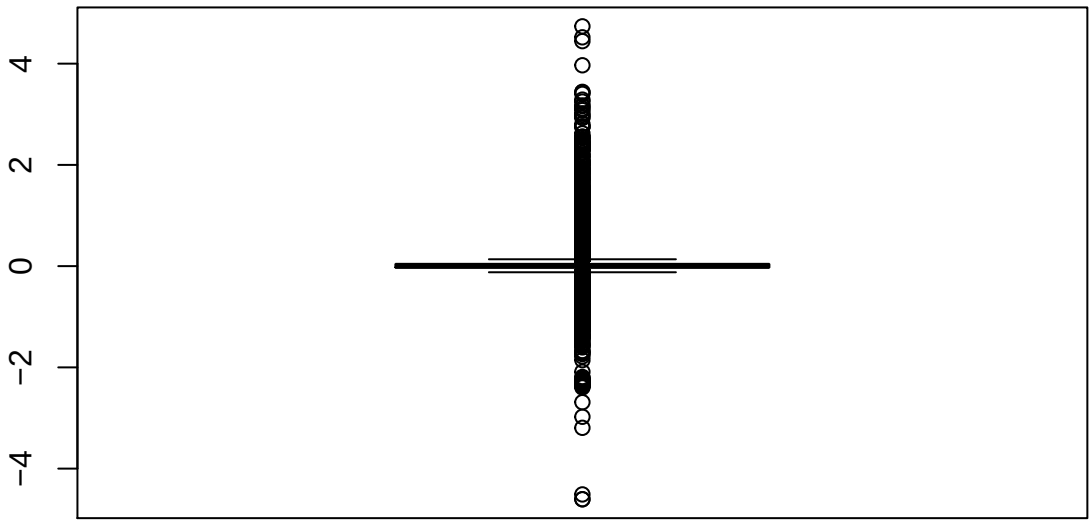
2: EDA

First let us take a look at the distribution of logerror

```
plot(density(train$logerror))
```



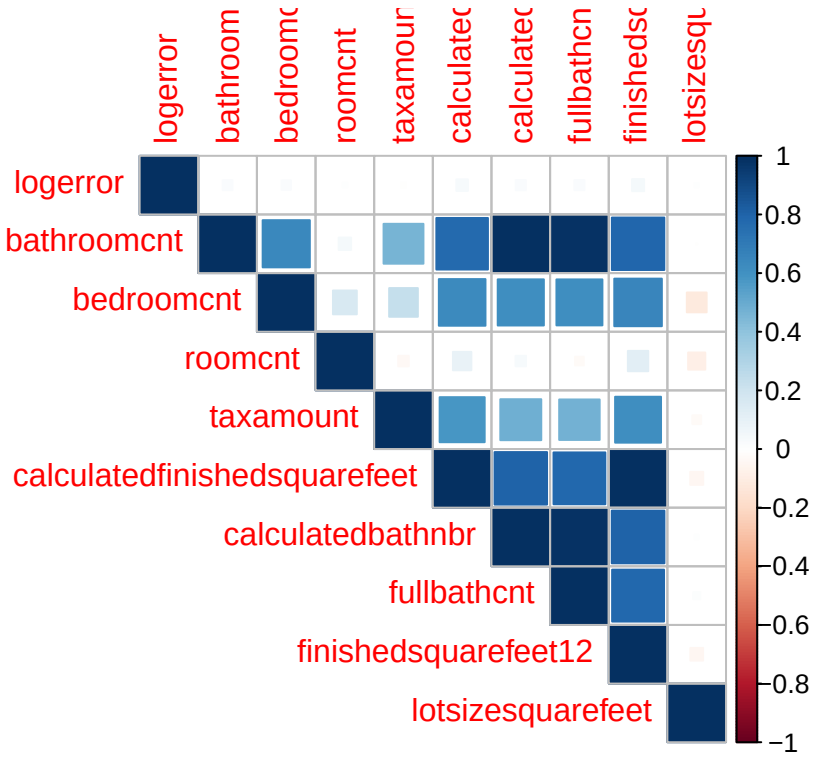

```
boxplot(train$logerror)
```



We can see it is pretty centered at zero. Just get a basic idea of the whole data set

Then, one narualy thing to do is to look at the correlation of different numeric features. #correlation -> use more in continuous variable

```
library(corrplot)
correlations <- cor(train[, c('logerror', 'bathroomcnt', 'bedroomcnt', 'roomcnt',
                              'taxamount', 'calculatedfinishedsquarefeet',
                              'calculatedbathnbr', 'fullbathcnt', 'finishedsquarefeet12', 'lotsizesquar
                    use = "pairwise.complete.obs")

corrplot(correlations, method = "square", tl.cex = 1, type = 'upper')
```

