# An Example Predictive Modeling Workflow Using The Zillow Prize Dataset

*Jesse Piburn*

*2018-07-21*

# Contents

# Welcome

This book is meant to be an illustrative guide for approaching a predictive modeling task. We'll step through the different parts of the modeling workflow and work through the Zillow Prize Kaggle Competition dataset and prediction tasks.

The Github source for this document can be found here


Figure 1: Zillow Prize

# Chapter 1

# Introduction

This project is meant to serve as an example workflow for making predictive models. The sections of the book are roughly broken into the major steps that are a part of the modeling process.

As with many things in life, their is rarely a one-size-fits-all, always correct, way of doing something and making a predictive model is no different. In light of that, I want to stress that the workflow and methods used in this book are meant to be illustrative not authoritative.

The only always correct answer in predictive modeling is, "It depends."

## 1.1 Problem

The problem we will workthrough in this book is the Zillow Prize compeitition on that took place on Kaggle. Although it is now closed, it provides a good problemset for us to work through.

From the site > In this million-dollar competition, participants will develop an algorithm that makes predictions about the future sale prices of homes. The contest is structured into two rounds, the qualifying round which opens May 24, 2017 and the private round for the 100 top qualifying teams that opens on Feb 1st, 2018. In the qualifying round, you'll be building a model to improve the Zestimate residual error. In the final round, you'll build a home valuation algorithm from the ground up, using external data sources to help engineer new features that give your model an edge over the competition.

## 1.2 Evaluation

The submission were evaluated based on the Mean Absolute Error between the predicted `logerror` and the actual `logerror`

The `logerror` is defined as

$$logerror = log(Zestimate) - log(SalePrice) \tag{1.1}$$

while Mean Absolute Error is defined as

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n} \tag{1.2}$$

## 1.3 Initital Thoughts

> "Location, Location, Location."
>
> — Some Real Estate Guy

The above quote is of course the number one rule of real estate. Through out this modeling process, let's try to keep this idea in mind when we are exploring, creating new features, and modeling the data.

An additional interesting thing about this problem is that it can be thought about as creating a model to predict where Zillow's model is bad. We aren't trying to predict home prices, we are predicting where Zillow had a bad estimate of home prices, so the residuals of their Zestimate model.Based on this idea, let's create some new features

## 1.4 Note on Using External Features

In the original competition, you were only allowed to use the features transformations of those included in the data they provided. Since our goal is to provide an illustrative workflow for making a predictive model in general and not actually competing in the competition, we are not going to adhere to that rule and use a few external sources of information.

# Chapter 2

# PreProcessing

The first step for any data driven project is getting to know the data. In this section we will look at the raw data that was provided by the competition and then do a little pre processing that will make the data easier to work with for the rest of the project

## 2.1 The Raw Data

The raw data from zillow contains the following data (desrciptions from the the data page)

- **properties_2016.csv** - all the properties with their home features for 2016. Note: Some 2017 new properties don't have any data yet except for their parcelid's. Those data points should be populated when properties_2017.csv is available.
- **properties_2017.csv** - all the properties with their home features for 2017 (released on 10/2/2017)
- **train_2016.csv** - the training set with transactions from 1/1/2016 to 12/31/2016
- **train_2017.csv** - the training set with transactions from 1/1/2017 to 9/15/2017 (released on 10/2/2017)
- **sample_submission.csv** - a sample submission file in the correct format
- **zillow_data_dictionary.xlsx** - Field Definitions and coded value meanings

### 2.1.1 Saving Raw Data Using `feather`

The R binding for the feather data store provides the ability for very fast read and write of data. For speed purposes we will save all raw data into a `.feather` file format to make all other read faster

```
library(feather)
library(readr)

dir.create("data-raw/feather")

prop_16 <- read_csv("data-raw/properties_2016.csv")
prop_17 <- read_csv("data-raw/properties_2017.csv")
train_16 <- read_csv("data-raw/train_2016_v2.csv")
train_17 <- read_csv("data-raw/train_2017.csv")

write_feather(prop_16, "data-raw/feather/properties_2016.feather")
```

```
write_feather(prop_17, "data-raw/feather/properties_2017.feather")
write_feather(train_16, "data-raw/feather/train_2016_v2.feather")
write_feather(train_17, "data-raw/feather/train_2017.feather")
```

## 2.2 Renaming Variables

Many of the feature names are not very consistant. To take advatange of helpful functions from the `tidyverse` set of packages, such as `starts_with()` and `one_of()` Let's rename them to something more consistant and easier to work with.

### 2.2.1 Renaming `properties` Features

```
library(tidyverse)

prop_16 <- read_feather("data-raw/feather/properties_2016.feather")
prop_17 <- read_feather("data-raw/feather/properties_2017.feather")

prop_16 <- prop_16 %>%
  rename(
    id_parcel = parcelid,
    build_year = yearbuilt,
    area_basement = basementsqft,
    area_patio = yardbuildingsqft17,
    area_shed = yardbuildingsqft26,
    area_pool = poolsizesum,
    area_lot = lotsizesquarefeet,
    area_garage = garagetotalsqft,
    area_firstfloor_finished_1 = finishedfloor1squarefeet,
    area_firstfloor_finished_2 = finishedsquarefeet50,
    area_living_finished_calc = calculatedfinishedsquarefeet,
    area_base = finishedsquarefeet6,
    area_living_finished = finishedsquarefeet12,
    area_living_perimeter = finishedsquarefeet13,
    area_total = finishedsquarefeet15,
    num_unit = unitcnt,
    num_story = numberofstories,
    num_room = roomcnt,
    num_bathroom = bathroomcnt,
    num_bedroom = bedroomcnt,
    num_bathroom_calc = calculatedbathnbr,
    num_bath = fullbathcnt,
    num_75_bath = threequarterbathnbr,
    num_fireplace = fireplacecnt,
    num_pool = poolcnt,
    num_garage = garagecarcnt,
    region_county = regionidcounty,
    region_city = regionidcity,
    region_zip = regionidzip,
    region_neighbor = regionidneighborhood,
    tax_total = taxvaluedollarcnt,
```

```
    tax_building = structuretaxvaluedollarcnt,
    tax_land = landtaxvaluedollarcnt,
    tax_property = taxamount,
    tax_year = assessmentyear,
    tax_delinquency = taxdelinquencyflag,
    tax_delinquency_year = taxdelinquencyyear,
    zoning_property = propertyzoningdesc,
    zoning_landuse = propertylandusetypeid,
    zoning_landuse_county = propertycountylandusecode,
    str_flag_fireplace = fireplaceflag,
    str_flag_tub = hashottuborspa,
    str_quality = buildingqualitytypeid,
    str_framing = buildingclasstypeid,
    str_material = typeconstructiontypeid,
    str_deck = decktypeid,
    str_story = storytypeid,
    str_heating = heatingorsystemtypeid,
    str_aircon = airconditioningtypeid,
    str_arch_style = architecturalstyletypeid
  )

# use 2016 names to rename 17
names(prop_17) <- names(prop_16)
```

### 2.2.2 renaming `train` features

```
trans_16 <- read_feather("data-raw/feather/train_2016_v2.feather")
trans_17 <- read_feather("data-raw/feather/train_2017.feather")

trans_16 <- trans_16 %>%
  rename(
  id_parcel = parcelid,
  date = transactiondate,
  log_error = logerror
  )

# use 2016 names to rename 17
names(trans_17) <- names(trans_16)
```

### 2.2.3 Basic Transformations

Based on the definitions in the `zillow_data_dictionary.xlsx` we can recode some of the features to have be more interpretable while we are exploring.

#### 2.2.3.1 Properties

```
library(forcats)

prop_16 <- prop_16 %>%
  mutate(
```

```
    tax_delinquency = ifelse(tax_delinquency == "Y", "Yes", "No") %>%
      as_factor(),
    str_flag_fireplace = ifelse(str_flag_fireplace == "Y", "Yes", "No") %>%
      as_factor(),
    str_flag_tub = ifelse(str_flag_tub == "Y", "Yes", "No") %>%
      as_factor(),
    zoning_landuse = factor(zoning_landuse, levels = sort(unique(zoning_landuse))),
    zoning_landuse = fct_recode(zoning_landuse,
      "Commercial/Office/Residential Mixed Used" = "31",
      "Multi-Story Store"                        = "46",
      "Store/Office (Mixed Use)"                 = "47",
      "Duplex (2 Units Any Combination)"         = "246",
      "Triplex (3 Units Any Combination)"        = "247",
      "Quadruplex (4 Units Any Combination)"     = "248",
      "Residential General"                      = "260",
      "Single Family Residential"                = "261",
      "Rural Residence"                          = "262",
      "Mobile Home"                              = "263",
      "Townhouse"                                = "264",
      "Cluster Home"                             = "265",
      "Condominium"                              = "266",
      "Cooperative"                              = "267",
      "Row House"                                = "268",
      "Planned Unit Development"                 = "269",
      "Residential Common Area"                  = "270",
      "Timeshare"                                = "271",
      "Bungalow"                                 = "273",
      "Zero Lot Line"                            = "274",
      "Manufactured Modular Prefabricated Homes" = "275",
      "Patio Home"                               = "276",
      "Inferred Single Family Residential"       = "279",
      "Vacant Land - General"                    = "290",
      "Residential Vacant Land"                  = "291"
      )
    )

prop_17 <- prop_17 %>%
  mutate(
    tax_delinquency = ifelse(tax_delinquency == "Y", "Yes", "No") %>%
      as_factor(),
    str_flag_fireplace = ifelse(str_flag_fireplace == "Y", "Yes", "No") %>%
      as_factor(),
    str_flag_tub = ifelse(str_flag_tub == "Y", "Yes", "No") %>%
      as_factor(),
    zoning_landuse = factor(zoning_landuse, levels = sort(unique(zoning_landuse))),
    zoning_landuse = fct_recode(zoning_landuse,
      "Commercial/Office/Residential Mixed Used" = "31",
      "Multi-Story Store"                        = "46",
      "Store/Office (Mixed Use)"                 = "47",
      "Duplex (2 Units Any Combination)"         = "246",
      "Triplex (3 Units Any Combination)"        = "247",
      "Quadruplex (4 Units Any Combination)"     = "248",
      "Residential General"                      = "260",
```

```
      "Single Family Residential"                = "261",
      "Rural Residence"                          = "262",
      "Mobile Home"                              = "263",
      "Townhouse"                                = "264",
      "Cluster Home"                             = "265",
      "Condominium"                              = "266",
      "Cooperative"                              = "267",
      "Row House"                                = "268",
      "Planned Unit Development"                 = "269",
      "Residential Common Area"                  = "270",
      "Timeshare"                                = "271",
      "Bungalow"                                 = "273",
      "Zero Lot Line"                            = "274",
      "Manufactured Modular Prefabricated Homes" = "275",
      "Patio Home"                               = "276",
      "Inferred Single Family Residential"       = "279",
      "Vacant Land - General"                    = "290",
      "Residential Vacant Land"                  = "291"
      )
    )
```

#### 2.2.3.2 Transactions

The transactions tables are where our response variable `log_error` (name changed from orginal `logerror`) and the dates of the transactions are recorded.

To make them easier to work with, let's combine all the transactions into one table and create a few basic transformations of the `date` (name changed from original `transactiondate`)

```
library(lubridate)

# combine transactions into one data frame
trans <- trans_16 %>%
  bind_rows(trans_17) %>%
  mutate(
    abs_log_error = abs(log_error),
    year = year(date),
    month_year = make_date(year(date), month(date)),
    month = month(date, label = TRUE),
    week = floor_date(date, unit = "week"),
    week_of_year = week(date),
    week_since_start = (min(date) %--% date %/% dweeks()) + 1,
    wday = wday(date, label = TRUE),
    day_of_month = day(date)
  )
```

Save our output

```
write_feather(prop_16, "data/properties_16.feather")
write_feather(prop_17, "data/properties_17.feather")
write_feather(trans, "data/transactions.feather")
```

## 2.3 Extracting Geographic Information

As noted in the 1 we are going to break from the rules of the competition and use external information to (hopefully) help improve our predictions. Since the data we are using relate to locations of individual properties and we have each of their geographic coordinates, `latitude` and `longitude` let's use those to get the U.S. Census Geographies they are apart of that we can make use of when adding external information.

