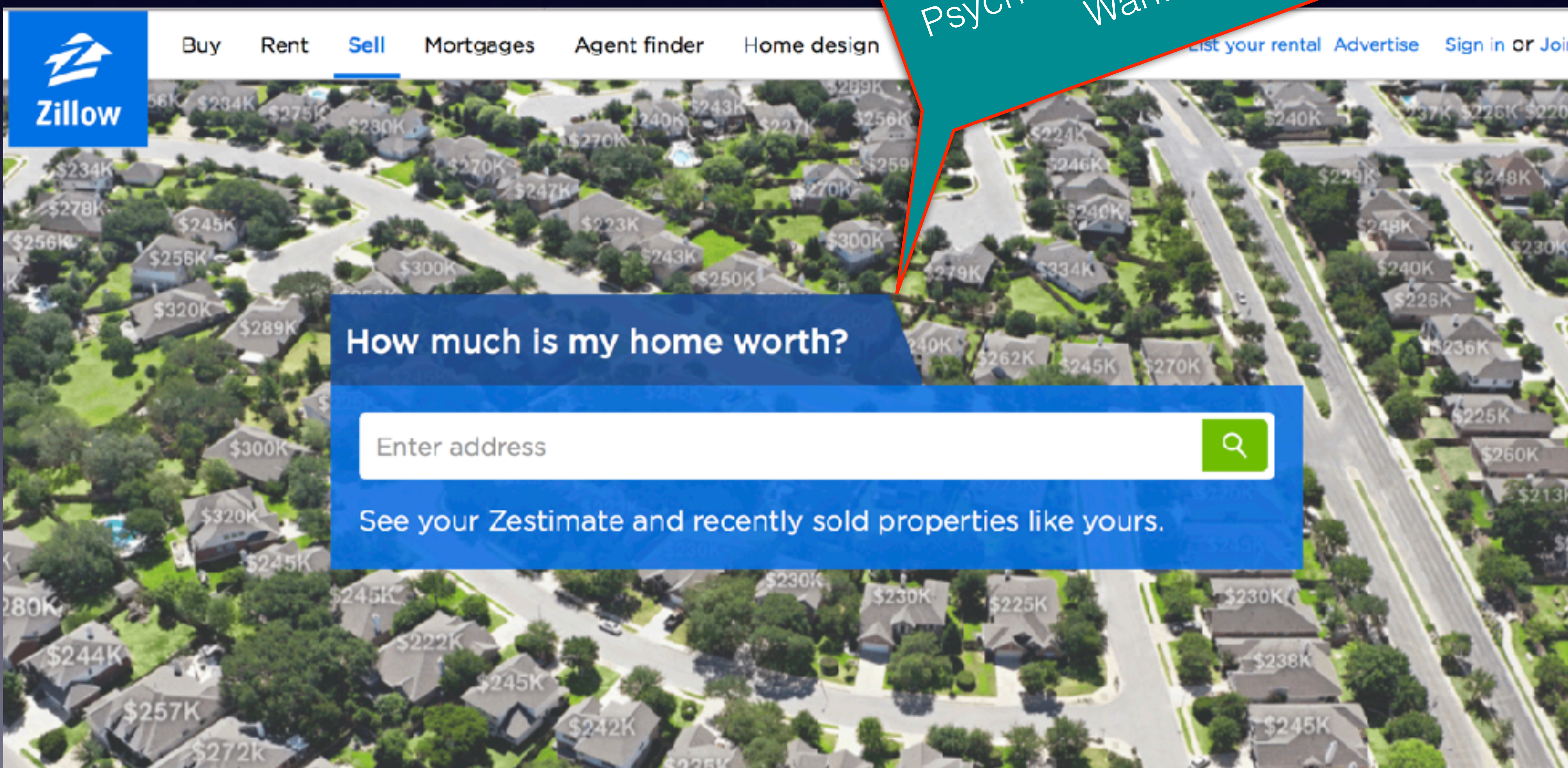
Zillow Case

Predict the "LogError" Kaggle / Zillow Challenge

Psyche! Not What They Want!



What are we predicting?
This …

$$logerror = \log(Zestimate) - \log(SalePrice)$$

$$logerror = \log\left(\frac{Zestimate}{SalePrice}\right)$$

$$e^{logerror} = \frac{Zestimate}{SalePrice}$$

Missingness & Imputation

```
Missingness Percent:

 airconditioningtypeid   architecturalstyletypeid                  basementsqft              bathroomcnt
            72.8154101                 99.7969662                    99.9454646                0.3839587
            bedroomcnt         buildingclasstypeid         buildingqualitytypeid         calculatedbathnbr
             0.3835567                 99.5769487                    35.0637491                4.3183460
            decktypeid      finishedfloor1squarefeet  calculatedfinishedsquarefeet    finishedsquarefeet12
            99.4273113                 93.2093044                     1.8613387                9.2466645
  finishedsquarefeet13       finishedsquarefeet15          finishedsquarefeet50       finishedsquarefeet6
            99.7430003                 93.6085718                    93.2093044               99.2630017
                  fips               fireplacecnt                   fullbathcnt             garagecarcnt
             0.3831212                 89.5271600                     4.3183460               70.4119667
        garagetotalsqft             hashottuborspa          heatingorsystemtypeid                 latitude
            70.4119667                 97.6881413                    39.4884526                0.3831212
             longitude          lotsizesquarefeet                       poolcnt              poolsizesum
             0.3831212                  9.2488754                    82.6634379               99.0633847
          pooltypeid10                pooltypeid2                   pooltypeid7  propertycountylandusecode
            98.7626025                 98.9255387                    83.7378991                0.4112599
  propertylandusetypeid          propertyzoningdesc         rawcensustractandblock             regionidcity
             0.3831212                 33.7190898                     0.3831212                2.1052071
        regionidcounty       regionidneighborhood                   regionidzip                  roomcnt
             0.3831212                 61.2623806                     0.4683077                0.3843942
           storytypeid          threequarterbathnbr         typeconstructiontypeid                  unitcnt
            99.9455986                 89.5608594                    99.7739863               33.7572444
    yardbuildingsqft17         yardbuildingsqft26                     yearbuilt           numberofstories
            97.3082359                 99.9113297                     2.0074923               77.1517782
         fireplaceflag  structuretaxvaluedollarcnt             taxvaluedollarcnt           assessmentyear
            99.8270477                  1.8418092                     1.4253570                0.3831882
  landtaxvaluedollarcnt                   taxamount           taxdelinquencyflag       taxdelinquencyyear
             2.2689473                  1.0468251                    98.1086132               98.1085462
    censustractandblock
             2.5166010
```

Is Anything Not Missing Values?

Missingness & Imputation

md.package() relationships

```r
full %>% select(regionidcity, latitude, longitude, fips) %>% md.pattern()
```

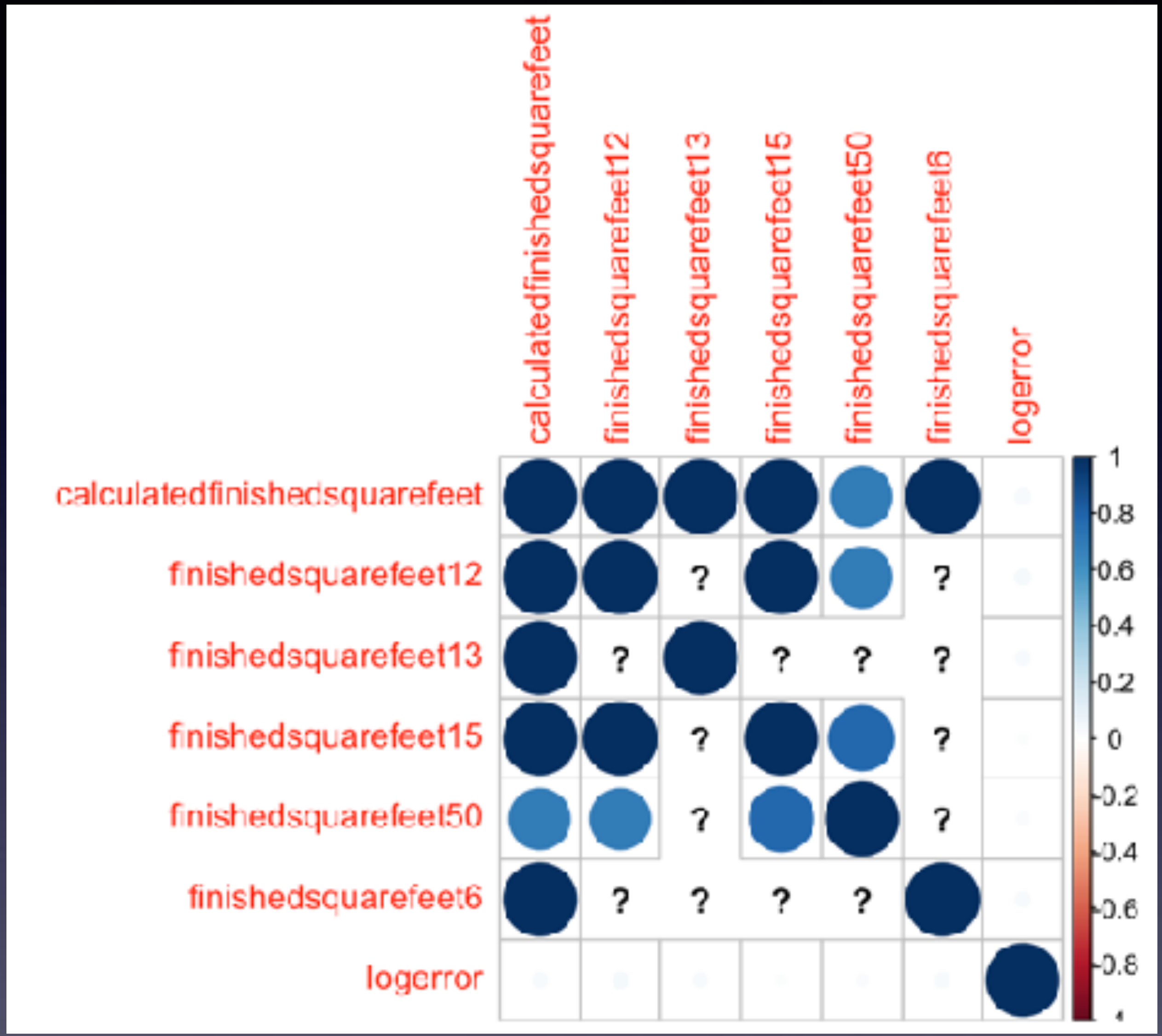
```
##         latitude longitude  fips regionidcity
## 2922495        1         1     1            1     0
##   51410        1         1     1            0     1
##   11437        0         0     0            0     4
##            11437     11437 11437        62847 97158
```