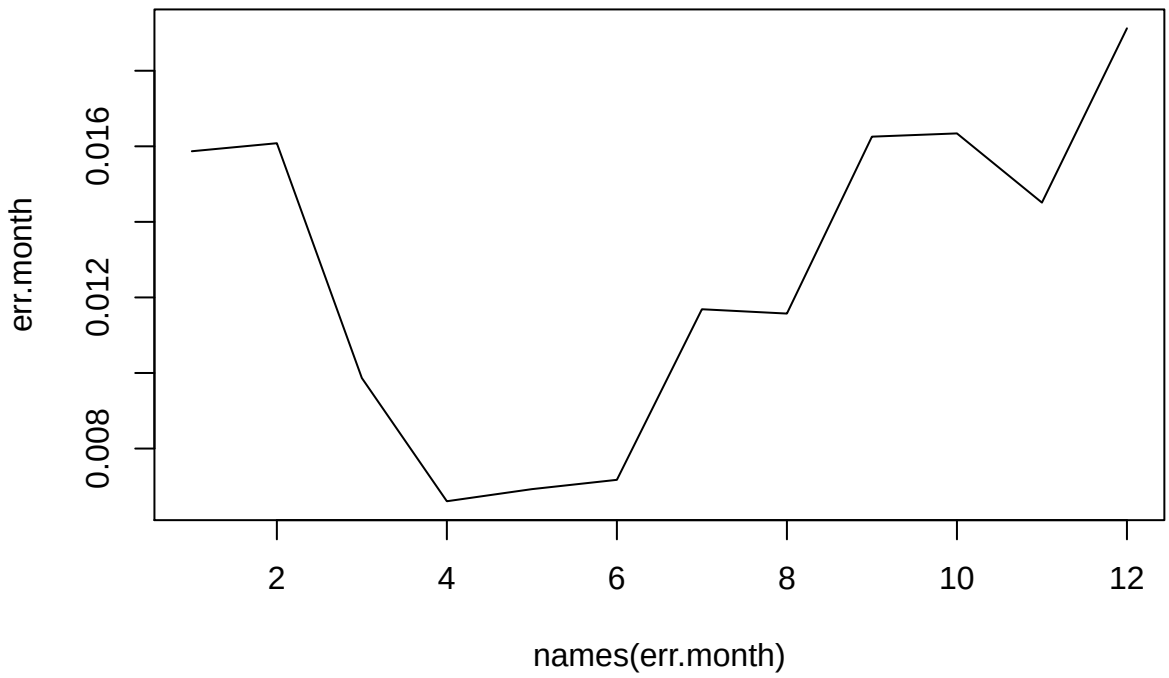


We can see all the coraltions are very small, which only means there are not linear relationship, but there might be other relationships.still we cannot draw the conclusion too easily.

Then let us take a look at the interaction between different features and logerror

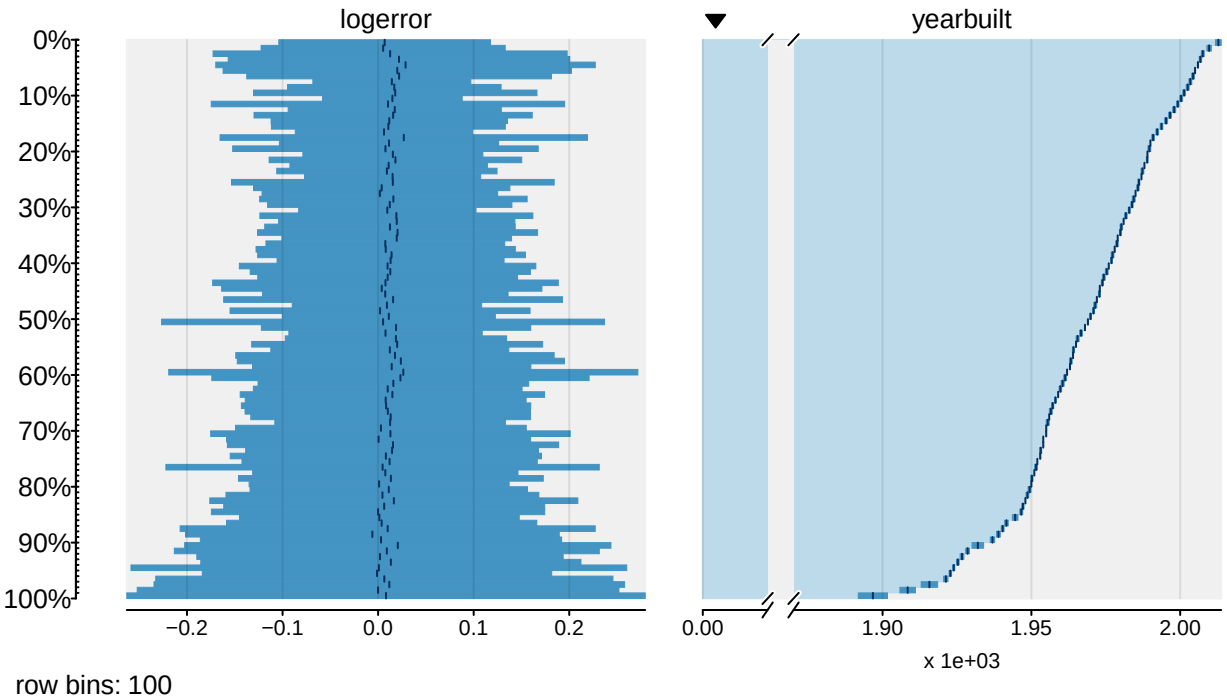
1. transaction month

```
train$txnmonth <- sapply(strsplit(train$transactiondate, '-'),
                         function(x) x[2])
err.month <- by(train,train$txnmonth,function(x) mean(x$logerror))
plot(names(err.month),err.month,type = "l")
```



The mean value is low from March to August, there are denitelt information here which can help us predict logerror in the future. ##2. built year