The original data contain the fields `rawcensustractandblock` and `censustractandblock` but after trying to parse those into a usable format and failing, I figured it was just easier to use the `latitude` and `longitude` fields and then join that to the Census information.

```
library(sf)
library(tidycensus)

# NAD83 / California zone 5 (ftUS)
# https://epsg.io/2229
crs_id <- 2229

api_key <- Sys.getenv("CENSUS_API_KEY")
census_api_key(api_key)

# some obs have no data at all included lat/long
# the original lat / lon are mulitpled by 10e5 so divide to
# get lat lon back when converting to sf
properties <- read_feather("data-raw/properties_2017") %>%
  filter(!is.na(latitude)) %>%
  mutate(
    lat = latitude / 10e5,
    lon = longitude / 10e5
    ) %>%
  st_as_sf(
    coords = c("lon", "lat"),
    crs = 4326, # WGS 84
    remove = FALSE # keep lat/long fields
    ) %>%
  st_transform(crs_id)

census_bgs <- get_acs(
  geography = "block group",
  variables = "B19013_001",
  state = "CA",
  county = c("Los Angeles", "Orange", "Ventura"),
  geometry = TRUE,
  keep_geo_vars = TRUE
  ) %>%
  st_transform(crs_id)

# inner join
# due to lat / lon error some points didn't intersect
# with block groups left = FALSE is inner join
properties_geo <- properties %>%
  st_join(census_bgs, left = FALSE)

# find all of the points that didn't intersect
```

```
# buffer them and then join to closest block
# then add back the already joined points
# the buffer distance I just played around with until
# all points joined with a block group
properties_geo <- properties %>%
  filter(!parcelid %in% properties_geo$parcelid) %>%
  st_buffer(dist = 1500) %>% # units are in us-ft based on crs_id
  st_join(census_bgs, left = FALSE, largest = TRUE) %>%
  rbind(properties_geo)


# remove geometry b/c feather can't store lists
properties_geo <- properties_geo %>%
  select(
    id_parcel = parcelid,
    id_geo_state = STATEFP,
    id_geo_county = COUNTYFP,
    id_geo_tract = TRACTCE,
    id_geo_bg = BLKGRPCE,
    id_geo_bg_fips = GEOID,
    id_geo_bg_name = NAME.y,
    geo_bg_arealand = ALAND,
    geo_bg_areawater = AWATER,
    lat,
    lon
    ) %>%
  mutate(
    id_geo_county_fips = paste0(id_geo_state, id_geo_county),
    id_geo_tract_fips = paste0(id_geo_county_fips, id_geo_tract),
    id_geo_county_name = factor(id_geo_county) %>%
      fct_recode(
        "Los Angeles" = "037",
        "Orange"      = "059",
        "Ventura"     = "111"
      )
  )
```

Now save our geographic features

```
# remove geometry b/c feather can't store lists
# add back in when needed from lat lon
properties_geo$geometry <- NULL

write_feather(properties_geo, "data/properties_geo_only.feather")
```

# Chapter 3

# Exploratory Analysis

After Preprocessing the next step is doing exploratory data analysis (EDA). I can't stess enough how critical this step is. It is tempting to want to jump right into making models and then start improving and tweaking them from there, but this can quickly take you down a rabbit hole, waste your time, and generally make you sad.

The time you spend doing EDA will pay dividends later.

Below we are first going to look at only our response variable `log_error` after that we will look at the predictor features in `properties`. Once we get a good handle on both of those, we'll look at how our response variable `log_error` varies across the predictors in `properties`

Throughout this section we will progressively pare down features in our `properties` data due to common things such as, missingness and redundancy, to only the features that we are going to continue with into the next stages.

```
library(skimr)
library(tidyverse)
library(feather)
library(DataExplorer)

trans <- read_feather("data/transactions.feather")
```

## 3.1 Response Variable

`log_error` something something text come back to when the processing is finished. Apologies ahead of time for the poor formating of the table. I'll work to fix that.

```
skim(trans) %>%
  skimr::pander()
```

Skim summary statistics
n obs: 167888
n variables: 12

Table 3.1: Table continues below

| variable | missing | complete | n | min | max |
|---|---|---|---|---|---|
| date | 0 | 167888 | 167888 | 2016-01-01 | 2017-09-25 |

| variable | missing | complete | n | min | max |
|---|---|---|---|---|---|
| month_year | 0 | 167888 | 167888 | 2016-01-01 | 2017-09-01 |
| week | 0 | 167888 | 167888 | 2015-12-27 | 2017-09-24 |

| median | n_unique |
|---|---|
| 2016-10-11 | 616 |
| 2016-10-01 | 21 |
| 2016-10-09 | 92 |

Table 3.3: Table continues below

| variable | missing | complete | n | n_unique |
|---|---|---|---|---|
| month | 0 | 167888 | 167888 | 12 |
| wday | 0 | 167888 | 167888 | 7 |

| top_counts | ordered |
|---|---|
| Jun: 22378, May: 20448, Aug: 20412, Jul: 19437 | FALSE |
| Fri: 44914, Thu: 34143, Wed: 32692, Tue: 31404 | FALSE |

Table 3.5: Table continues below

| variable | missing | complete | n | mean | sd | p0 |
|---|---|---|---|---|---|---|
| day_of_month | 0 | 167888 | 167888 | 16.43 | 8.99 | 1 |
| id_parcel | 0 | 167888 | 167888 | 1.3e+07 | 3e+06 | 1.1e+07 |

| p25 | p50 | p75 | p100 |
|---|---|---|---|
| 9 | 16 | 24 | 31 |
| 1.2e+07 | 1.3e+07 | 1.4e+07 | 1.7e+08 |

Table 3.7: Table continues below

| variable | missing | complete | n | mean | sd | p0 |
|---|---|---|---|---|---|---|
| abs_log_error | 0 | 167888 | 167888 | 0.069 | 0.15 | 0 |
| log_error | 0 | 167888 | 167888 | 0.014 | 0.17 | -4.66 |
| week_of_year | 0 | 167888 | 167888 | 22.15 | 11.5 | 1 |
| week_since_start | 0 | 167888 | 167888 | 46.31 | 26.84 | 1 |
| year | 0 | 167888 | 167888 | 2016.46 | 0.5 | 2016 |

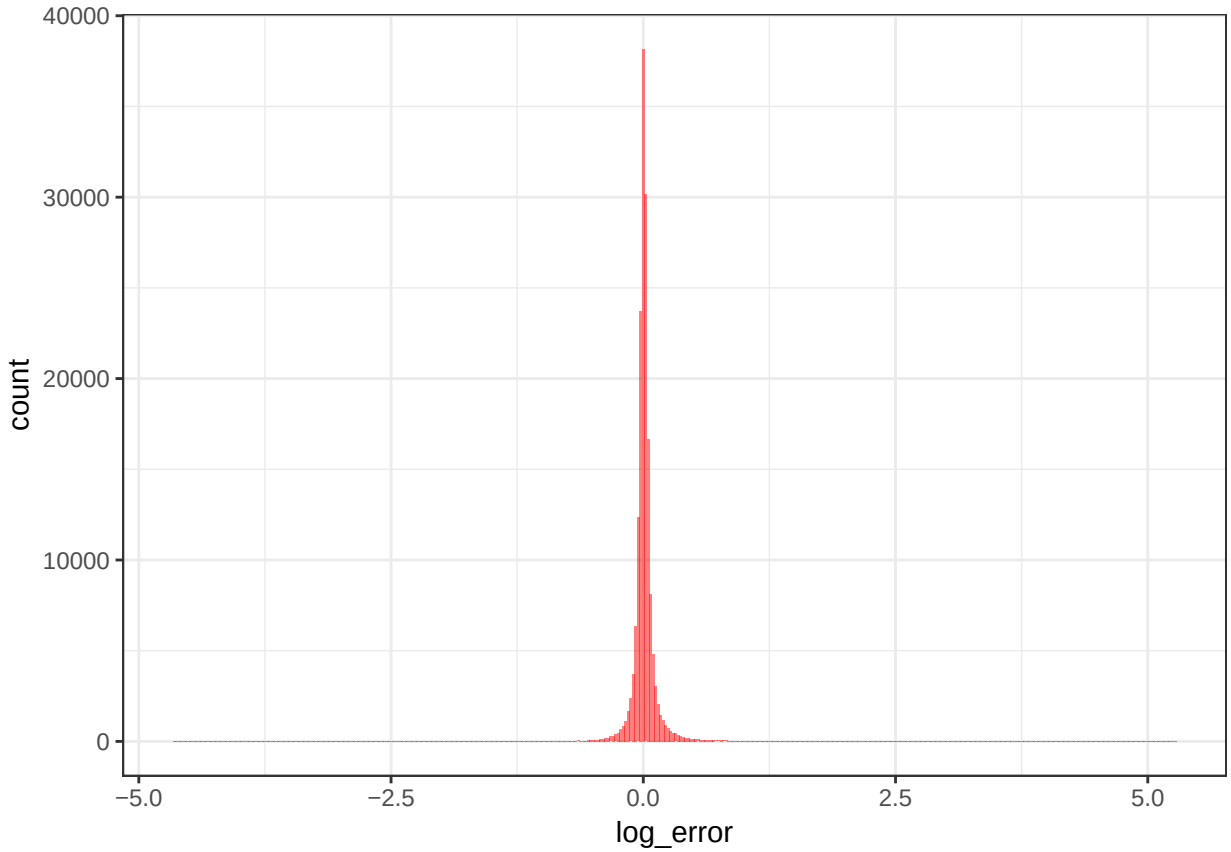



Figure 3.1: Distribution of Log Error

| p25 | p50 | p75 | p100 |
|---|---|---|---|
| 0.014 | 0.032 | 0.069 | 5.26 |
| -0.025 | 0.006 | 0.039 | 5.26 |
| 13 | 22 | 31 | 53 |
| 23 | 41 | 72 | 91 |
| 2016 | 2016 | 2017 | 2017 |

```
trans %>%
  ggplot(aes(x = log_error)) +
  geom_histogram(bins=400, fill = "red", alpha = 0.5) +
  theme_bw()
```

```
trans %>%
  filter(
    log_error > quantile(log_error, probs = c(.05)),
    log_error < quantile(log_error, probs = c(.95))
  ) %>%
  ggplot(aes(x = log_error)) +
  geom_histogram(fill = "red", alpha = 0.5) +
  theme_bw()
```