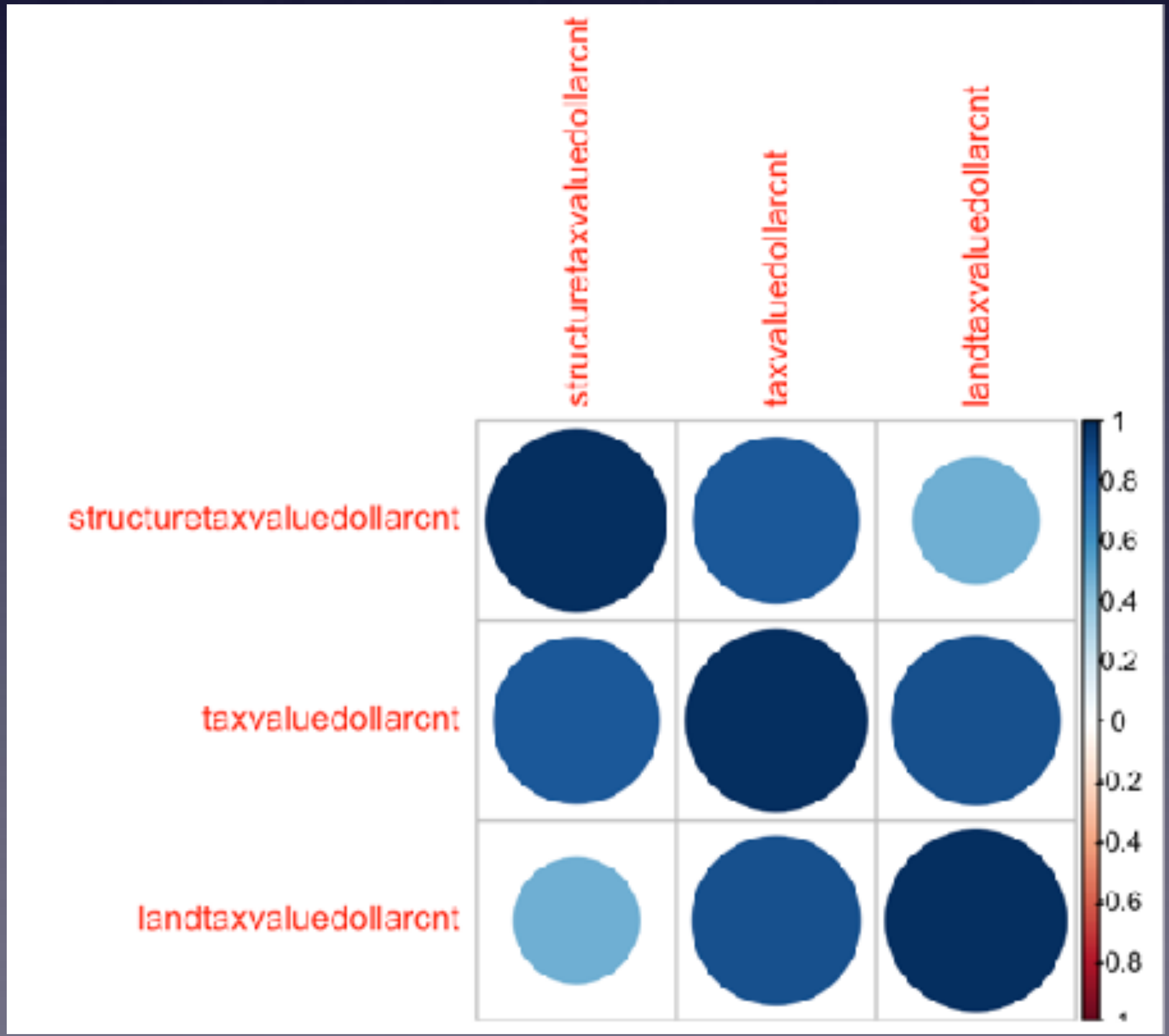
```r
full %>% select(regionidcity, latitude, longitude, fips,
                regionidcounty, regionidneighborhood, regionidzip) %>% md.pattern() #
```

```
##         latitude longitude  fips regionidcounty regionidzip regionidcity  regionidneighborhood
## 1156377        1         1     1              1           1            1                     1       0
## 1765541        1         1     1              1           1            1                     0       1
##      81        1         1     1              1           0            1                     1       1
##   49444        1         1     1              1           1            0                     0       2
##     496        1         1     1              1           0            1                     0       2
##    1966        1         1     1              1           0            0                     0       3
##   11437        0         0     0              0           0            0                     0       7
##            11437     11437 11437          11437       13980        62847               1828884 1951459
```

```
        calculatedfinishedsquarefeet finishedsquarefeet12 finishedsquarefeet50 finishedsquarefeet15 logerror finishedsquarefeet6 finishedsquarefeet13
      5                            1                    0                    1                    1        1                   0                    0   3
   6851                            1                    1                    1                    0        1                   0                    0   3
      4                            1                    1                    1                    1        0                   0                    0   3
    421                            1                    0                    0                    0        1                   1                    0   4
   3559                            1                    0                    0                    1        1                   0                    0   4
     33                            1                    0                    0                    0        1                   0                    1   4
  78745                            1                    1                    0                    0        1                   0                    0   4
    370                            1                    0                    1                    1        0                   0                    0   4
 195493                            1                    1                    1                    0        0                   0                    0   4
  21582                            1                    0                    0                    0        0                   1                    0   5
 186869                            1                    0                    0                    1        0                   0                    0   5
   7639                            1                    0                    0                    0        0                   0                    1   5
2428202                            1                    1                    0                    0        0                   0                    0   5
    661                            0                    0                    0                    0        1                   0                    0   6
```

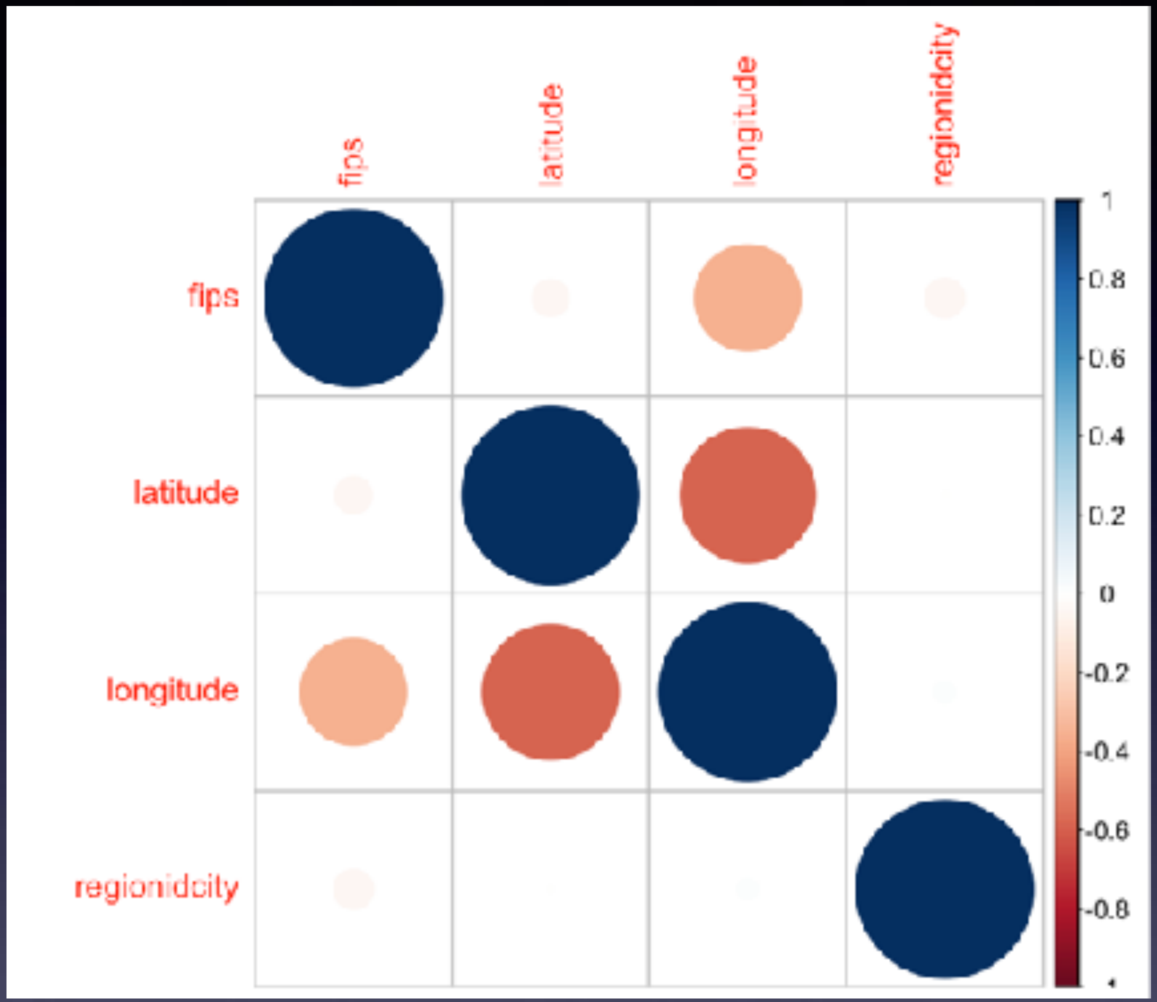
Missingness & Imputation
Correlations - Visually