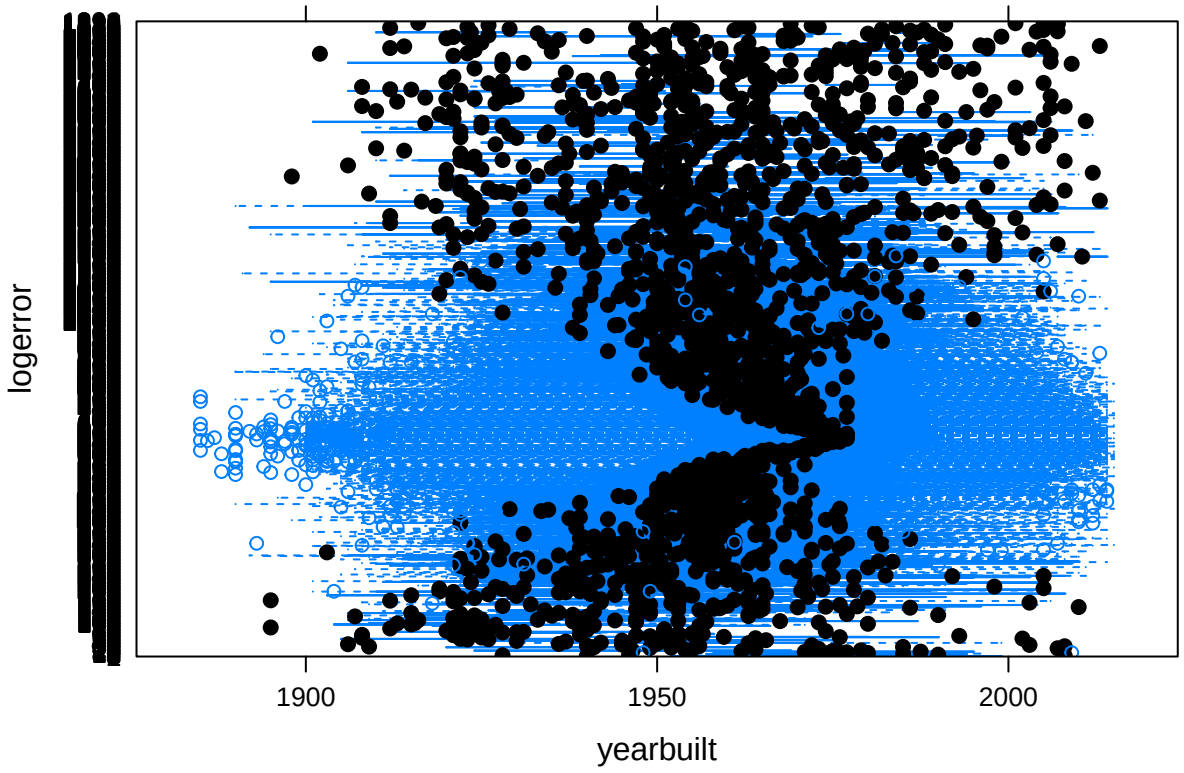
```
tableplot(train, select = c('logerror', 'yearbuilt'),sortCol = "yearbuilt")
```



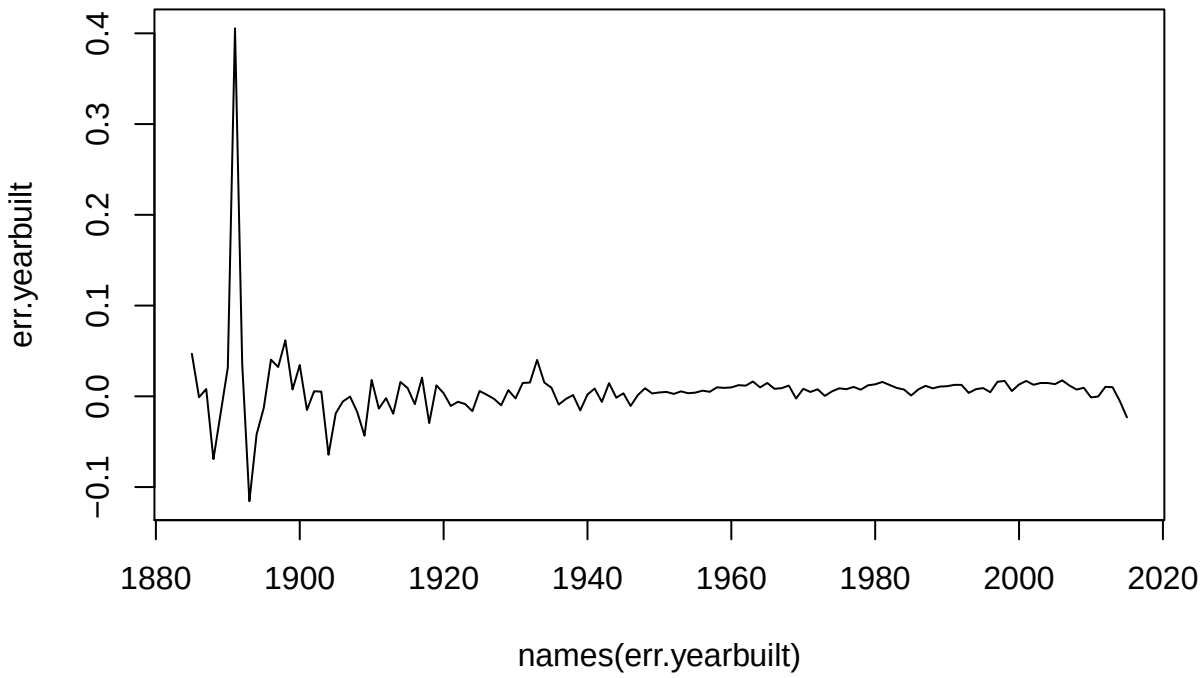
row bins: 100

objects:
90,275
903 (per bin)

```
bwplot(logerror ~ yearbuilt, data = train)
```




```
err.yearbuilt <- by(subset(train,train$logerror<0.9), subset(train,train$logerror<0.9)$yearbuil, functi
plot(names(err.yearbuilt), err.yearbuilt,type = "l")
```



built year Seem like does not influence too much, however there are some sparks we might consider in the future.