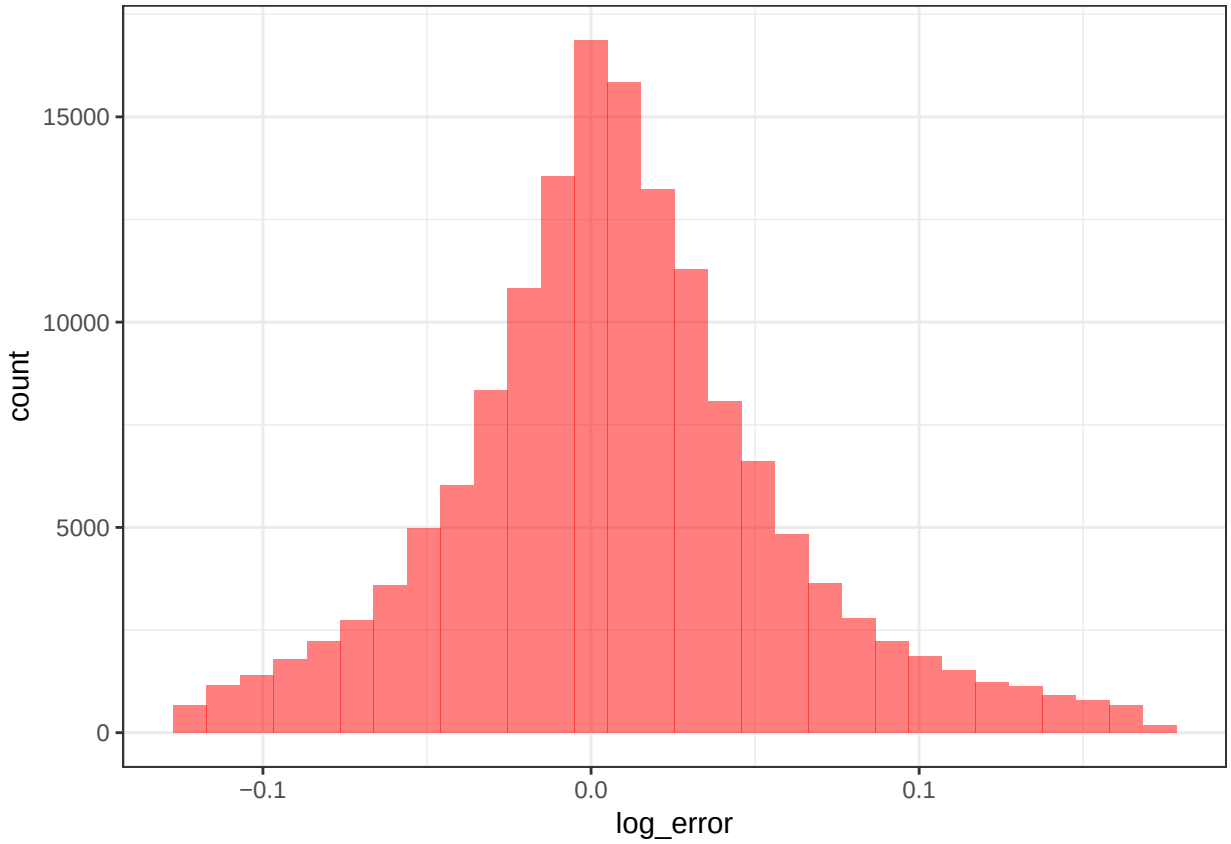



Figure 3.2: Distribution of Log Error Between 5 and 95 Percentile

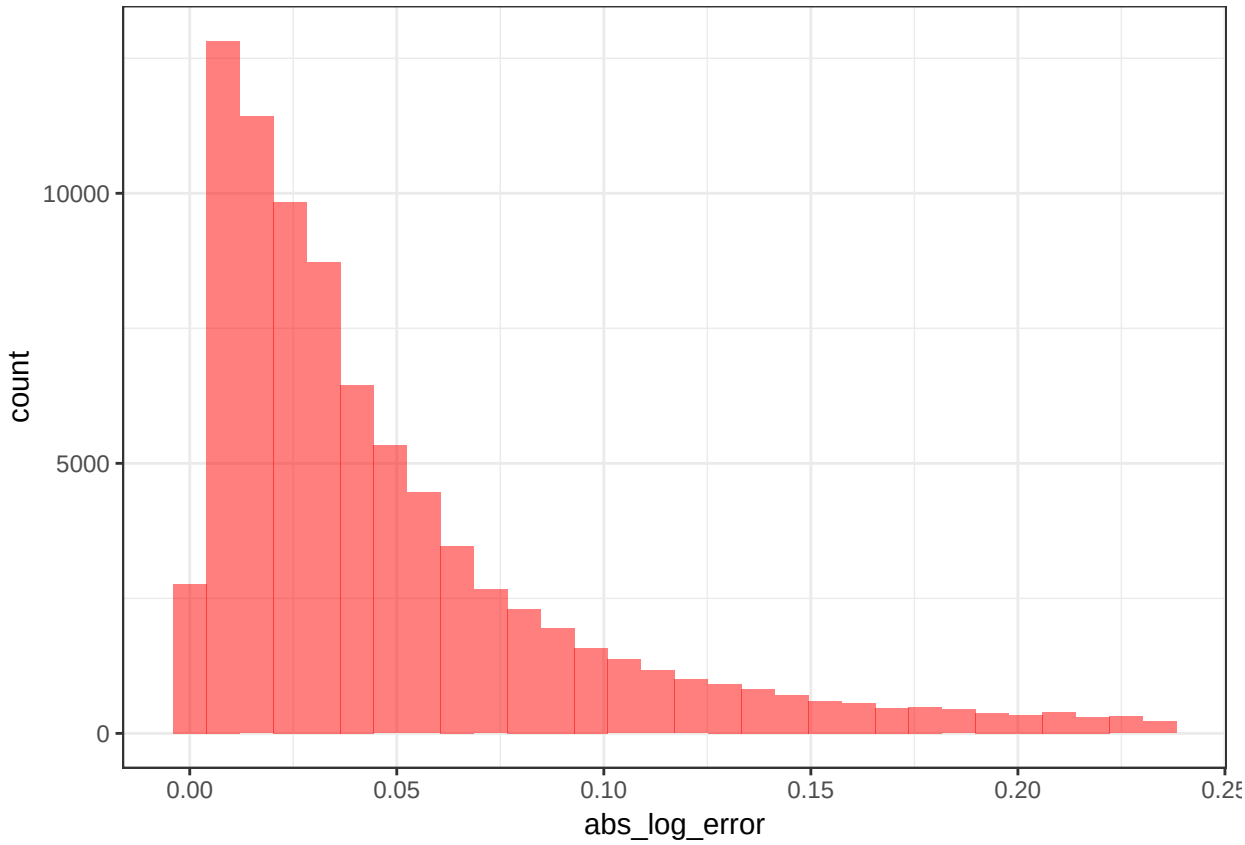



Figure 3.3: Distribution of Absolute value of Log Error Between 5 and 95 Percentile

```
trans %>%
  filter(
    log_error > quantile(abs_log_error, probs = c(.05)),
    log_error < quantile(abs_log_error, probs = c(.95))
  ) %>%
  ggplot(aes(x = abs_log_error)) +
  geom_histogram(fill = "red", alpha = 0.5) +
  theme_bw()
```

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

```
trans %>%
  group_by(month_year) %>%
  summarise(mean_log_error = mean(log_error)) %>%
  ggplot(aes(x = month_year, y = mean_log_error)) +
  geom_line(size = 1, colour = "red") +
  geom_point(size = 3, colour = "red") +
  theme_bw()
```

```
trans %>%
  group_by(month_year, year, month) %>%
  summarise(mean_log_error = mean(log_error)) %>%
  ungroup() %>%
  ggplot(aes(x = as.numeric(month), y = mean_log_error)) +
```

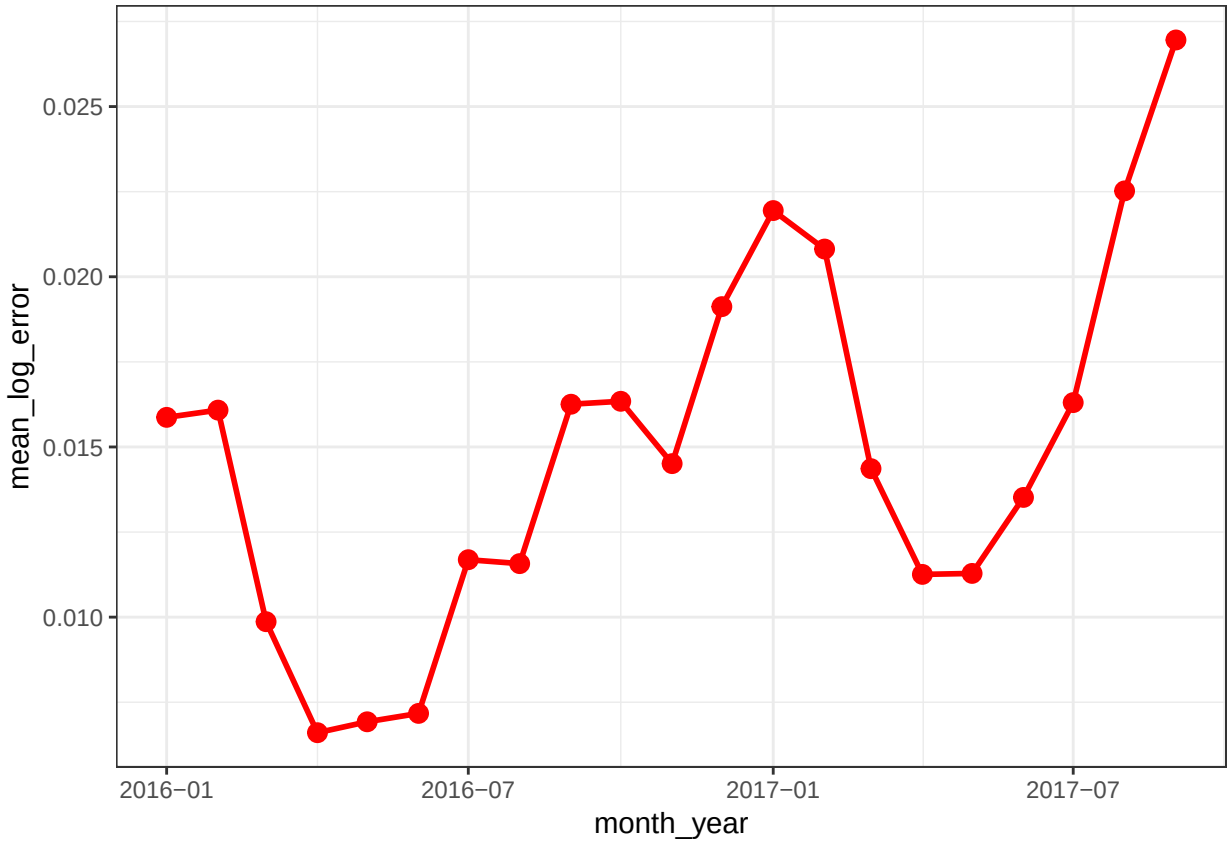



Figure 3.4: Average Log Error by Month

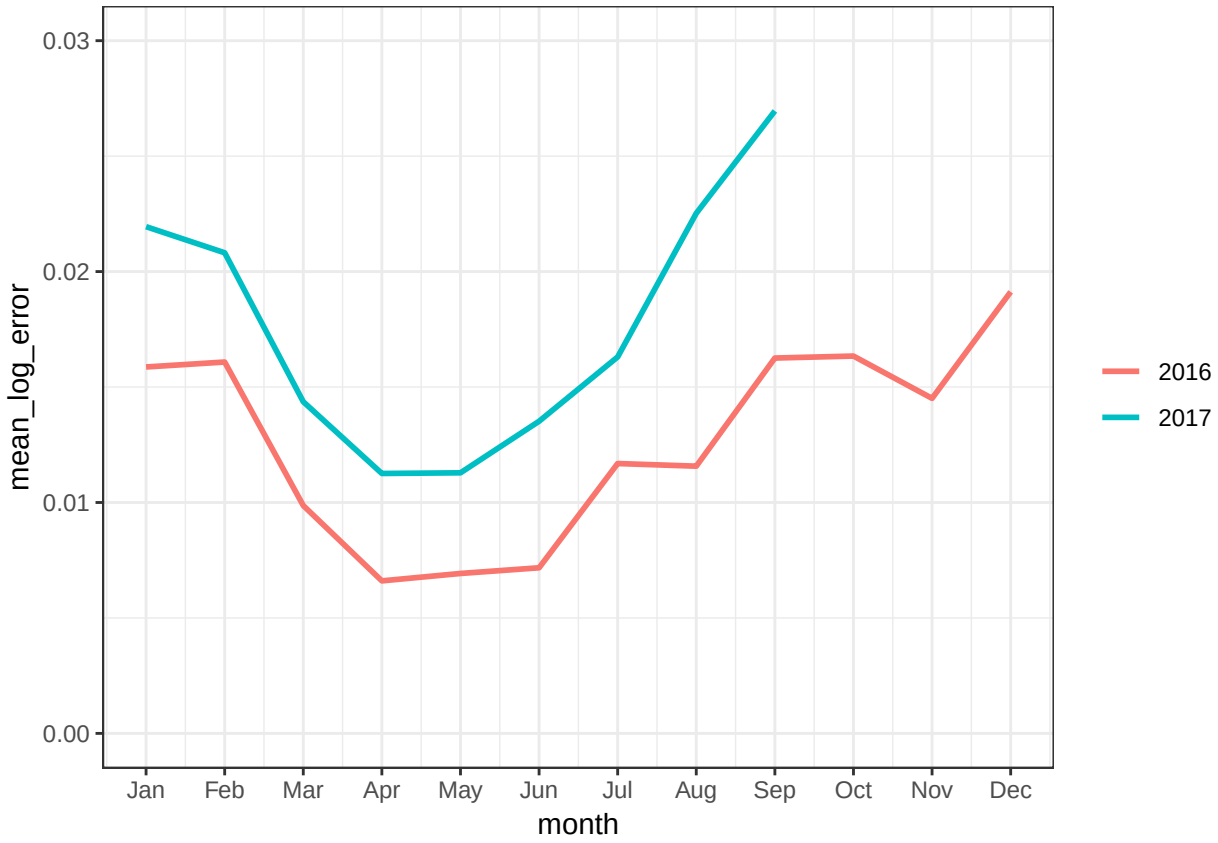



Figure 3.5: Average Log Error by Month. 2017 Looks to have a higher baseline

```
  geom_path(aes(colour = as.factor(year)), size = 1) +
  theme_bw() +
  ylim(c(0, .03)) +
  scale_x_continuous(breaks = 1:12, labels = levels(trans$month)) +
  labs(
    colour = NULL,
    x = "month"
  )
```

```
trans %>%
  group_by(week_since_start) %>%
  summarise(mean_log_error = mean(log_error)) %>%
  ggplot(aes(x = week_since_start, y = mean_log_error)) +
  geom_line(colour = "red", size = 1) +
  geom_smooth() +
  theme_bw()
```