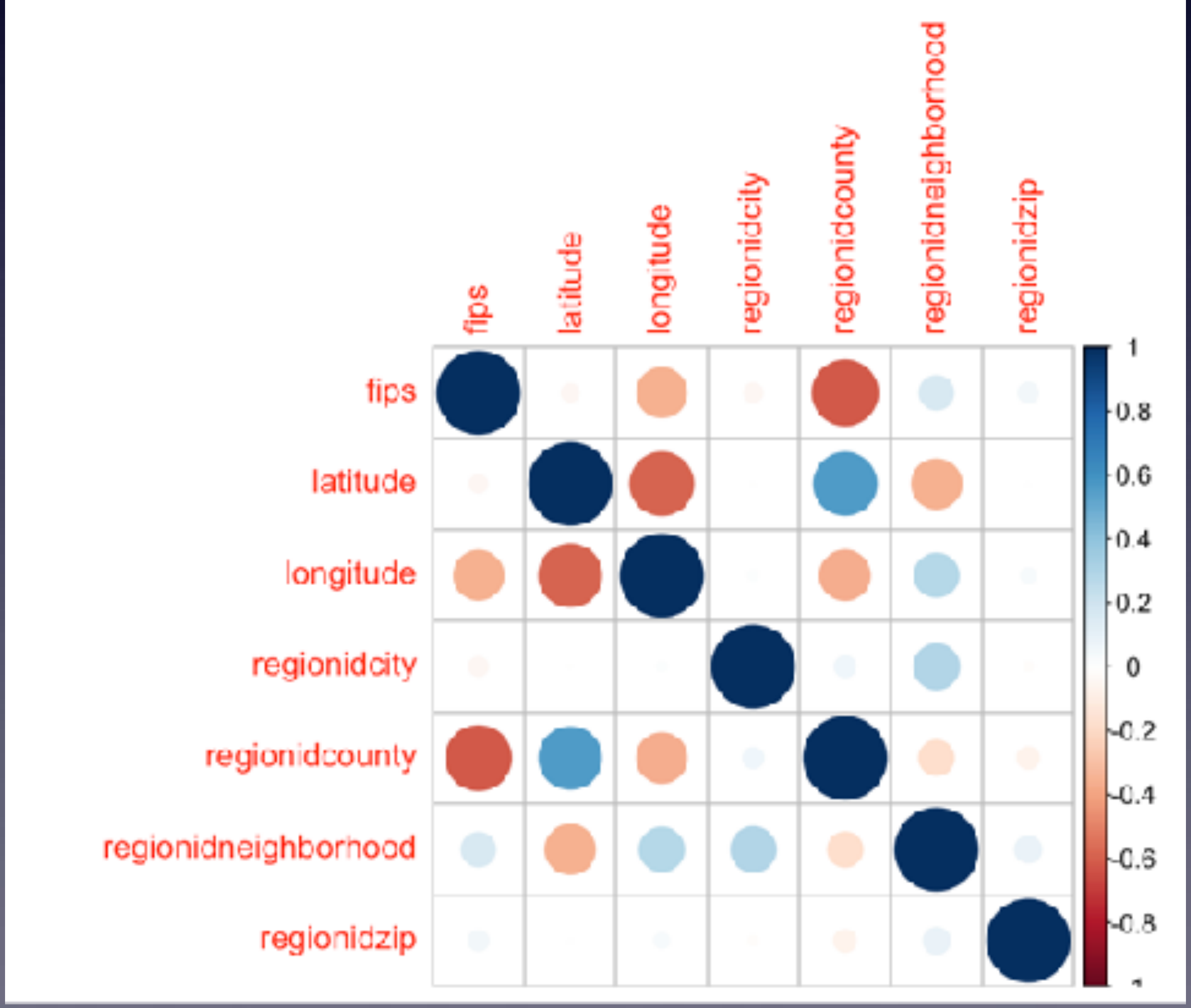




Missingness & Imputation

Correlations - Visually





Looks Correlated - LM() Imputations?

```
fips.impute.model <- lm(fips ~ regionidcity, data=full)
summary(fips.impute.model)
```

```
##
## Call:
## lm(formula = fips ~ regionidcity, data = full)
##
## Residuals:
##     Min      1Q Median      3Q     Max
## -11.72 -11.54 -10.88   10.64   63.28
##
## Coefficients:
##                  Estimate Std. Error   t value Pr(>|t|)
## (Intercept)    6.049e+03  1.443e-02 419197.17   <2e-16 ***
## regionidcity -1.985e-05  2.341e-07    -84.76   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.3 on 2922493 degrees of freedom
##   (62847 observations deleted due to missingness)
## Multiple R-squared:  0.002452,   Adjusted R-squared:  0.002452
## F-statistic:  7185 on 1 and 2922493 DF,  p-value: < 2.2e-16
```

```
fips.impute.model <- lm(latitude ~ regionidcity, data=full)
summary(fips.impute.model)
```

```
##
## Call:
## lm(formula = latitude ~ regionidcity, data = full)
```

- P-Values looked good
- R^2 usually crap:

```
R-squared:  9.404e-07
```

Tiny text Blurb …

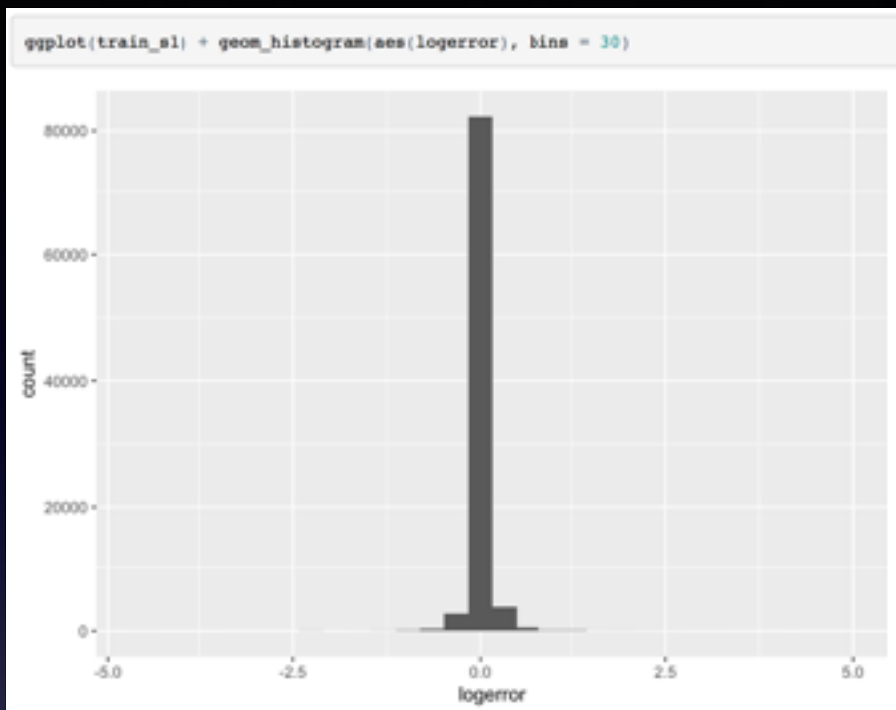
Looks Correlated - LM() Imputations?