3. bedroom

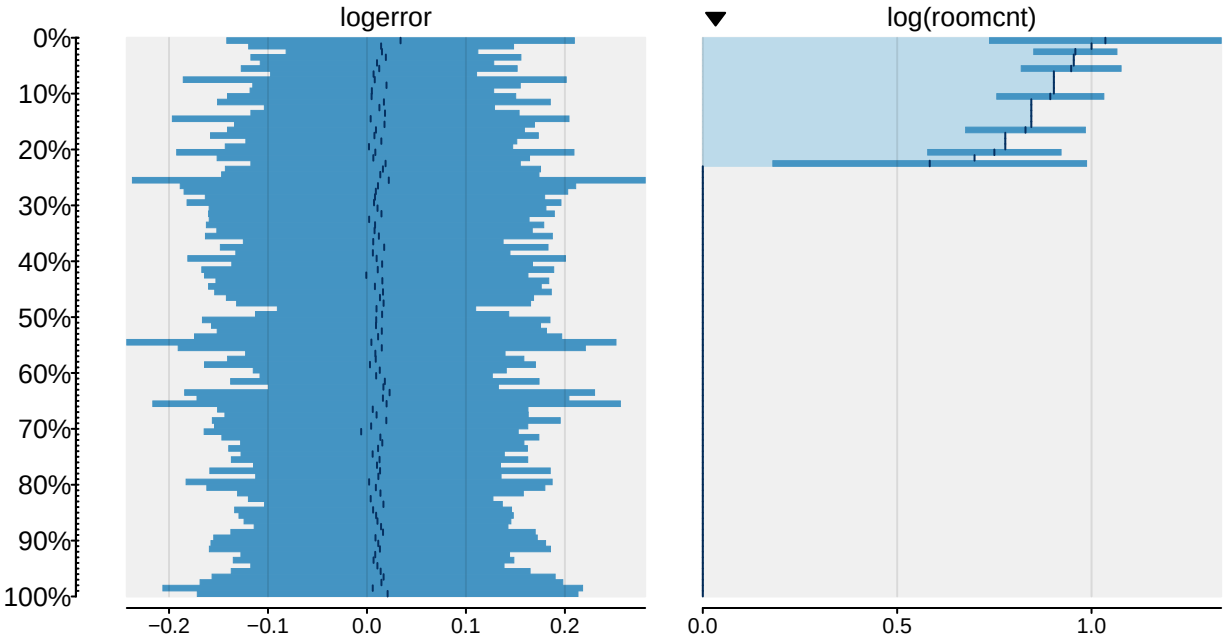
```
err.bedroomcnt <- by(train, train$bedroomcnt, function(x) mean(x$logerror))
plot(names(err.bedroomcnt), err.bedroomcnt,type = "l")
```

It seems like it decline a little bit when bedroom number is larger ##4. bathroom

```
err.bathroomcnt <- by(train, train$bathroomcnt, function(x) mean(x$logerror))
plot(names(err.bathroomcnt), err.bathroomcnt,type = "l")
```

the trend is prettly similar with the previosu situation. ##5. roomcnt

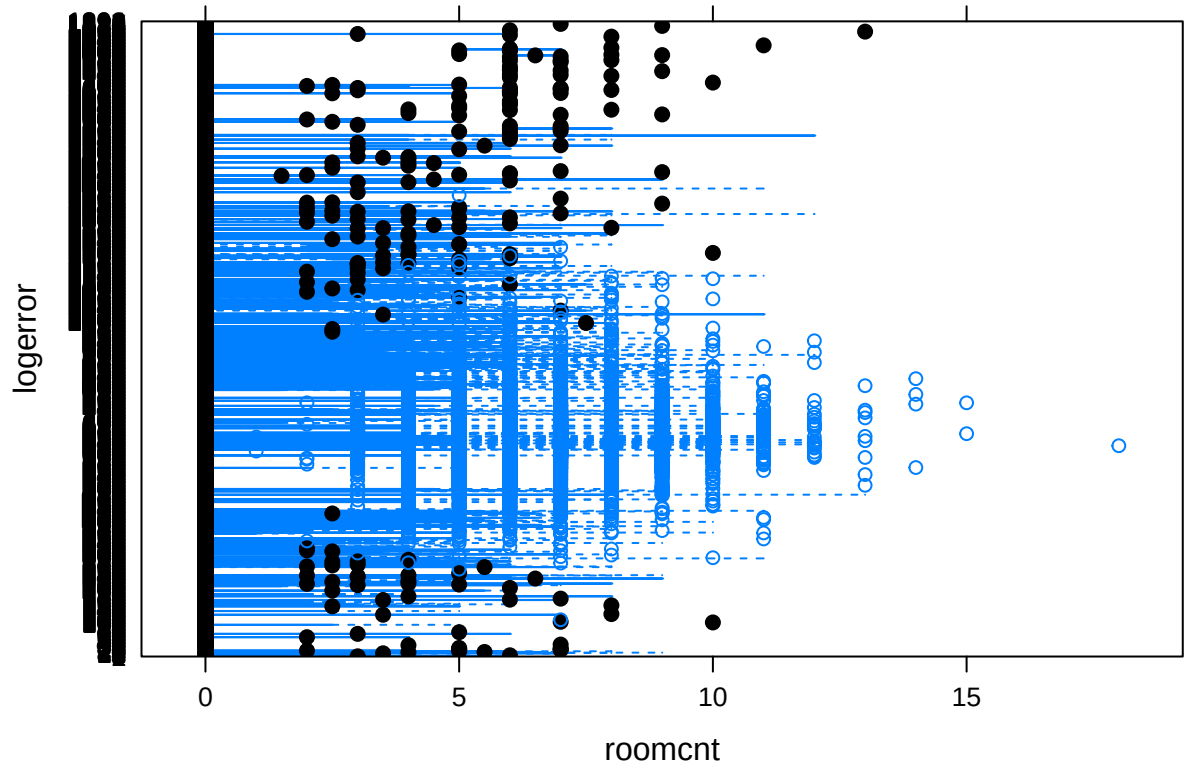
```
tableplot(train, select = c('logerror', 'roomcnt'),sortCol = "roomcnt")
```