### 3.1.1 Transactions Over Time

```
trans %>%
  group_by(week_since_start) %>%
```

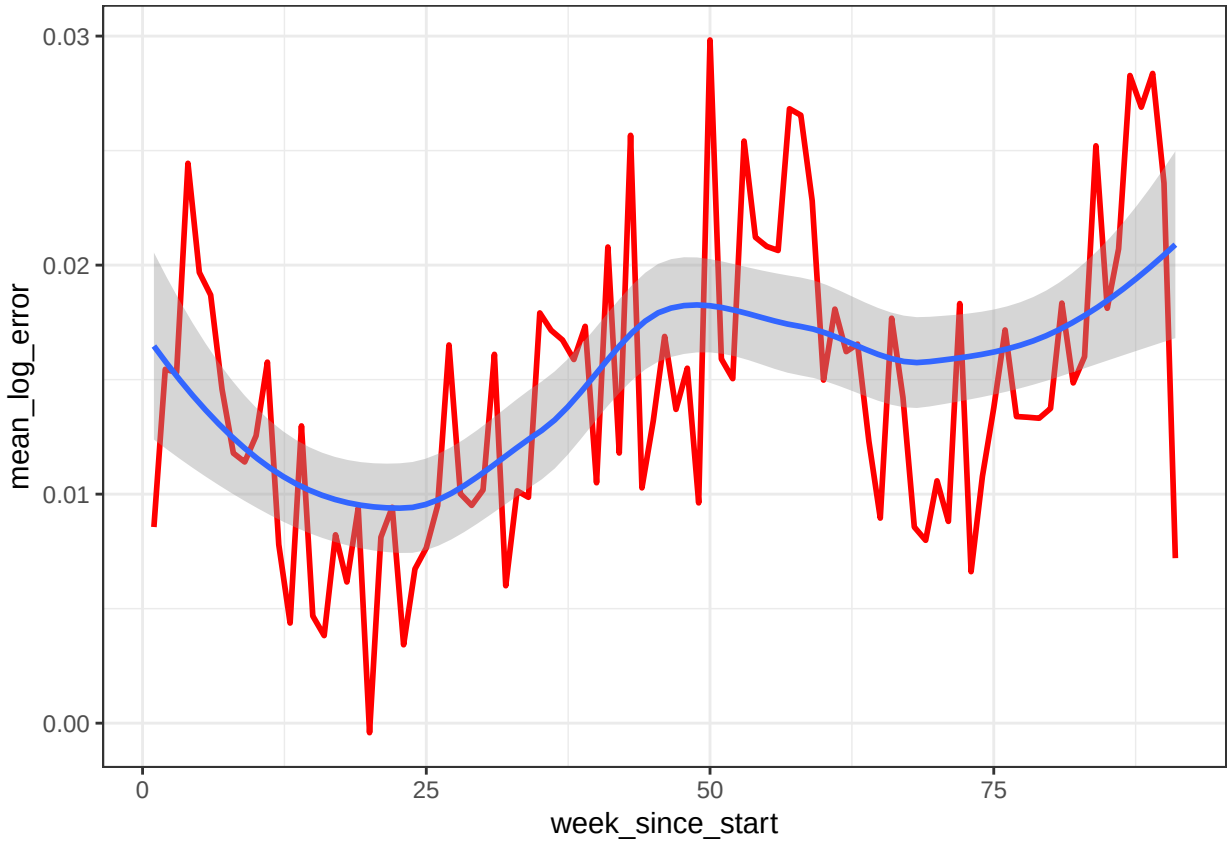



Figure 3.6: Average Log Error by Week

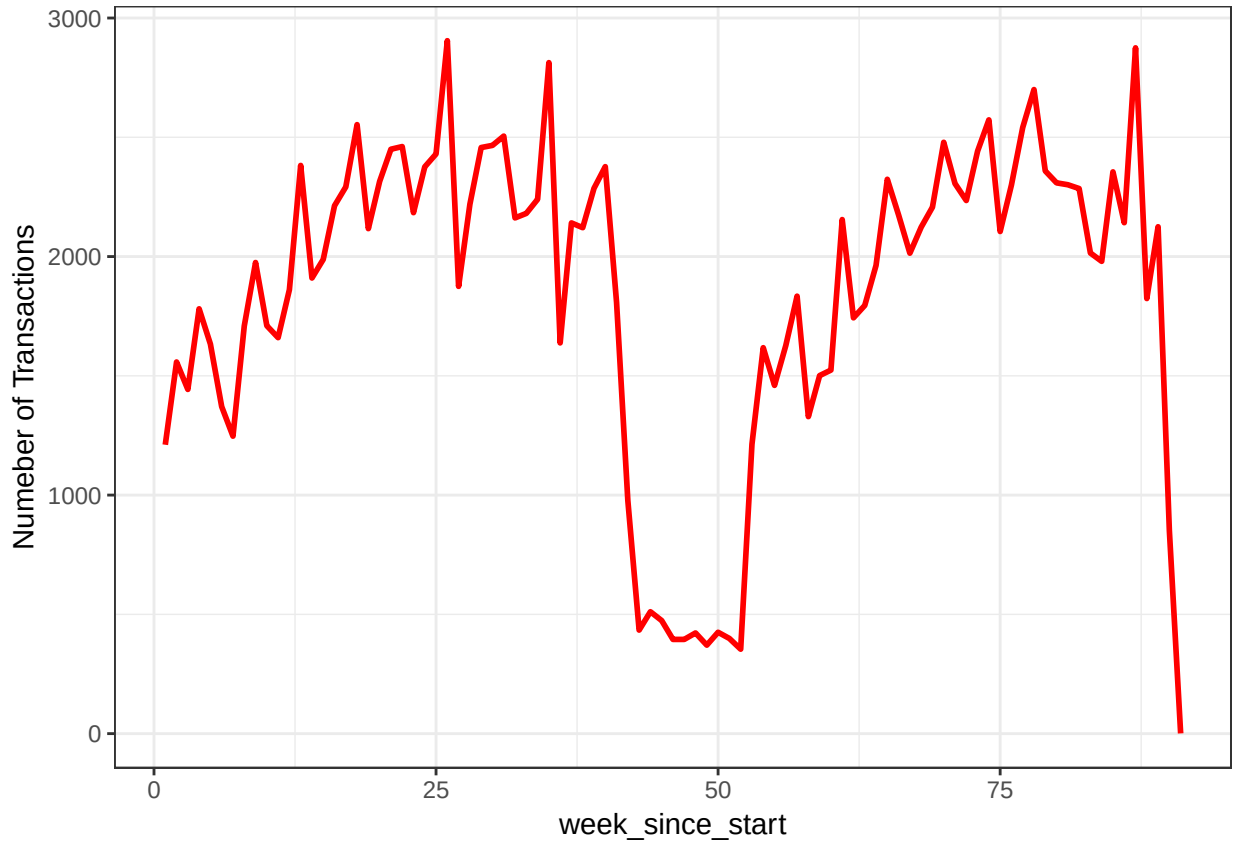



Figure 3.7: Number of Transactions per Week. The dip in the middle corresponds to the hold out testing data

```
  summarise(n = n()) %>%
  ggplot(aes(x = week_since_start, y = n)) +
  geom_line(colour = "red", size = 1) +
  theme_bw() +
  labs(
    y = "Numeber of Transactions"
  )
```

```
trans %>%
  group_by(wday) %>%
  count() %>%
  ggplot(aes(x = wday, y = n)) +
  geom_bar(stat = "identity", fill = "red", alpha = 0.5) +
  theme_bw()
```

### 3.1.2 Spatial Distribution of `log_error`

```
library(leaflet)
library(leaflet.extras)

read_feather("data/properties_geo_only.feather") %>%
```

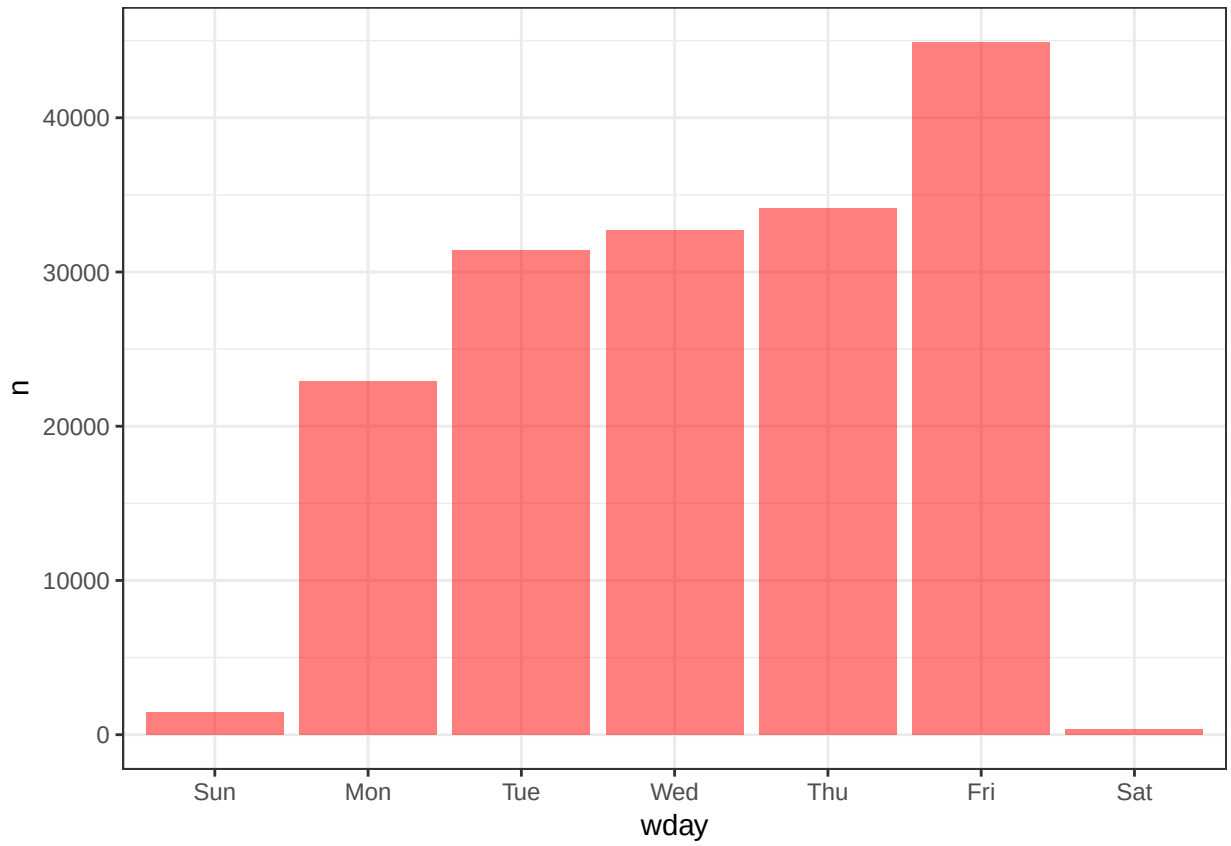



Figure 3.8: Number of Transactions by Day of the Week.