- Tax amount ~ taxvaluedollarcnt
- R^2 about 90%

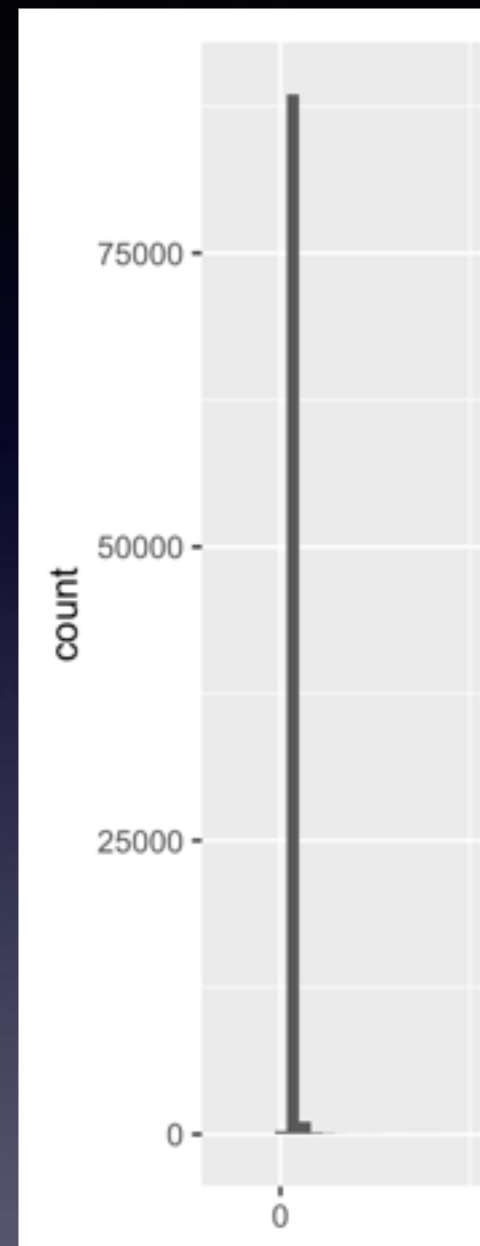
```
#An imputation for taxamount from taxvaluedollarcnt (may include landvaluedollarcnt later)
lm1 = lm(formula = taxamount ~ taxvaluedollarcnt, data = full)

## test results for above model:
# Call:
#   lm(formula = taxamount ~ taxvaluedollarcnt, data = full)
# Residuals:
#   Min       1Q  Median      3Q     Max
# -862470    -349    -134     103 1871995
# Coefficients:
#   Estimate Std. Error t value Pr(>|t|)
# (Intercept)        2.411e+02  1.957e+00   123.2   <2e-16 ***
#   taxvaluedollarcnt 1.229e-02  2.368e-06  5192.8   <2e-16 ***
#   ---
#   Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
# Residual standard error: 2883 on 2930063 degrees of freedom
# (55152 observations deleted due to missingness)
# Multiple R-squared:  0.902, Adjusted R-squared:  0.902
# F-statistic: 2.697e+07 on 1 and 2930063 DF,  p-value: < 2.2e-16
```

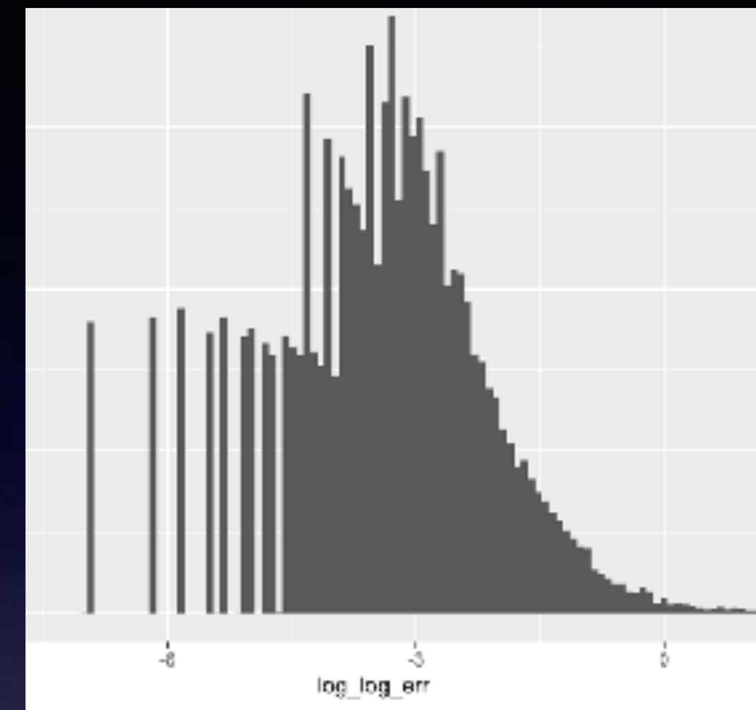
Looking At The “Log” in LogError

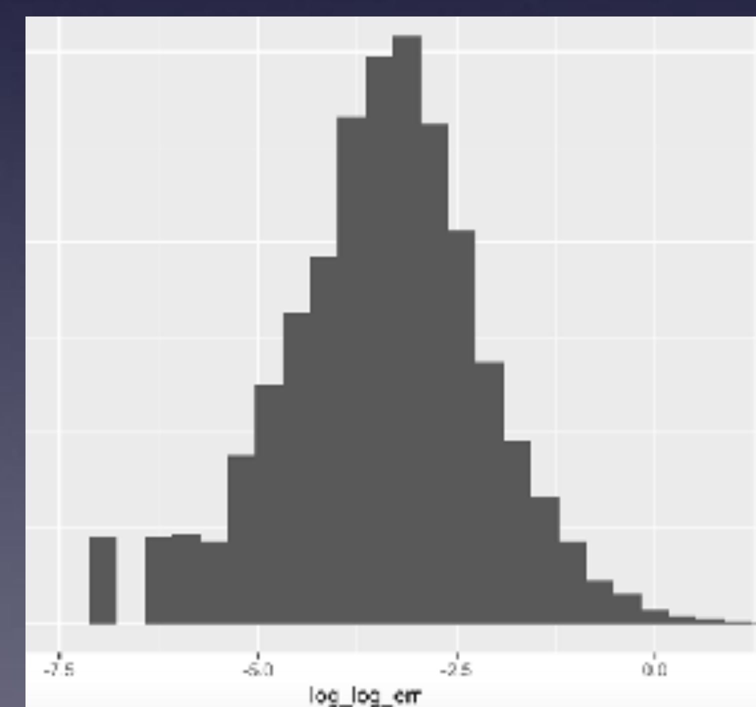


Logerror



exp(logerror)



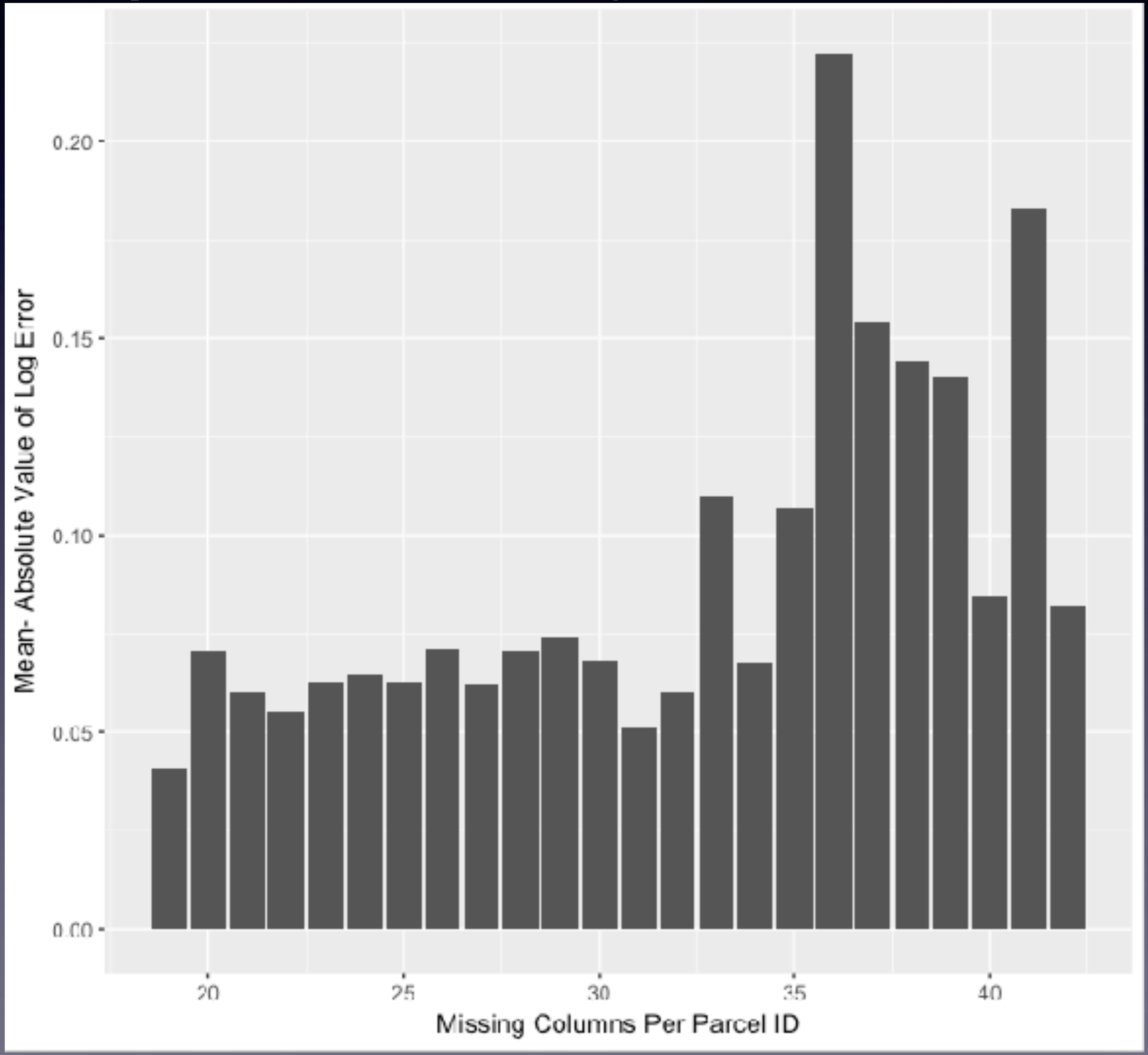


log(logerror)