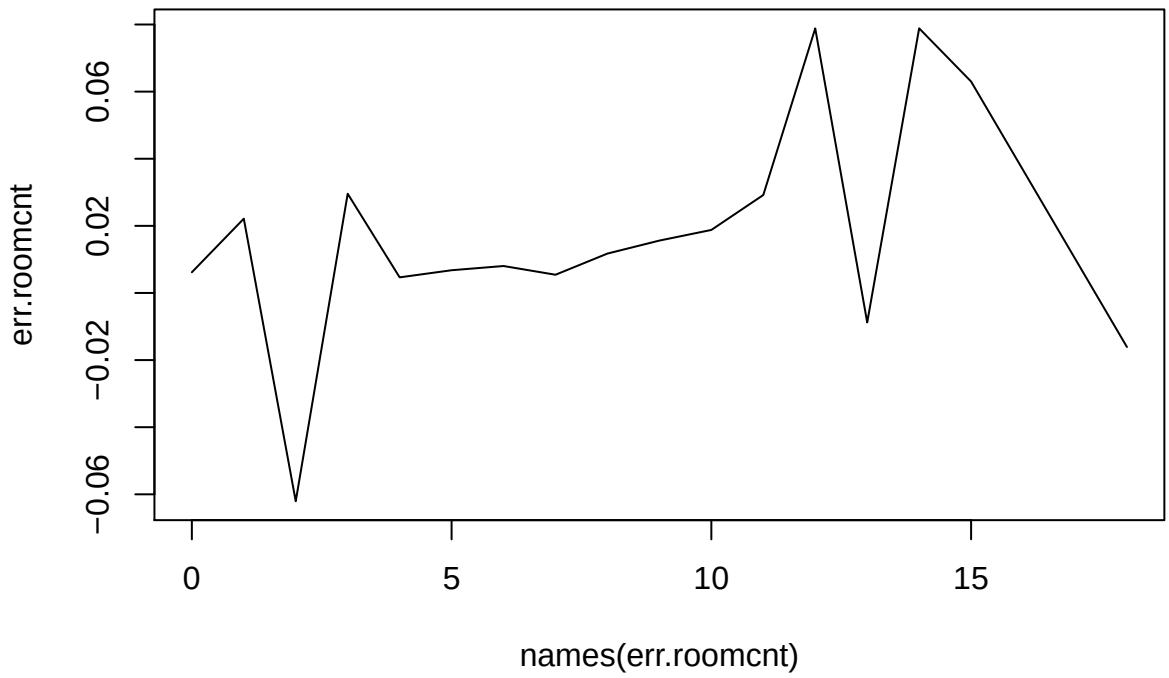
row bins: 100

objects:
90,275
903 (per bin)

```
bwplot(logerror ~ roomcnt, data = train)
```

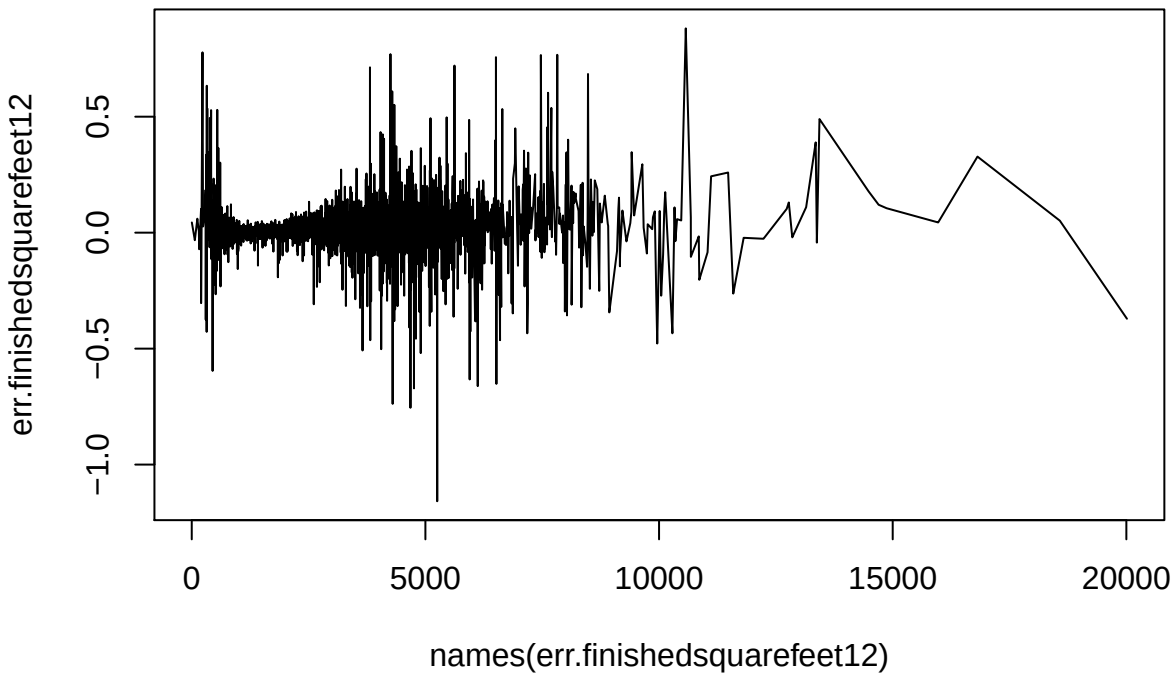



```
err.roomcnt <- by(subset(train,train$logerror<0.9),
                  subset(train,train$logerror<0.9)$roomcnt,
                  function(x) mean(x$logerror))
plot(names(err.roomcnt), err.roomcnt,type = "l")
```



This feature influence the mean logerror as well, we can see 2 minimizes the mean logerror. ##6.finishedsquarefeet12