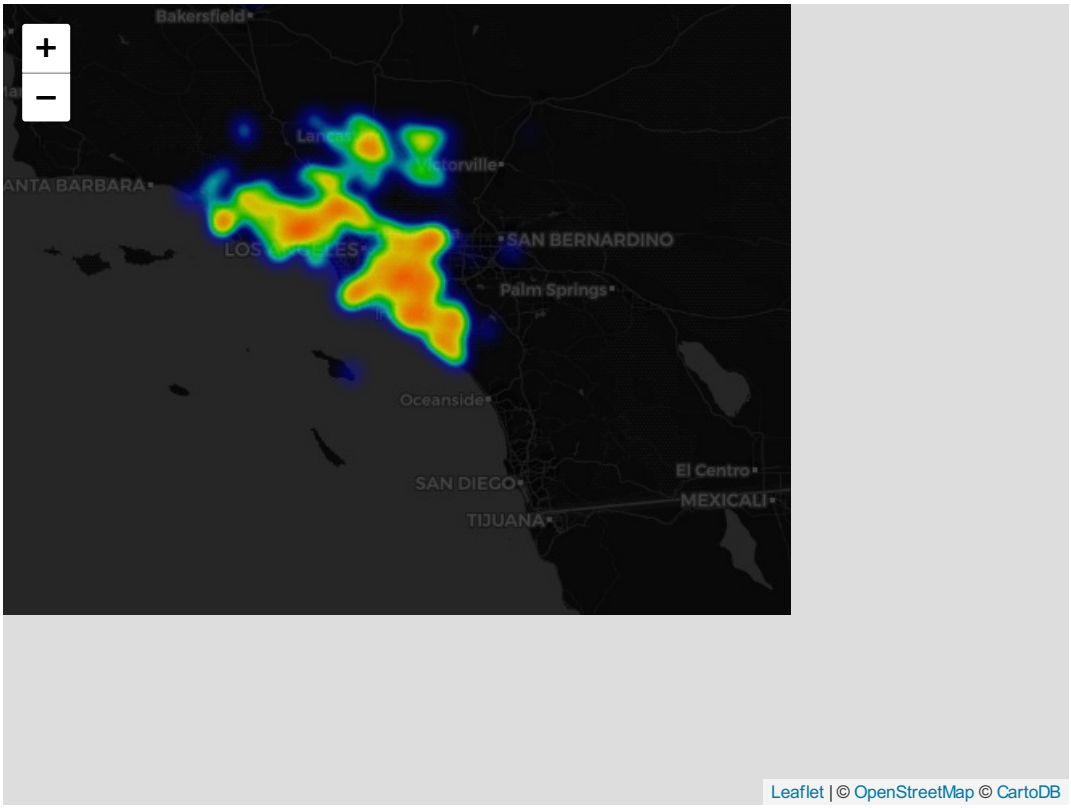



Figure 3.9: Spatial Distribution of Log Errors

```
  right_join(trans, by = "id_parcel") %>%
  filter(
    !is.na(lat)
    ) %>%
leaflet() %>%
  addProviderTiles(providers$CartoDB.DarkMatter) %>%
  addHeatmap(lng=~lon, lat=~lat, intensity = ~log_error,
             radius = 5, minOpacity = 0.2, cellSize = 6)
```

## 3.2 Predictor Variables

Now lets take a look at the `properties` dataset. Based on the descriptions from Kaggle, it seem's like the `properties_17.csv` has updated information and is a replacement from that of `properties_16.csv`. For our purposes we are only going to use `properties_17.csv`, however given more space, it would be interesting to look into the differences in these files to see if there were any patterns that could be useful.

```
properties <- read_feather("data/properties_17.feather")
```

Again apologies for the table formatting. Useful information none the less.

```
skim(properties) %>%
  skimr::pander()
```

```
## Warning: Skimr's histograms incorrectly render with pander on Windows.
```

```
## Removing them. Use kable() if you'd like them rendered.
```

Skim summary statistics
n obs: 2985217
n variables: 58

| variable | missing | complete | n | min | max | empty | n_unique |
|---|---|---|---|---|---|---|---|
| fips | 2932 | 2982285 | 2985217 | 5 | 5 | 0 | 3 |
| pooltypeid10 | 2968211 | 17006 | 2985217 | 1 | 1 | 0 | 1 |
| pooltypeid2 | 2952161 | 33056 | 2985217 | 1 | 1 | 0 | 1 |
| rawcensustractandblock | 2932 | 2982285 | 2985217 | 12 | 16 | 0 | 100529 |
| str_arch_style | 2979156 | 6061 | 2985217 | 1 | 2 | 0 | 8 |
| str_material | 2978471 | 6746 | 2985217 | 1 | 2 | 0 | 5 |
| zoning_landuse_county | 2999 | 2982218 | 2985217 | 1 | 4 | 0 | 234 |
| zoning_property | 1002746 | 1982471 | 2985217 | 1 | 10 | 0 | 5651 |

Table 3.10: Table continues below

| variable | missing | complete | n | n_unique |
|---|---|---|---|---|
| str_flag_fireplace | 2980054 | 5163 | 2985217 | 1 |
| str_flag_tub | 2935155 | 50062 | 2985217 | 1 |
| tax_delinquency | 2928702 | 56515 | 2985217 | 1 |
| zoning_landuse | 2932 | 2982285 | 2985217 | 16 |

| top_counts | ordered |
|---|---|
| NA: 2980054, No: 5163 | FALSE |
| NA: 2935155, No: 50062 | FALSE |
| NA: 2928702, Yes: 56515 | FALSE |
| Sin: 2152863, Con: 483789, Dup: 114415, Pla: 61559 | FALSE |

Table 3.12: Table continues below

| variable | missing | complete | n | mean |
|---|---|---|---|---|
| area_base | 2963735 | 21482 | 2985217 | 2427.56 |
| area_basement | 2983590 | 1627 | 2985217 | 647.22 |
| area_firstfloor_finished_1 | 2781459 | 203758 | 2985217 | 1379.78 |
| area_firstfloor_finished_2 | 2781459 | 203758 | 2985217 | 1392.03 |
| area_garage | 2094209 | 891008 | 2985217 | 383.16 |
| area_living_finished | 264431 | 2720786 | 2985217 | 1764.04 |
| area_living_perimeter | 2977546 | 7671 | 2985217 | 1178.92 |
| area_patio | 2903629 | 81588 | 2985217 | 321.54 |
| area_pool | 2957259 | 27958 | 2985217 | 519.72 |
| area_shed | 2982571 | 2646 | 2985217 | 278.37 |
| area_total | 2795032 | 190185 | 2985217 | 2754.87 |
| id_parcel | 0 | 2985217 | 2985217 | 1.3e+07 |
| latitude | 2932 | 2982285 | 2985217 | 3.4e+07 |
| longitude | 2932 | 2982285 | 2985217 | -1.2e+08 |
| num_75_bath | 2668860 | 316357 | 2985217 | 1.01 |

| variable | missing | complete | n | mean |
|---|---|---|---|---|
| num_bath | 117156 | 2868061 | 2985217 | 2.25 |
| num_fireplace | 2672093 | 313124 | 2985217 | 1.17 |
| num_garage | 2094209 | 891008 | 2985217 | 1.83 |
| num_pool | 2445585 | 539632 | 2985217 | 1 |
| num_story | 2299541 | 685676 | 2985217 | 1.4 |
| num_unit | 1004175 | 1981042 | 2985217 | 1.18 |
| pooltypeid7 | 2479322 | 505895 | 2985217 | 1 |
| region_city | 62128 | 2923089 | 2985217 | 34987.66 |
| region_county | 2932 | 2982285 | 2985217 | 2569.09 |
| region_neighbor | 1828476 | 1156741 | 2985217 | 193538.7 |
| region_zip | 12714 | 2972503 | 2985217 | 96553.29 |
| str_aircon | 2169855 | 815362 | 2985217 | 1.95 |
| str_deck | 2967838 | 17379 | 2985217 | 66 |
| str_framing | 2972486 | 12731 | 2985217 | 3.73 |
| str_heating | 1116053 | 1869164 | 2985217 | 4.08 |
| str_quality | 1043822 | 1941395 | 2985217 | 6.28 |
| str_story | 2983594 | 1623 | 2985217 | 7 |
| tax_delinquency_year | 2928700 | 56517 | 2985217 | 13.89 |
| tax_year | 2933 | 2982284 | 2985217 | 2016 |

| sd | p0 | p25 | p50 | p75 | p100 |
|---|---|---|---|---|---|
| 7786.19 | 117 | 1072 | 2008 | 3411 | 952576 |
| 538.79 | 20 | 272 | 535 | 847.5 | 8516 |
| 634.42 | 1 | 1010 | 1281 | 1615 | 31303 |
| 682.32 | 3 | 1012 | 1284 | 1619 | 41906 |
| 246.22 | 0 | 312 | 441 | 494 | 7749 |
| 1031.38 | 1 | 1198 | 1542 | 2075 | 427079 |
| 357.09 | 120 | 960 | 1296 | 1440 | 2688 |
| 236.88 | 10 | 190 | 270 | 390 | 7983 |
| 191.33 | 19 | 430 | 495 | 594 | 17410 |
| 369.78 | 10 | 96 | 168 | 320 | 6141 |
| 5999.38 | 112 | 1696 | 2173 | 2975 | 820242 |
| 7909966.39 | 1.1e+07 | 1.2e+07 | 1.3e+07 | 1.4e+07 | 1.7e+08 |
| 243515.71 | 3.3e+07 | 3.4e+07 | 3.4e+07 | 3.4e+07 | 3.5e+07 |
| 345591.77 | -1.2e+08 | -1.2e+08 | -1.2e+08 | -1.2e+08 | -1.2e+08 |
| 0.12 | 1 | 1 | 1 | 1 | 7 |
| 0.99 | 1 | 2 | 2 | 3 | 32 |
| 0.46 | 1 | 1 | 1 | 1 | 9 |
| 0.61 | 0 | 2 | 2 | 2 | 25 |
| 0 | 1 | 1 | 1 | 1 | 1 |
| 0.54 | 1 | 1 | 1 | 2 | 41 |
| 2.49 | 1 | 1 | 1 | 1 | 997 |
| 0 | 1 | 1 | 1 | 1 | 1 |
| 50709.68 | 3491 | 12447 | 25218 | 45457 | 4e+05 |
| 788.68 | 1286 | 1286 | 3101 | 3101 | 3101 |
| 165725.27 | 6952 | 46736 | 118920 | 274800 | 764167 |
| 3680.82 | 95982 | 96180 | 96377 | 96974 | 4e+05 |
| 3.16 | 1 | 1 | 1 | 1 | 13 |
| 0 | 66 | 66 | 66 | 66 | 66 |
| 0.5 | 1 | 3 | 4 | 4 | 5 |
| 3.29 | 1 | 2 | 2 | 7 | 24 |

| sd | p0 | p25 | p50 | p75 | p100 |
|---|---|---|---|---|---|
| 1.73 | 1 | 5 | 6 | 8 | 12 |
| 0 | 7 | 7 | 7 | 7 | 7 |
| 2.56 | 0 | 14 | 14 | 15 | 99 |
| 0.06 | 2000 | 2016 | 2016 | 2016 | 2016 |

Table 3.14: Table continues below

| variable | missing | complete | n | mean |
|---|---|---|---|---|
| area_living_finished_calc | 45097 | 2940120 | 2985217 | 1831.46 |
| area_lot | 272706 | 2712511 | 2985217 | 22603.76 |
| build_year | 47833 | 2937384 | 2985217 | 1964.44 |
| censustractandblock | 74985 | 2910232 | 2985217 | 6e+13 |
| num_bathroom | 2957 | 2982260 | 2985217 | 2.22 |
| num_bathroom_calc | 117156 | 2868061 | 2985217 | 2.3 |
| num_bedroom | 2945 | 2982272 | 2985217 | 3.09 |
| num_room | 2969 | 2982248 | 2985217 | 1.47 |
| tax_building | 46464 | 2938753 | 2985217 | 178142.89 |
| tax_land | 59926 | 2925291 | 2985217 | 268455.77 |
| tax_property | 22752 | 2962465 | 2985217 | 5408.95 |
| tax_total | 34266 | 2950951 | 2985217 | 443527.93 |

| sd | p0 | p25 | p50 | p75 | p100 |
|---|---|---|---|---|---|
| 1954.2 | 1 | 1215 | 1574 | 2140 | 952576 |
| 249983.63 | 100 | 5683 | 7000 | 9893 | 3.7e+08 |
| 23.64 | 1801 | 1950 | 1963 | 1981 | 2016 |
| 3.2e+11 | -1 | 6e+13 | 6e+13 | 6.1e+13 | 4.8e+14 |
| 1.08 | 0 | 2 | 2 | 3 | 32 |
| 1 | 1 | 2 | 2 | 3 | 32 |
| 1.27 | 0 | 2 | 3 | 4 | 25 |
| 2.84 | 0 | 0 | 0 | 0 | 96 |
| 460050.31 | 1 | 77666 | 127066 | 2e+05 | 2.6e+08 |
| 486509.71 | 1 | 79700 | 176619 | 326100 | 9.4e+07 |
| 9675.57 | 0.24 | 2468.62 | 4007.62 | 6230.5 | 3823175.65 |
| 816336.63 | 1 | 188220 | 321161 | 514072 | 3.2e+08 |

### 3.2.1 Missingness

Missing values in data is a cold cruel reality. It is one of the most contraining factors there is when it comes to predictive power. Having a good understanding of the prevalence of missing values and any patterns to them is needed to make the most out of what data you do have.

```
missing_data <- plot_missing(properties, theme = theme_bw())
```

```
missing_data
```

```
## # A tibble: 58 x 4
##    feature           num_missing pct_missing group
##    <fct>                   <int>       <dbl> <chr>
```