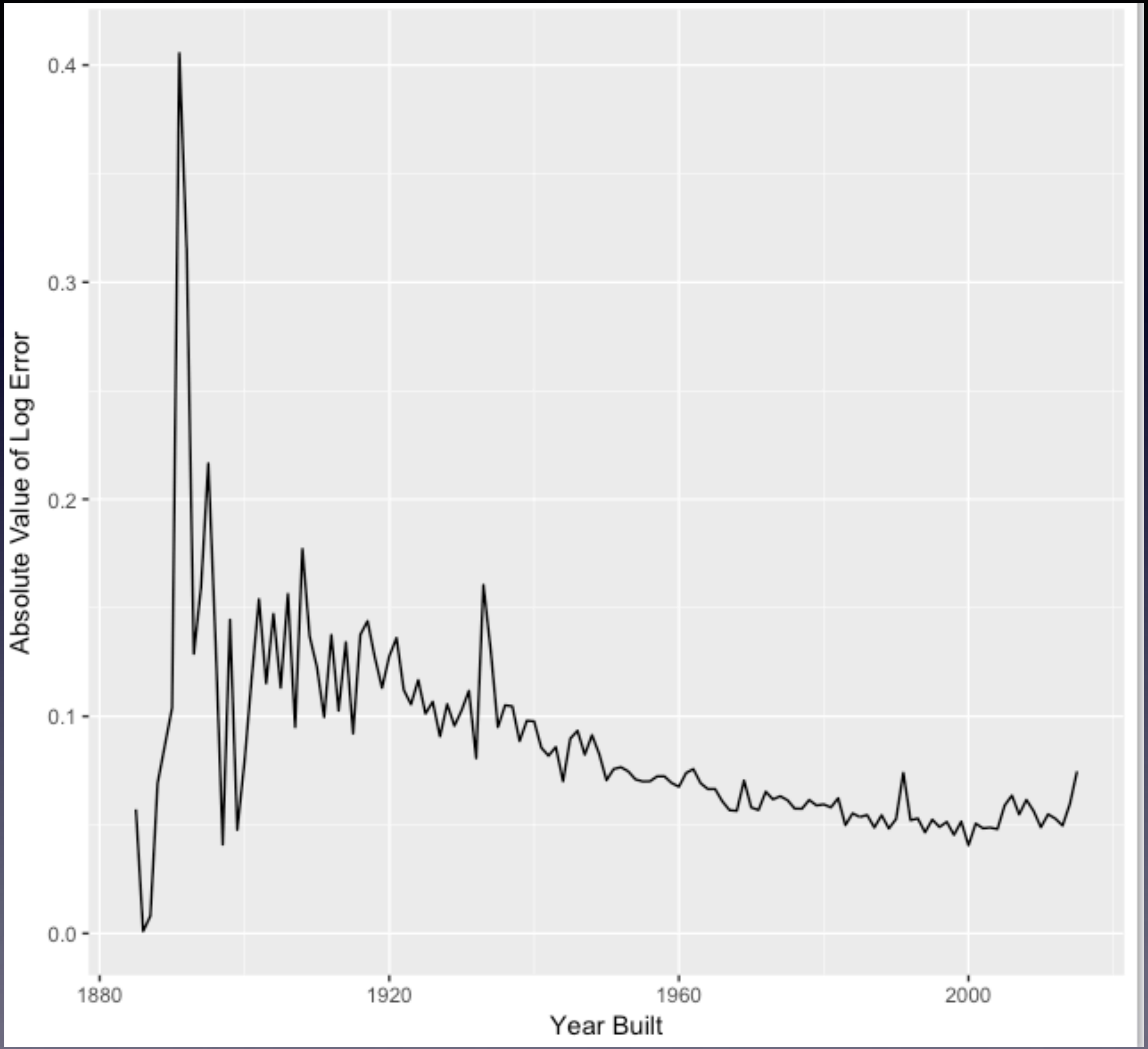
The real relationship:

$$logerror = log(Zestimate) - log(SalePrice)$$

Missingness as an explanatory variable?



Year Built vs Absolute Value of Log Error



Multivariate Outliers/ Inaccurate Data

- Even when values were NOT missing, many of them were baffling- to the point of seeming wildly inaccurate (or being extreme outliers.)
- IF these values can be eliminated from the training process, maybe predictive accuracy can increase?
- Examples?

Multivariate Outliers/ Inaccurate Data

	parcelid	bathroomcnt	bedroomcnt	logerror
1	12325767	20	0	NA
2	12875313	20	0	NA
3	10875978	20	0	NA
4	11843438	20	0	NA
5	12718575	20	0	NA

20 bathrooms

0 bedrooms

YES!
My Dream Home!!
❤️❤️❤️

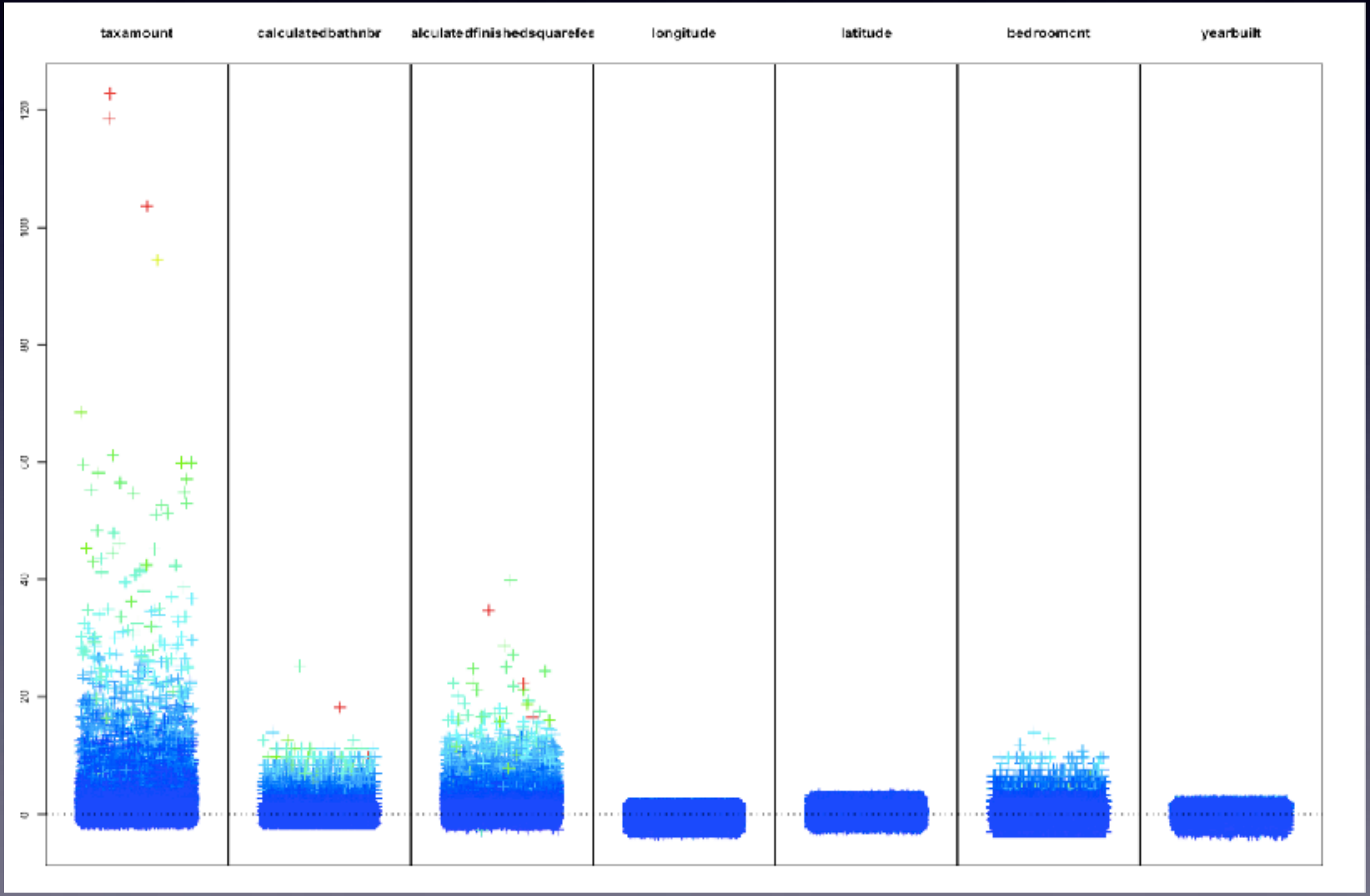
	parcelid	bathroomcnt	bedroomcnt	roomcnt	fireplacecnt	poolcnt	taxamount	landtaxvaluedollarcnt	logerror
1	14167696	0	0	0	1	1	97.7	11151	NA
2	14167459	0	0	0	1	1	97.7	6700	NA

Who needs rooms when you have a fireplace AND a pool??