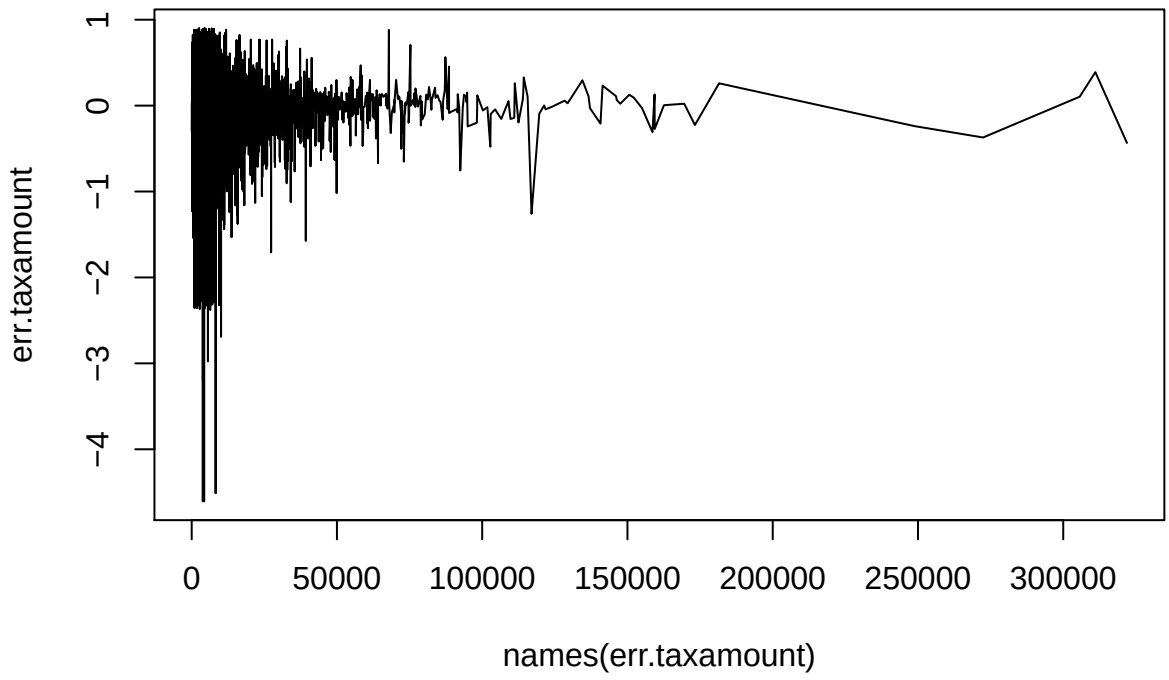
```
err.finishedsquarefeet12 <- by(subset(train,train$logerror<0.9),
                  subset(train,train$logerror<0.9)$finishedsquarefeet12,
                  function(x) mean(x$logerror))
plot(names(err.finishedsquarefeet12), err.finishedsquarefeet12,type = "l")
```



Look like a siginal, however, it can just be noise. I don't think this can be a good predictor.

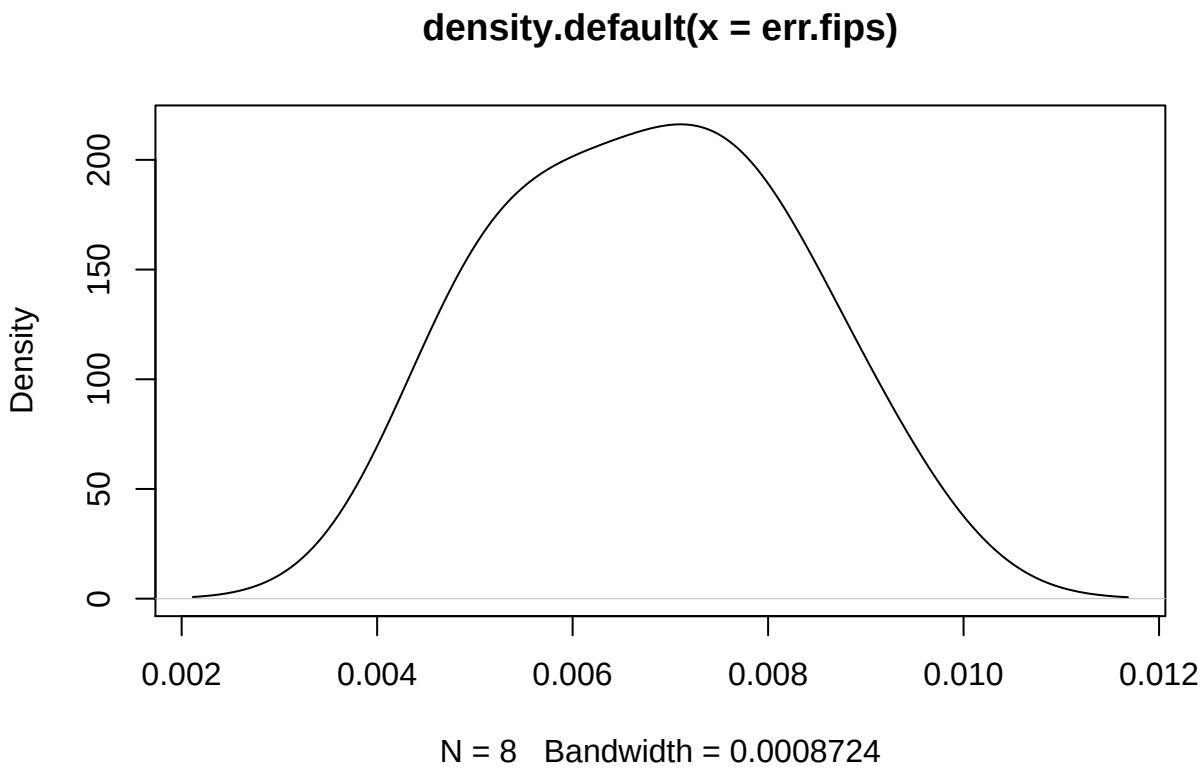
7. taxamont

```
err.taxamount <- by(subset(train,train$logerror<0.9),
                    subset(train,train$logerror<0.9)$taxamount,
                    function(x) mean(x$logerror))
plot(names(err.taxamount), err.taxamount,type = "l")
```