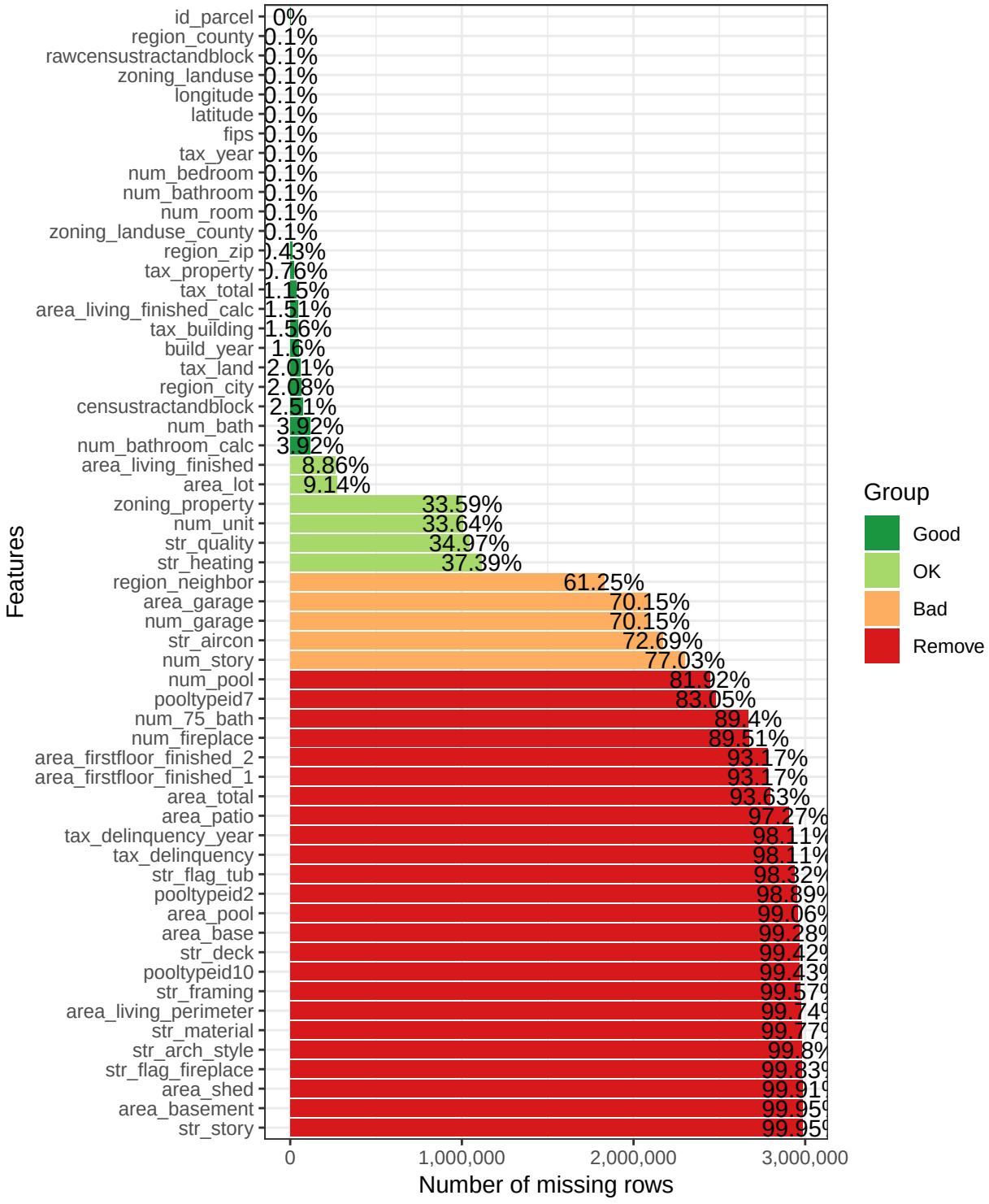



Figure 3.10: Completeness by Feature. Many are extremely sparse

```
##  1 id_parcel                  0    0        Good
##  2 str_aircon           2169855    0.727    Bad
##  3 str_arch_style       2979156    0.998    Remove
##  4 area_basement        2983590    0.999    Remove
##  5 num_bathroom            2957    0.000991 Good
##  6 num_bedroom             2945    0.000987 Good
##  7 str_framing          2972486    0.996    Remove
##  8 str_quality          1043822    0.350    OK
##  9 num_bathroom_calc     117156    0.0392   Good
## 10 str_deck             2967838    0.994    Remove
## # ... with 48 more rows
```

There seem to be quite a lot of missing features. For now lets remove the ones that are over 50% missing and continue on with those that are more than 50% complete. We could come back to the ones we dropped and try to recover some of those missing values with more sophisticated methods, for example we could impute the missing values based on their spatial neighbors but for now we will continue with the ones that have over 50% of their values.

A few of the features, `rawcensustractandblock`, `fips`, and `censustractandblock`, and `region_county` are ID fields for their census geography units. Since we have already extracted that information earlier in `properties_geo` we will drop them here as well since we can add the information contained in those features in a cleaner format later.

Additionally, based on the descriptions, `zoning_landuse`, `zoning_landuse_county`, and `zoning_property` all seem to contain pretty similar information.Since the number of unique categories are fairly large for each one, if they are redundant they could add needless complexity and computation time to our model. Let's use a chi-squared test to see what it looks like

```
chisq.test(properties$zoning_landuse, properties$zoning_property)
```

```
##
##  Pearson's Chi-squared test
##
## data:  properties$zoning_landuse and properties$zoning_property
## X-squared = 4377000, df = 73450, p-value < 2.2e-16
```

```
chisq.test(properties$zoning_landuse, properties$zoning_landuse_county)
```

```
##
##  Pearson's Chi-squared test
##
## data:  properties$zoning_landuse and properties$zoning_landuse_county
## X-squared = 37455000, df = 3262, p-value < 2.2e-16
```

Based on that, let's remove `zoning_property` and `zoning_landuse_county`

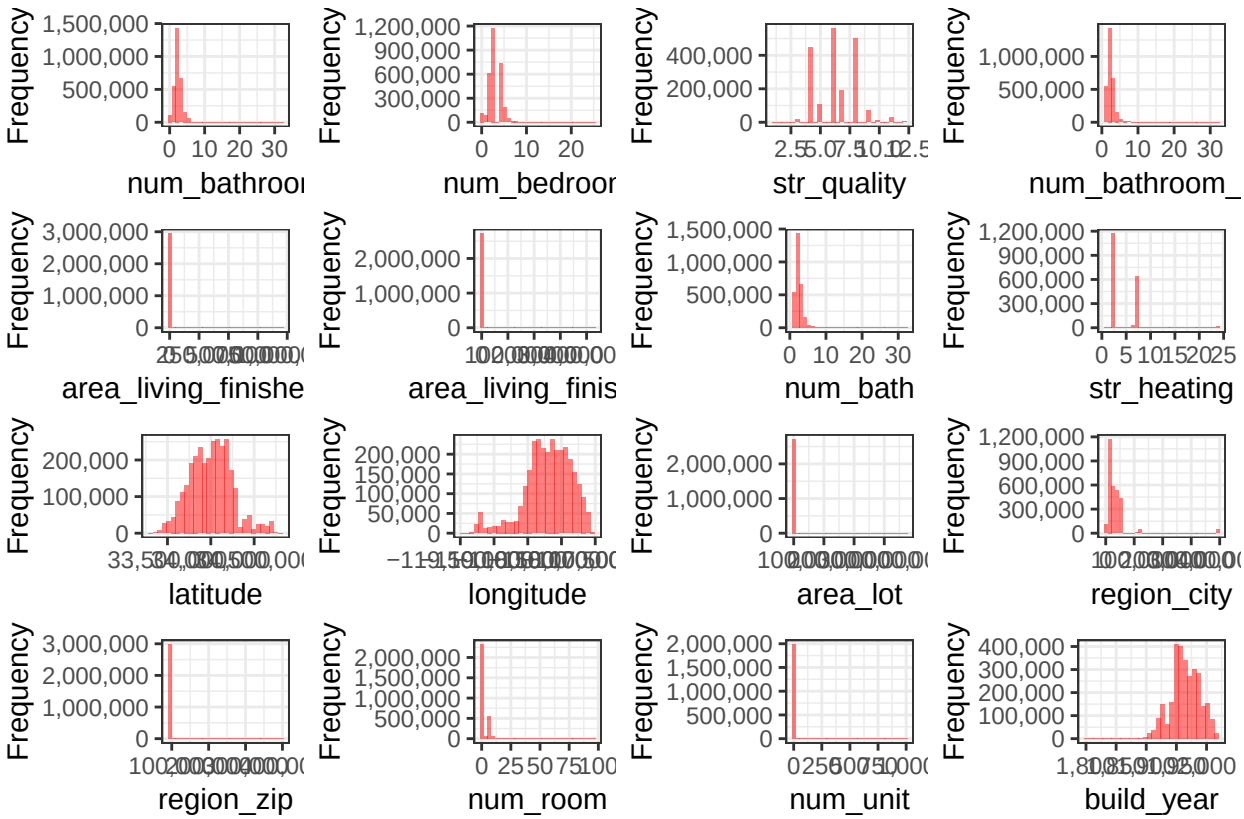
```
features_to_keep <- missing_data %>%
  filter(
    pct_missing <= .50,
    !feature %in% c("rawcensustractandblock", "fips",
                    "censustractandblock", "region_county",
                    "zoning_property", "zoning_landuse_county")
    ) %>%
  select(feature) %>%
  .$feature %>%
  as.character()

properties <- properties %>%
```

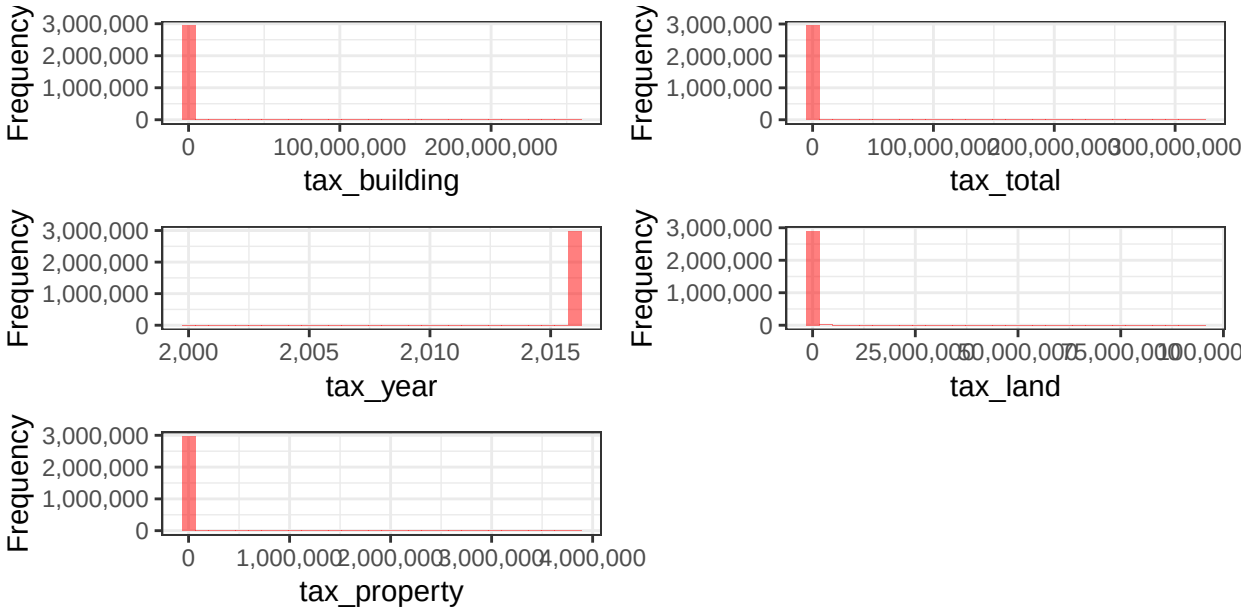
```
  select(features_to_keep)
```

### 3.2.2 Numeric Features

Lets look at the histograms of all the numeric features

```
properties %>%
  select(
    -id_parcel
  ) %>%
plot_histogram(ggtheme = theme_bw(),  fill = "red", alpha = 0.5)
```






Page 2

Looking at the histograms a few things become obvious. There are huge outliers in many of the features and there are some features that are currently encoded as numeric but should not be treated as such. For example, `str_quality` is an ordinal scale 1 (best qaulity) to 12 (worst) but if we leave them as numeric they will be treated as ratio. `str_heating` is nominal so the order doesn't have meaning. Other that need to be changed are `region_city`, `region_zip`

Once we do this, we'll look again at the relationships between our numeric features.

```
properties <- properties %>%
  mutate(
    str_quality = factor(str_quality,
                         levels = min(str_quality, na.rm = TRUE):max(str_quality, na.rm = TRUE),
                         ordered = TRUE),
    str_heating = factor(str_heating,
                         levels = na.omit(unique(str_heating)),
                         ordered = FALSE),
    region_city = factor(region_city,
                         levels = na.omit(unique(region_city)),
                         ordered = FALSE),
    region_zip = factor(region_zip,
                         levels = na.omit(unique(region_zip)),
                         ordered = FALSE)
  )
```