Uni Plot

(Univariate Presentation of Multivariate Outliers)

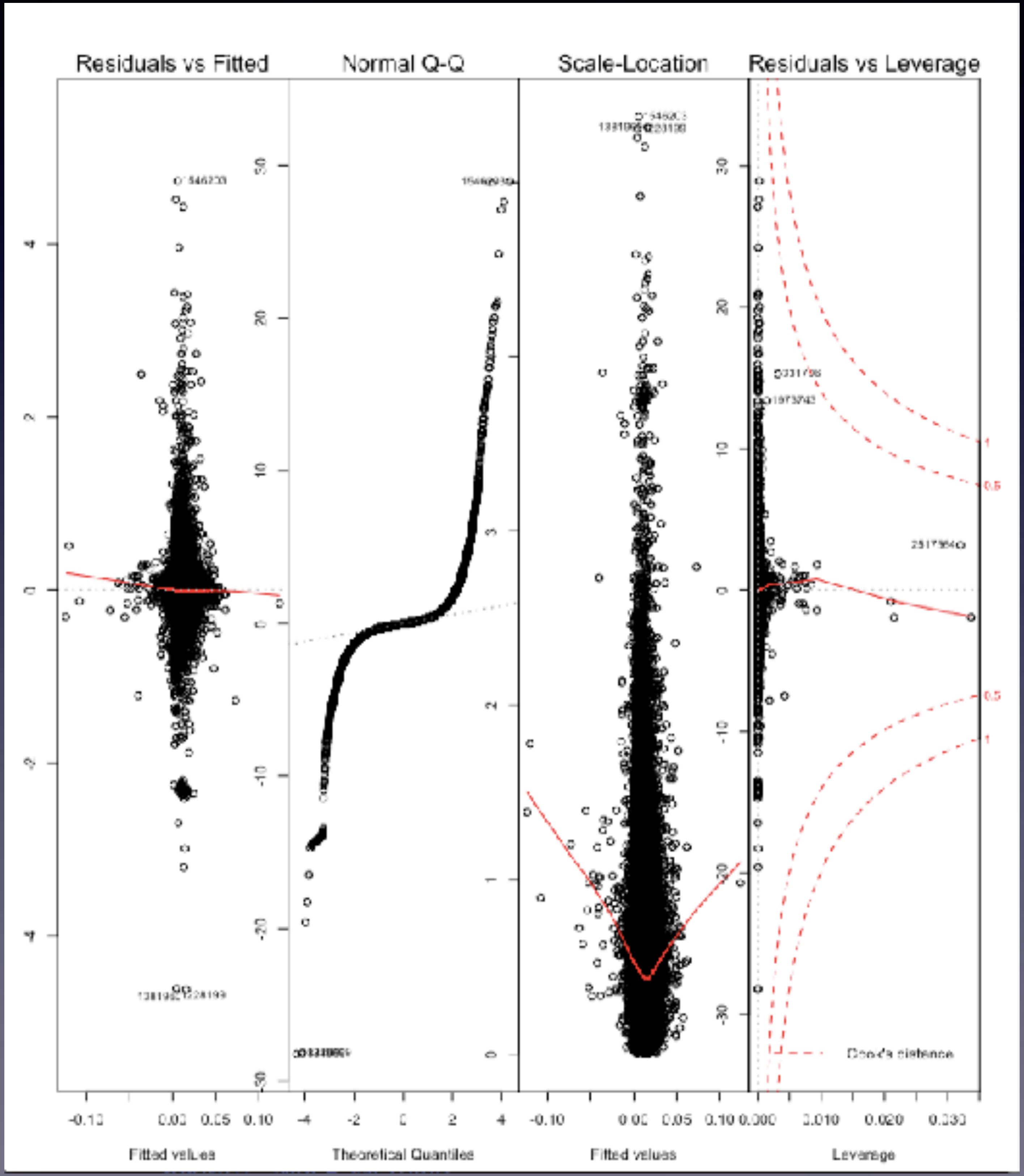
Tax Bath Sq-Ft Long Lat Bed Year Built



The Models

- Linear
- Linear - with transformation (Yeo-Johnson)
- Regularization (Ridge / Lasso / Elastic Net)
- RandomForest
- Gradient Boosting
- XGBoost

Linear Models



- Linearity violated
- Constant variance violated
- Normality violated

What about transformation?

We have negative values, and Box-Cox cannot take those

.....

Yeo-Johnson Transformation

```
model_yeo = train(logerror ~ yearbuilt + calculatedfinishedsquarefeet,
                  method ='lm', data = sub_train,
                  preProcess = "YeoJohnson", trControl = myControl)
# Linear model with Yeo-Johnson
yeo1 = predict(model_yeo, newdata = sub_test)
# Predicting on test data
sum(abs(yeo1-sub_test$logerror))/nrow(sub_test)
# 0.06674093 MAE
```

- Works very similarly to Box-Cox but CAN handle negative values

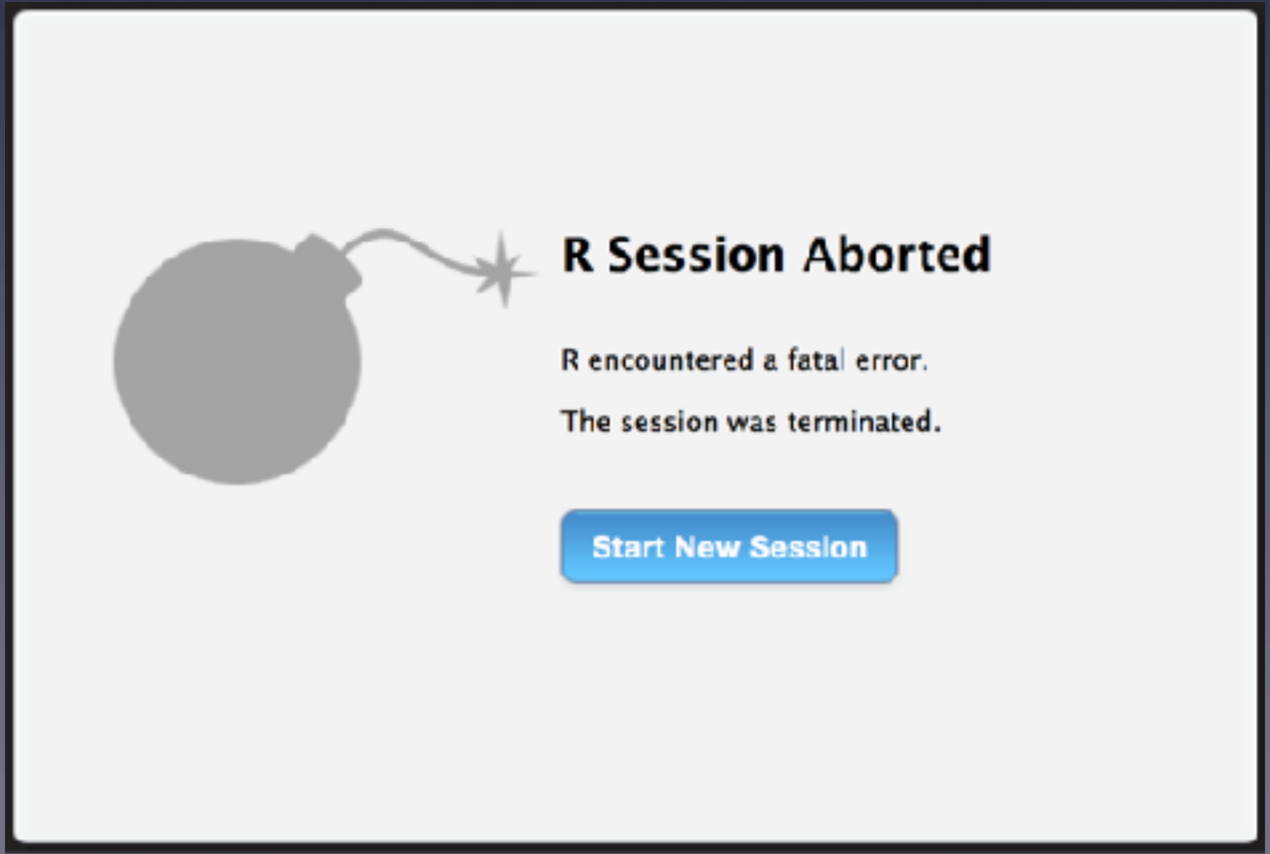
- Slight improvement, but still not great

Regularization Regressions

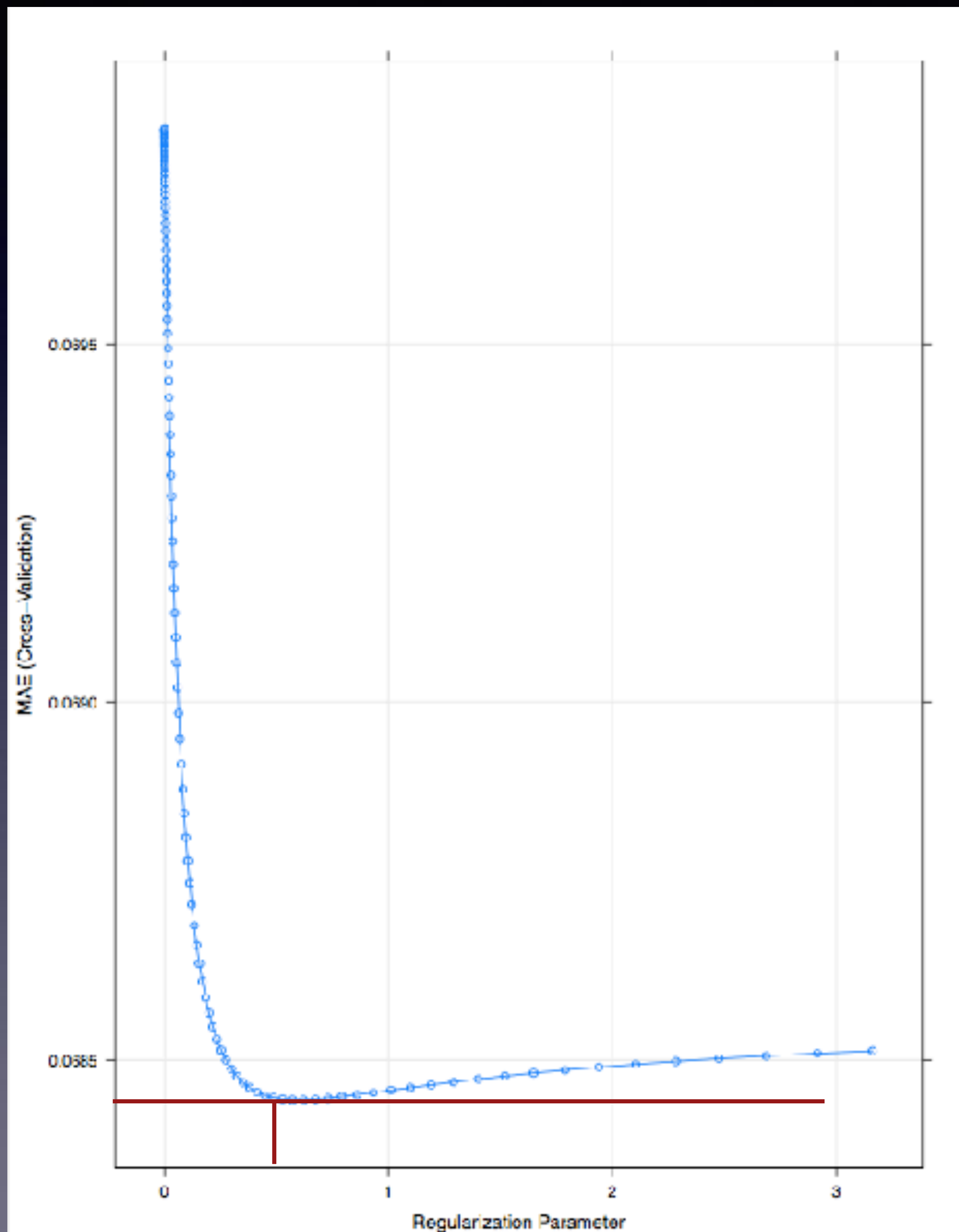
- Performed Ridge, Lasso, and Elastic Net Regressions (mix of L1 and L2 penalties)