The same conclusion as the previous one. ##8.fips

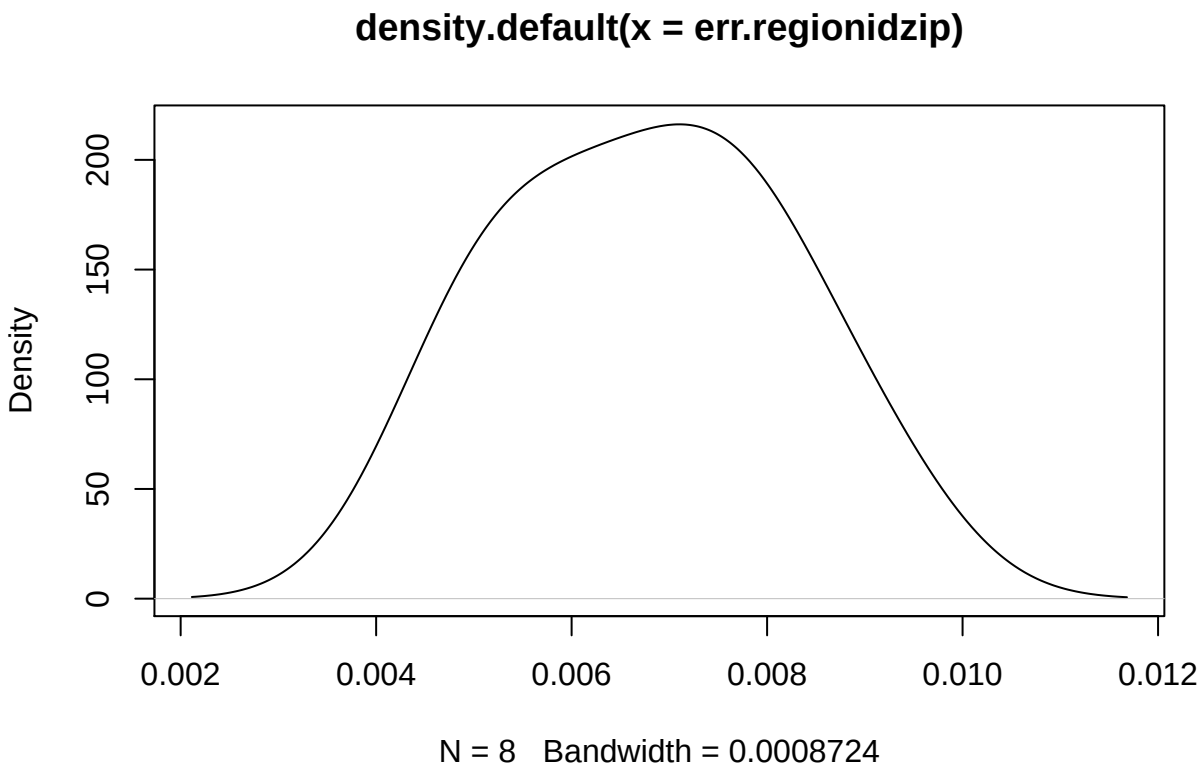
```
err.fips <- by(subset(train,train$logerror<0.9),
                    subset(train,train$logerror<0.9)$fips,
                    function(x) mean(x$logerror))
plot(density(err.fips))
```



We can see the densitly is like a normal distribution. So fips does influence logerror.

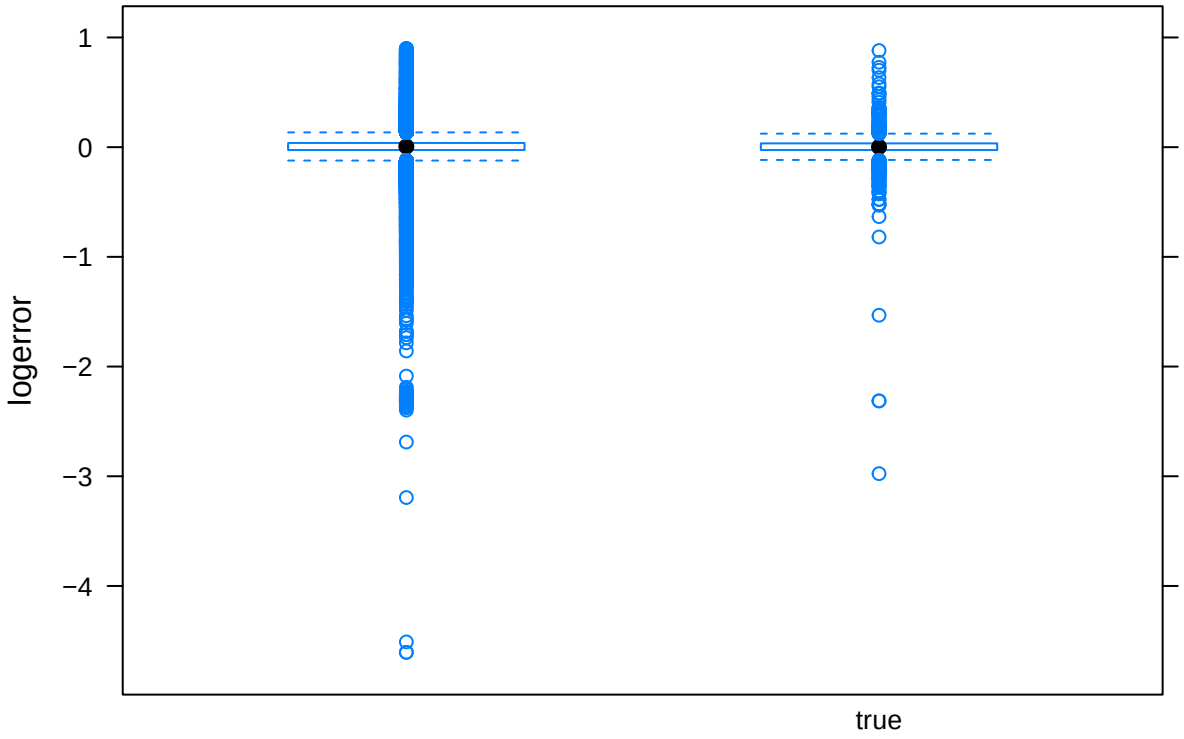
9.regionidzip

```
err.regionidzip <- by(subset(train,train$logerror<0.9),
               subset(train,train$logerror<0.9)$regionidzip,
               function(x) mean(x$logerror))
plot(density(err.regionidzip))
```



The same as the previous one, they are all considered as region factors. ##10.hashottuborspa

```
bwplot(logerror~hashottuborspa, data = subset(train,train$logerror < 0.9))
```