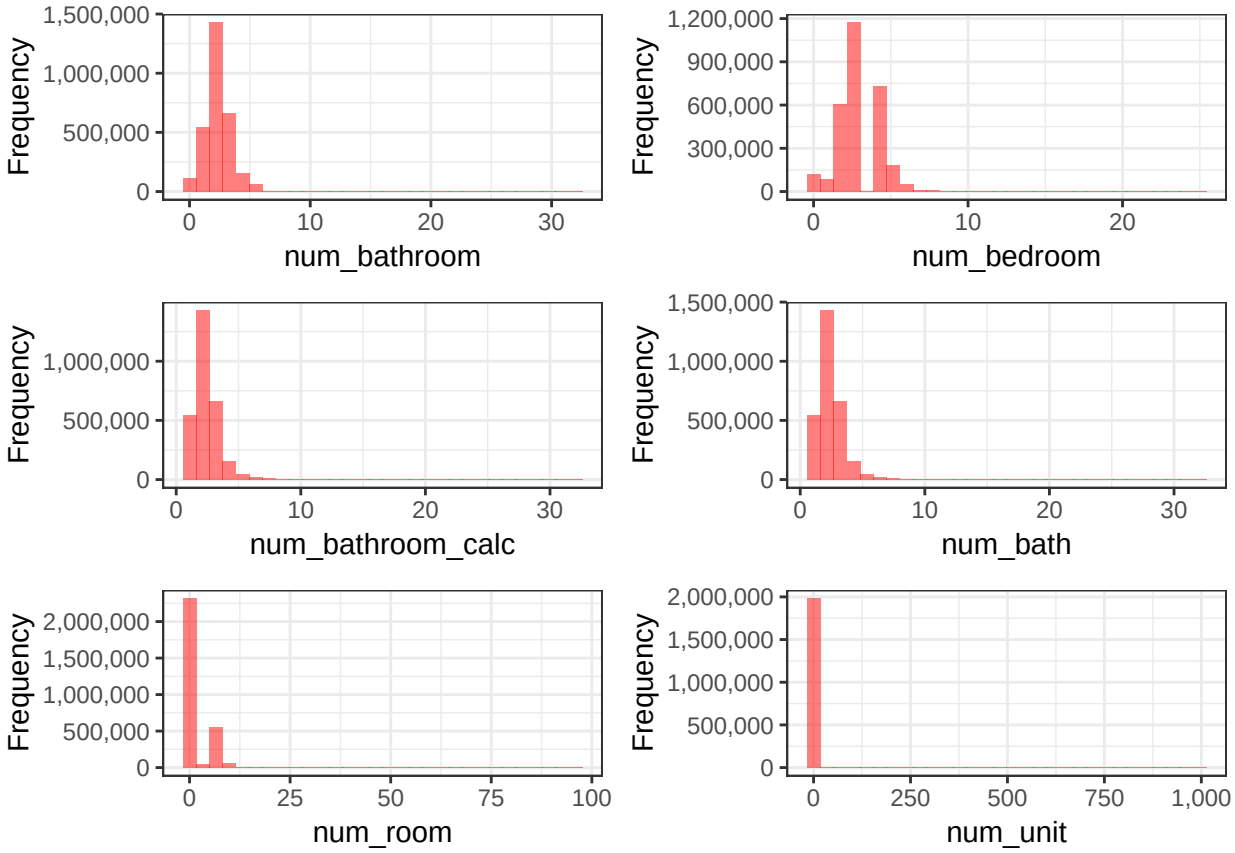



Figure 3.11: Distriubtions of 'num_*' Features

### 3.2.3 Numeric Outliers

Based on the histograms there looks to be lots of outliers in many of our numeric features. Two groups of features pop out, the `num_*` features and the `tax_*`features. Let's take a closer look.

```
properties %>%
  select(starts_with("num_")) %>%
plot_histogram(ggtheme = theme_bw(),  fill = "red", alpha = 0.5)
```

Looking at the `num_bathroom`, `num_bathroom_calc`, `num_bath` is pretty interesting. `num_bathroom` was one of the most complete features we had however, looking at the distributions, it seems strange that there would be so many houses with `0` bathrooms.

```
sum(properties$num_bathroom == 0, na.rm = TRUE)
```

```
## [1] 113470
```

```
sum(properties$num_bathroom_calc == 0, na.rm = TRUE)
```

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

Now for comparing all 3

```
properties %>%
  group_by(
    num_bathroom_calc,
```

```
    num_bath,
    num_bathroom
    ) %>%
  count() %>%
  DT::datatable()
```

Show 10 entries Search:

| | num_bathroom_calc | num_bath | num_bathroom | n |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 499324 |
| 2 | 1.5 | 1 | 1.5 | 45427 |
| 3 | 2 | 1 | 2 | 40 |
| 4 | 2 | 2 | 2 | 1219759 |
| 5 | 2.5 | 1 | 2.5 | 1 |
| 6 | 2.5 | 2 | 2.5 | 208577 |
| 7 | 3 | 2 | 3 | 559 |
| 8 | 3 | 3 | 3 | 632529 |
| 9 | 3.5 | 1 | 3.5 | 2 |
| 10 | 3.5 | 2 | 3.5 | 21 |

Showing 1 to 10 of 96 entries Previous 1 2 3 4 5 … 10 Next

If you sort by descending by `n` you'll see that one of the most frequent combinations is blank values of `num_bathroom_calc` and `num_bath` which are `NA` values and `0` for `num_bathroom`. Based on this I am interpreting that as either `0` being a coded value for `NA` or it just being wrong. Either way it looks like `num_bathroom_calc` is the one to keep out of all 3, since it has calculations of half-baths as well.

Applying the same logic to `num_room` and `num_bedroom` we can set all values equal to `0` to `NA`. One side effect of this is that the `num_room` feature is now almost 100% missing and not very useful anymore. So we will just remove it.

Quickly looking at `area_living_finished_calc` and `area_living_finished` reveals a similar `*_calc` being a corrected version of the feature. Becasue of this we will go ahead and remove `area_living_finished` as well

```
properties <- properties %>%
  select(
    -num_bath,
    -num_bathroom,
    -num_room,
    -area_living_finished
    ) %>%
  mutate(
    num_bedroom = ifelse(num_bedroom == 0, NA, num_bedroom)
    )
```

Now let's look at the tax related features

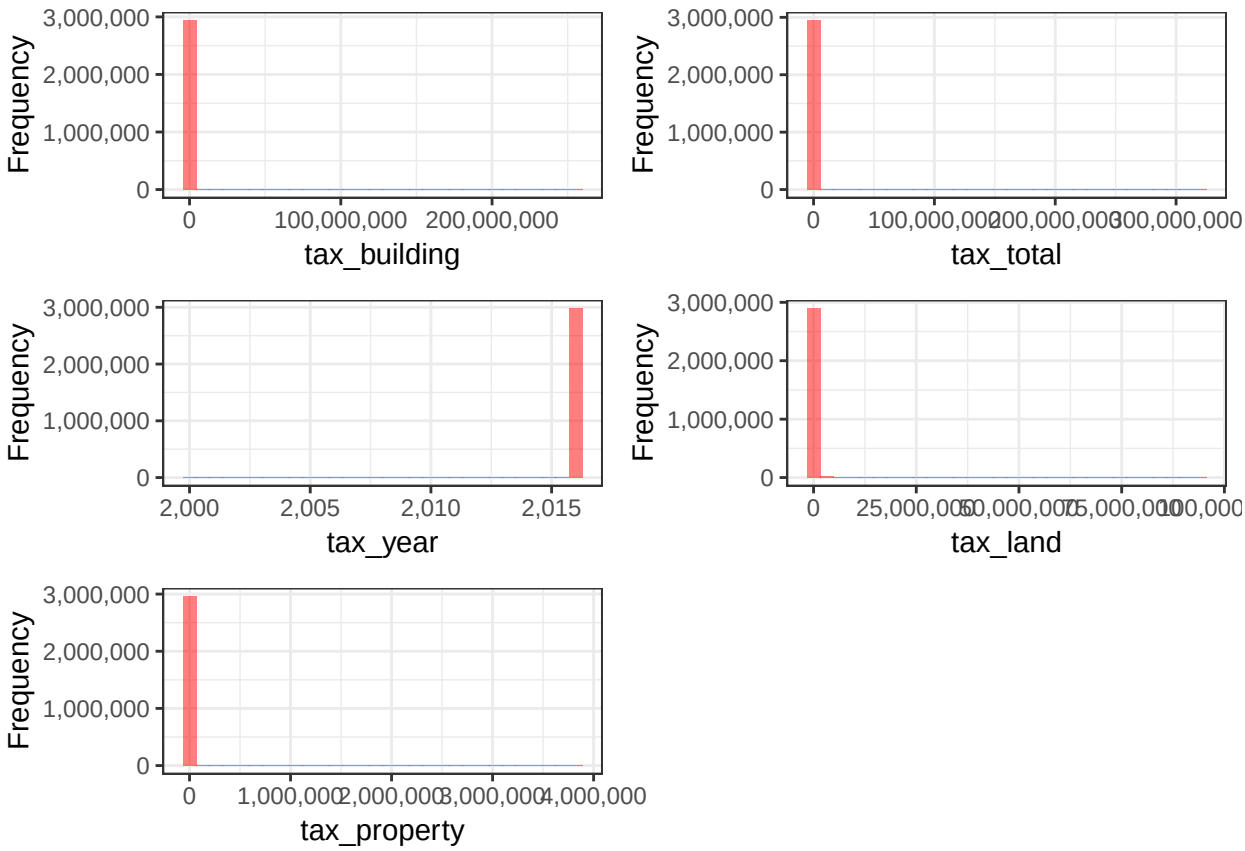



Figure 3.12: Distriubtions of 'tax_*' Features

```
properties %>%
  select(starts_with("tax_")) %>%
plot_histogram(ggtheme = theme_bw(),  fill = "red", alpha = 0.5)
```

Lets look at the highest values for `tax_total` and see if something jumps out

```
properties %>%
  mutate(tax_rank = rank(desc(tax_total))) %>%
  filter(tax_rank <= 20) %>%
  select(
    zoning_landuse,
    starts_with("area_"),
    starts_with("tax_")
    ) %>%
  arrange(tax_rank) %>%
  DT::datatable(
    extensions = 'FixedColumns',
    options = list(
    dom = 't',
    scrollX = TRUE,
    scrollCollapse = TRUE
    )
    )
```

| | zoning_landuse | area_living_finished_calc | area_lot | tax_building | tax_total | tax_year | tax_land | t |
|---|---|---|---|---|---|---|---|---|
| 1 | Residential General | | | 228000000 | 319622473 | 2016 | 91622473 | |
| 2 | Store/Office (Mixed Use) | 520825 | | 255321161 | 287098486 | 2016 | 31777325 | |
| 3 | Store/Office (Mixed Use) | 472363 | | 222334475 | 271004605 | 2016 | 48670130 | |
| 4 | Residential General | | | 157500000 | 224345565 | 2016 | 66845565 | |
| 5 | Residential General | | | 74000000 | 164246219 | 2015 | 90246219 | |
| 6 | Commercial/Office/Residential Mixed Used | 522511 | | 141417470 | 151895087 | 2016 | 10477617 | |
| 7 | Residential General | | | 55128075 | 149139154 | 2016 | 94011079 | |
| 8 | Commercial/Office/Residential Mixed Used | 319611 | | 123371992 | 146257183 | 2016 | 22885191 | |
| 9 | Residential General | | | 136062640 | 137493421 | 2016 | 1430781 | |
| 10 | Residential General | | | 54300000 | 134574879 | 2015 | 80274879 | |

While the values are extremely large, they appear to look legitimate. We won't remove these, but it does indicate that we should perhaps apply some transformations to our tax features before we start applying our model.

Now a look at the relationships between our remaining numeric features

```
library(heatmaply)

properties %>%
  select(-id_parcel) %>%
  select_if(is.numeric) %>%
  cor(use = "pairwise.complete.obs") %>%
  heatmaply_cor()
```

### 3.2.4 Categorical Features

```
plot_bar(properties, ggtheme = theme_bw())
```

```
## 2 columns ignored with more than 50 categories.
## region_city: 187 categories
## region_zip: 404 categories
```

The distribution across categories are extremely non-uniform, especially `str_heating` and `zoning_landuse`. This imbalance could cause use some pain later one when trying to fit our model. One way we can avoid some of this pain is by collapsing some of the rare categories into an `other` category. The number of categories we collapse to is not a hard and fast decision, it can be based on number of observations, subject matter expertise, heterogentity of the response variable within categories, or some mix of all of these).