- Ridge performed the best of the three

- Elastic Net, (after multiple “R-bombs”), yielded an optimal α of ~0.01 through cross-validation, which is essentially Ridge.



Ridge Regression



Optimal λ ~ 0.446

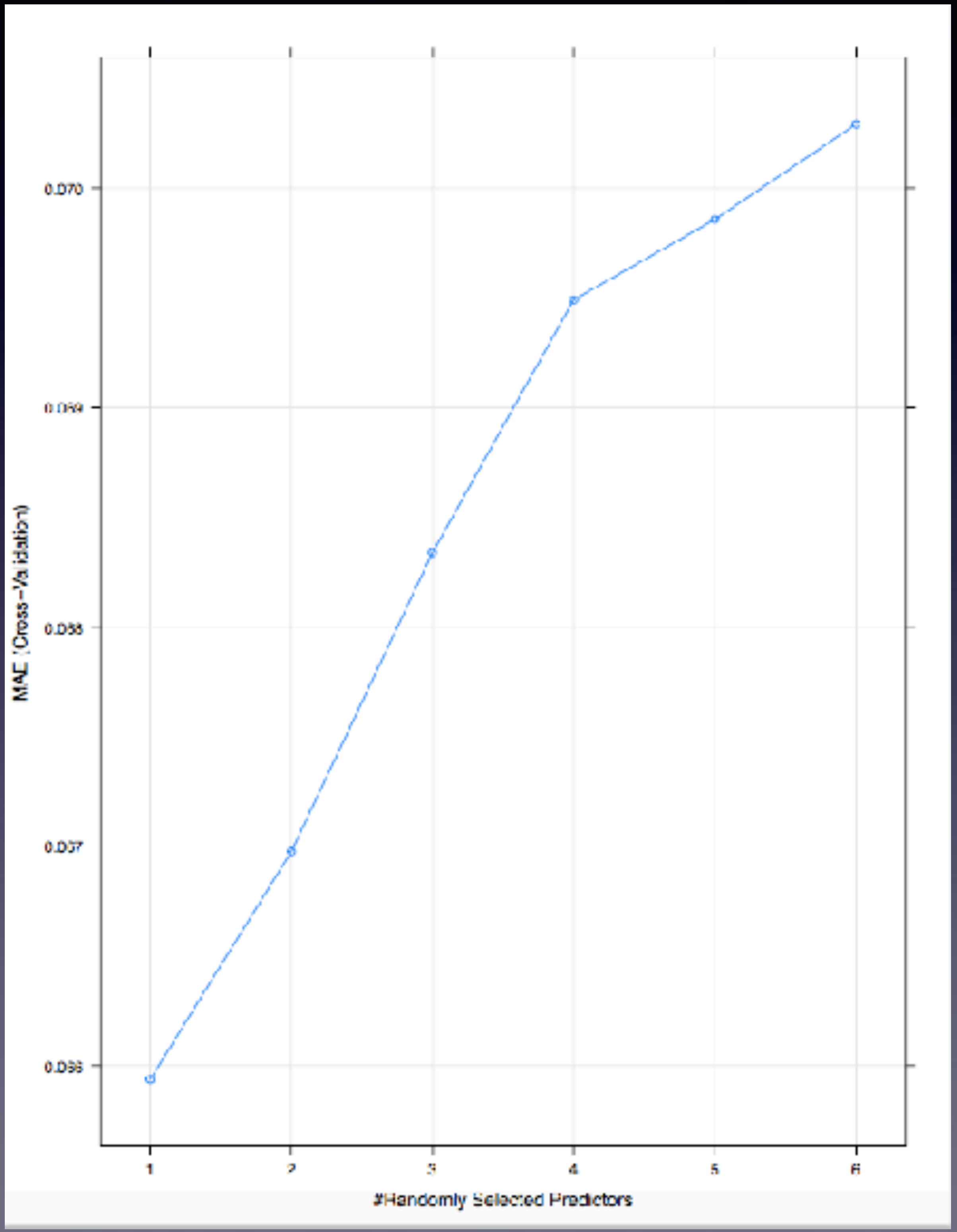
One of the better Kaggle Scores!!

(Did not top Will's "stupid multi regression")