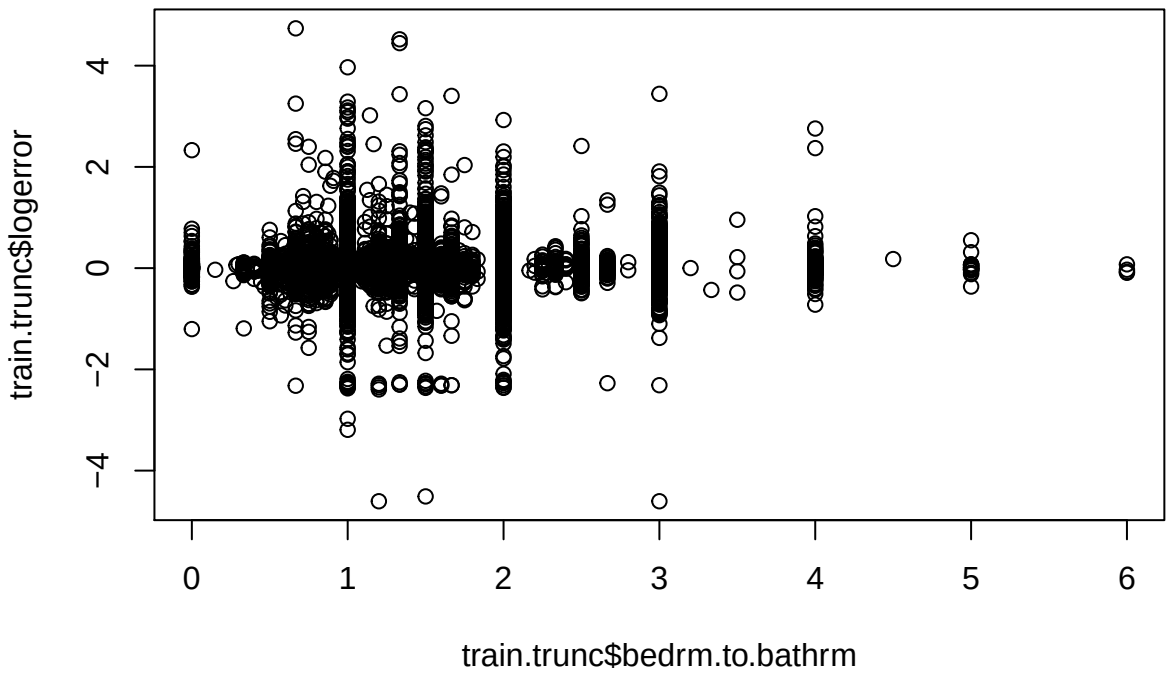
I thought this one might influence the result, however, it seems like it does not.

Except those feature, we create some new features.

new features

1. bedroom to bathroom count

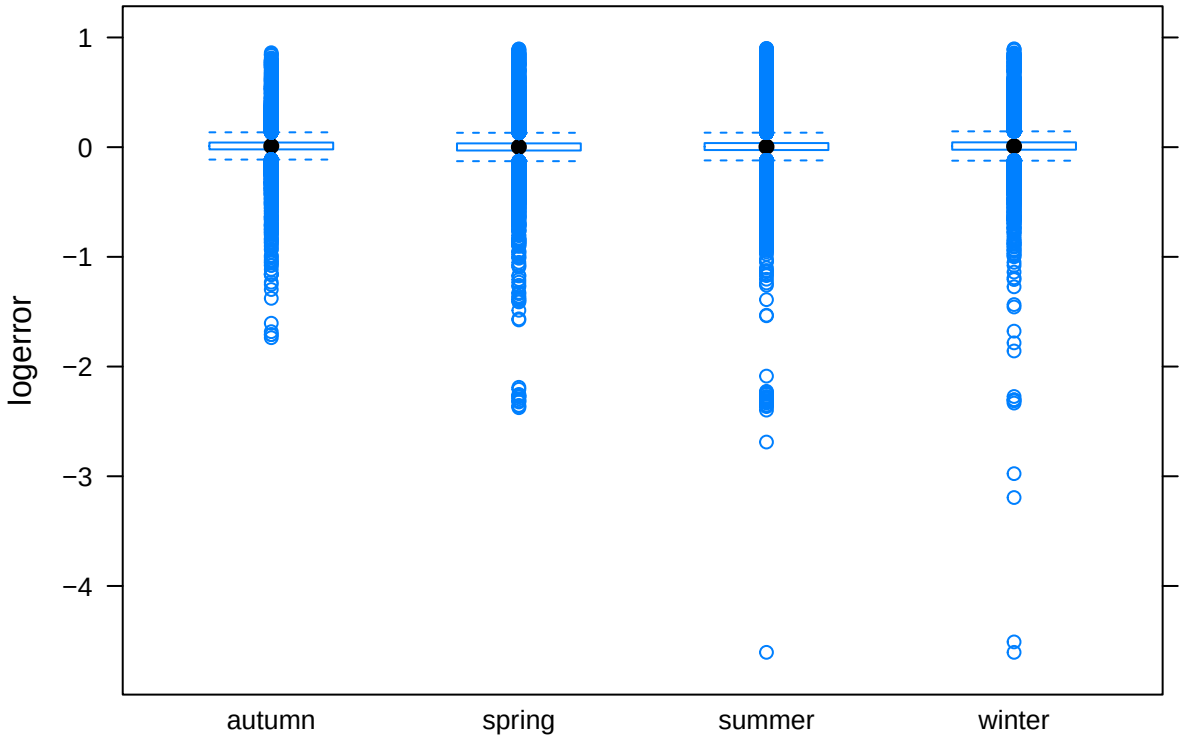
```
train$bedrm.to.bathrm <- train$bedroomcnt/train$bathroomcnt

train.trunc <- subset(train,!is.na(train$bedrm.to.bathrm))
plot(train.trunc$bedrm.to.bathrm, train.trunc$logerror)
```



We can see that When the ratio is low, it seems logerror is bigger.

2. season

```
season <- function(num){
  num <- as.integer(num)
  ifelse(num %in% c(1,2,12),"winter",
                  ifelse(num %in% c(3,4,5),"spring",
                         ifelse(num %in% c(6,7,8),"summer","autumn")))
}
train$season <- sapply(train$txnmonth, season)
bwplot(logerror~season,data=subset(train,train$logerror < 0.9))
```



It seems like it does not differ too much from season to season

Next steps:

keep exploring what other features can be and take a deeper look at current features.