MAE = 0.0649250

4

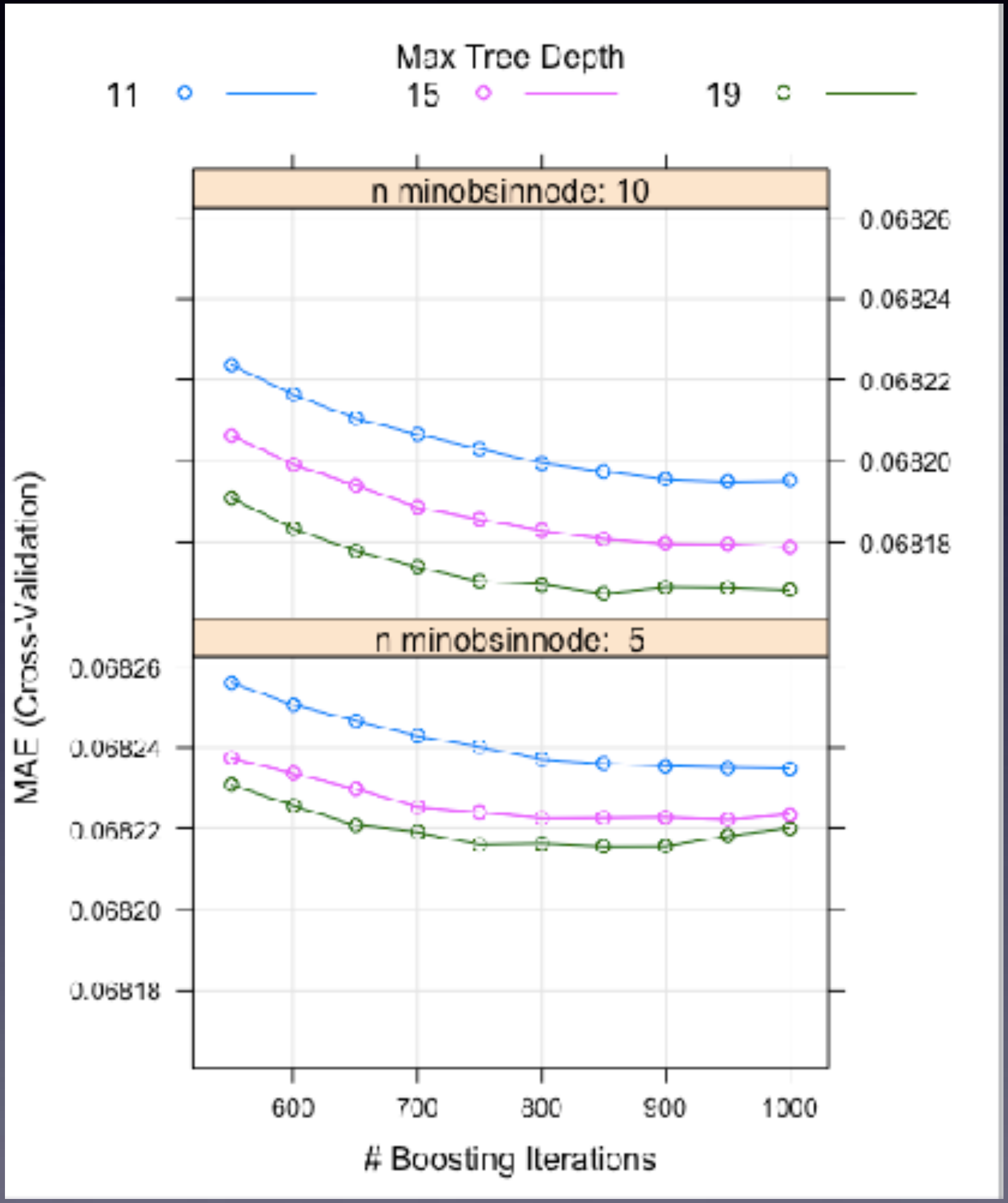
Random Forest



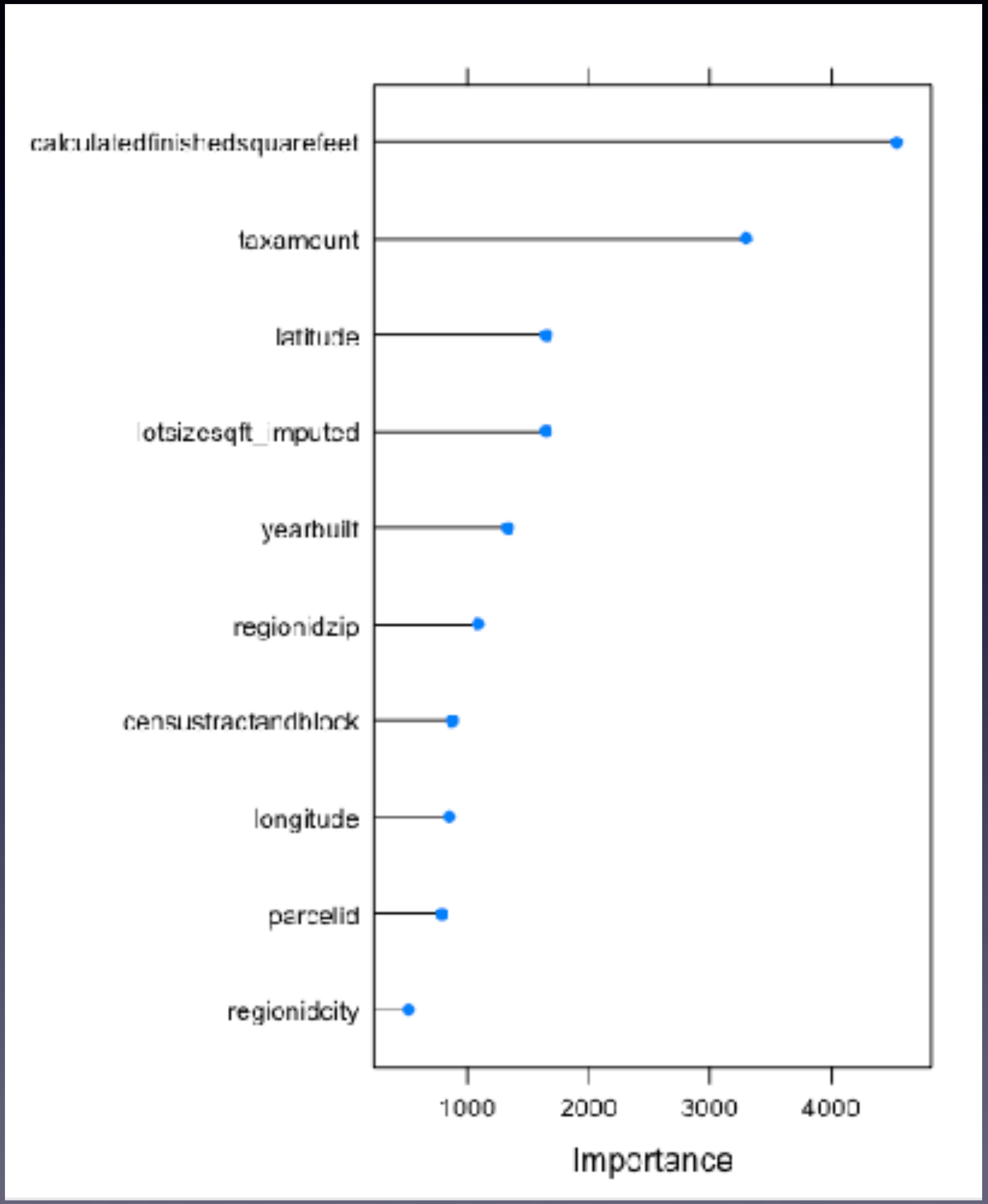
GBM Caret Tune

```r
gridSearch <- trainControl(method = "cv",
                           number = 3,
                           summaryFunction = maeSummary,
                           verboseIter = TRUE)

gbmGrid <-  expand.grid(interaction.depth = c(11,15,19),
                        n.trees = (11:20)*50,
                          shrinkage = c(.001),
                          n.minobsinnode = c(5,10))
set.seed(0)
gbmFit4 <- train(logerror ~ . - propertycountylandusecode,
                 data = full.train1,
                 method = "gbm",
                 preProcess = c("center", "scale"),
                 metric = "MAE",
                 maximize = FALSE,
                 tuneGrid = gbmGrid,
                 trControl = gridSearch,
                 verbose = FALSE)
```



Gradient Boosted Model



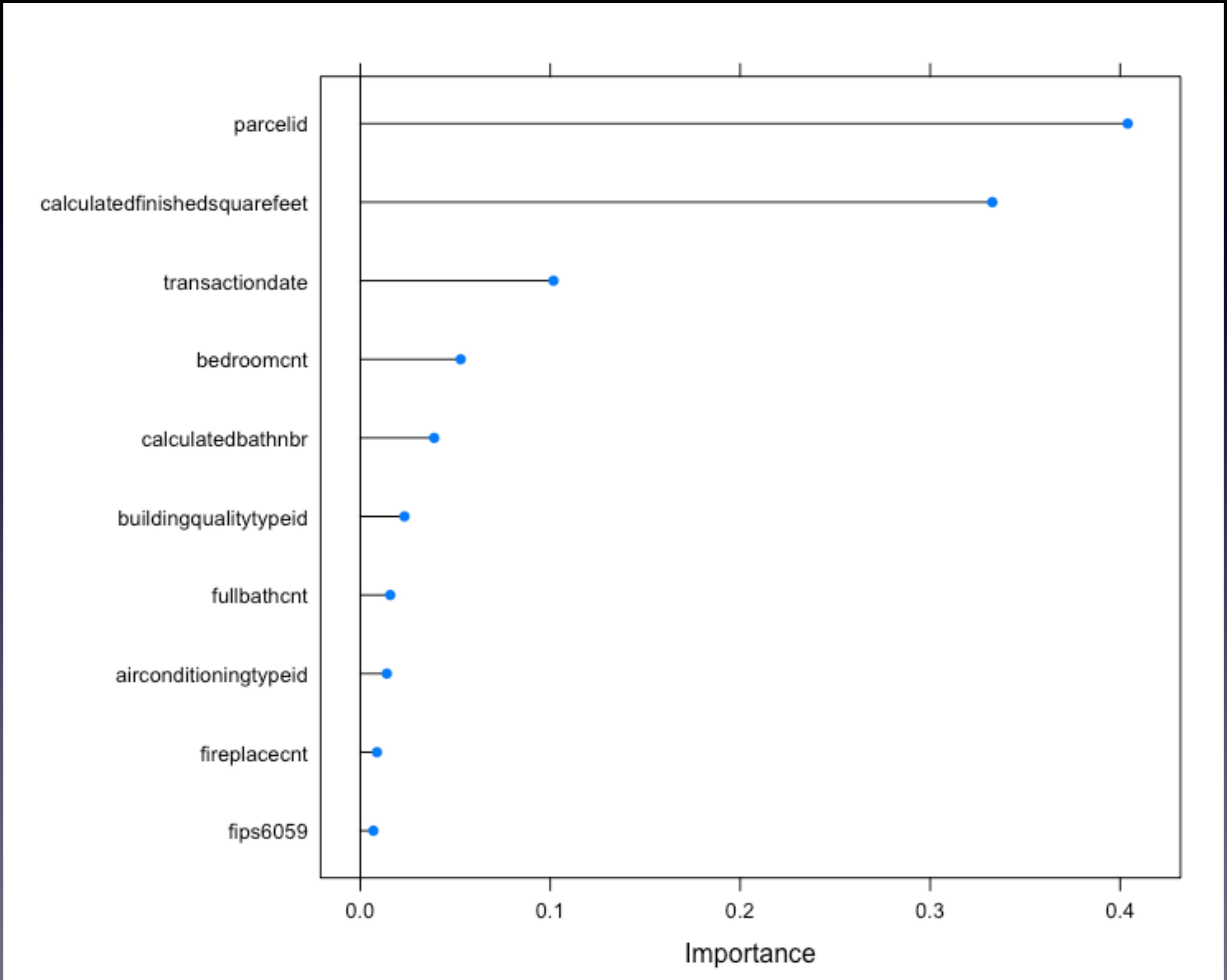
XGBoost Caret Tune

```r
cv.ctrl <- trainControl(method = "cv",number = 4,
                        classProbs = TRUE,
                        summaryFunction = maeSummary,
                        verboseIter = TRUE,
                        allowParallel=T)

ntrees = 100
xgbGrid <- expand.grid( #Owen Zhang parameter tuning slides
  eta = (2:10)/ntrees, #learning rate
  max_depth = c(4,6,8,10),
  nrounds = ntrees,
  gamma = 0,                #default=0
  colsample_bytree = c(.4, .6,.8, 1),     #default=1
  min_child_weight = c(1,3,5),     #default=1
  subsample = c(.5, .75, 1)
)

set.seed(45)
xgb_tune <-train(logerror ~ . -propertycountylandusecode-numberofstories,
                 data=small.full.train1,
                 method="xgbTree",
                 trControl=cv.ctrl,
                 tuneGrid=xgbGrid,
                 verbose=T,
                 verboseIter = T,
                 #preProcess = c("center", "scale"),
                 metric="MAE",
                 maximize = FALSE
                 #objective = 'reg:linear',
)
```

XGBoost Importance



Best Kaggle Score

```
#stupid multi regression
lr1 <- lm(logerror ~ calculatedfinishedsquarefeet + yearbuilt, data=full)
```

+ GBM

=

1297	▲82	WillMarkowitz	0.0648091	8	~10s

Your Best Entry ↑

You advanced 95 places on the leaderboard!

Your submission scored 0.0648091, which is an improvement of your previous score of 0.0648835. Great job!

Tweet this!