Let's look at what the distribution of `log_error` looks like across these categories.

Figure 3.13: Correlation of Numeric Features

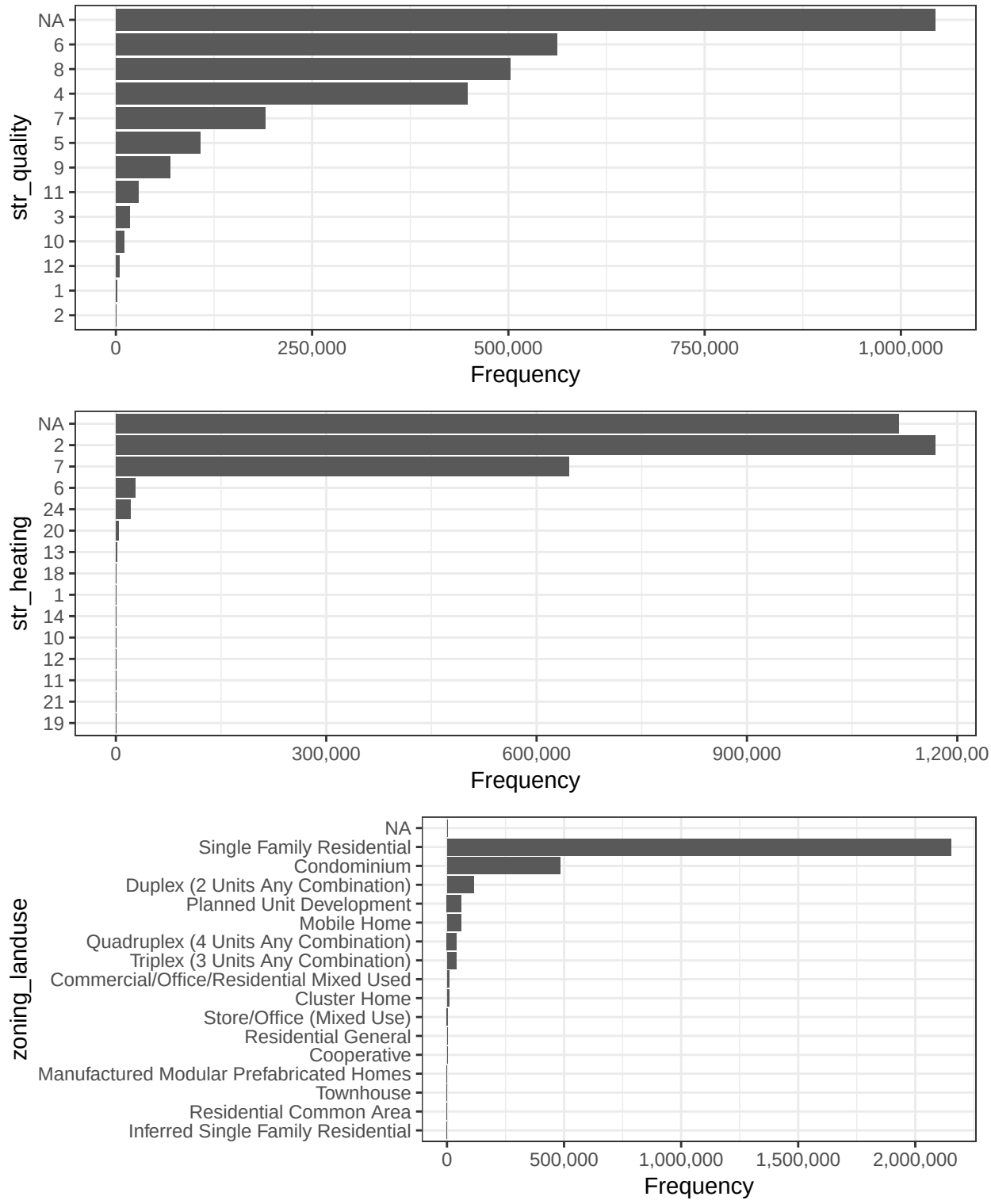



Figure 3.14: Distriubtions of All Categorical Features

```r
library(ggridges)

properties %>%
  select(
    id_parcel,
    str_quality
  ) %>%
  right_join(trans, by = "id_parcel") %>%
  ggplot(aes(x = log_error, y = fct_reorder(str_quality, log_error), fill = factor(..quantile..))) +
  stat_density_ridges(
    geom = "density_ridges_gradient",
    calc_ecdf = TRUE,
    quantiles = c(0.05, 0.95)
    ) +
  scale_fill_manual(
    name = "Probability",
    values = c("#FF0000A0", "#A0A0A0A0", "#0000FFA0"),
    labels = c("(0, 0.05]", "(0.05, 0.95]", "(0.95, 1]")
    ) +
  xlim(c(-0.5, 0.5)) +
  theme_bw() +
  labs(
    y = "str_quality"
  )
```

```r
library(ggridges)

properties %>%
  select(
    id_parcel,
    str_heating
  ) %>%
  right_join(trans, by = "id_parcel") %>%
  ggplot(aes(x = log_error, y = fct_reorder(str_heating, log_error), fill = factor(..quantile..))) +
  stat_density_ridges(
    geom = "density_ridges_gradient",
    calc_ecdf = TRUE,
    quantiles = c(0.05, 0.95)
    ) +
  scale_fill_manual(
    name = "Probability",
    values = c("#FF0000A0", "#A0A0A0A0", "#0000FFA0"),
    labels = c("(0, 0.05]", "(0.05, 0.95]", "(0.95, 1]")
    ) +
  xlim(c(-0.5, 0.5)) +
  theme_bw() +
  labs(
    y = "str_heating"
  )
```

```r
library(ggridges)

properties %>%
  select(
```

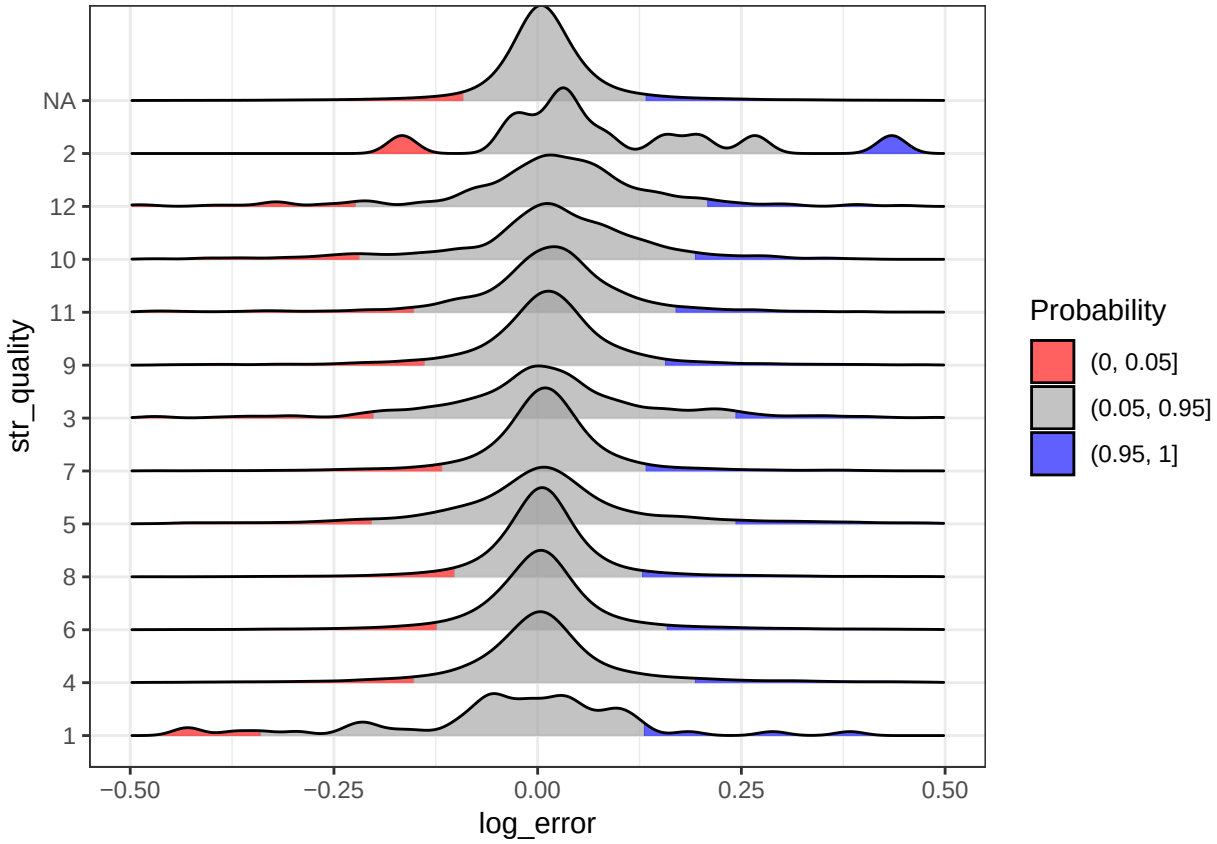



Figure 3.15: Distribution of Log Error Across Structure Quality Feature

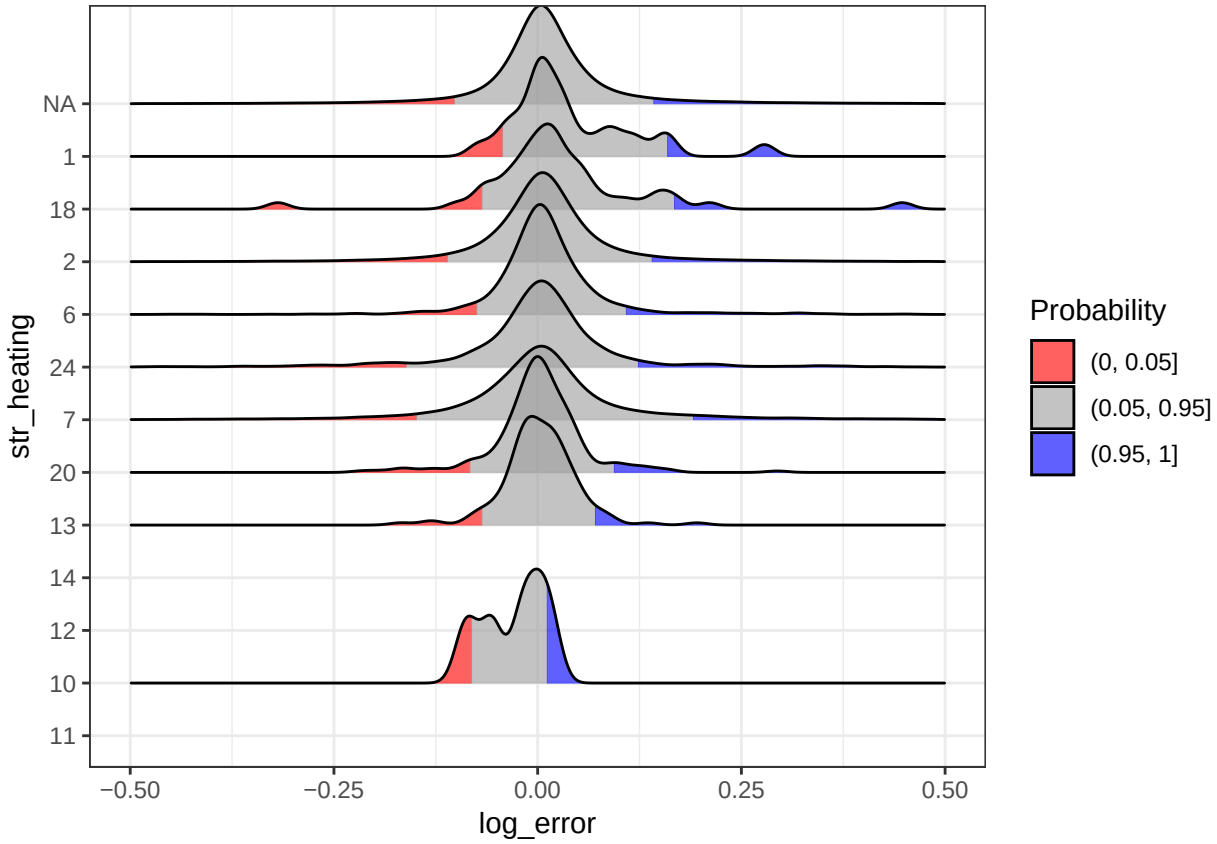



Figure 3.16: Distribution of Log Error Across Heating Type Feature

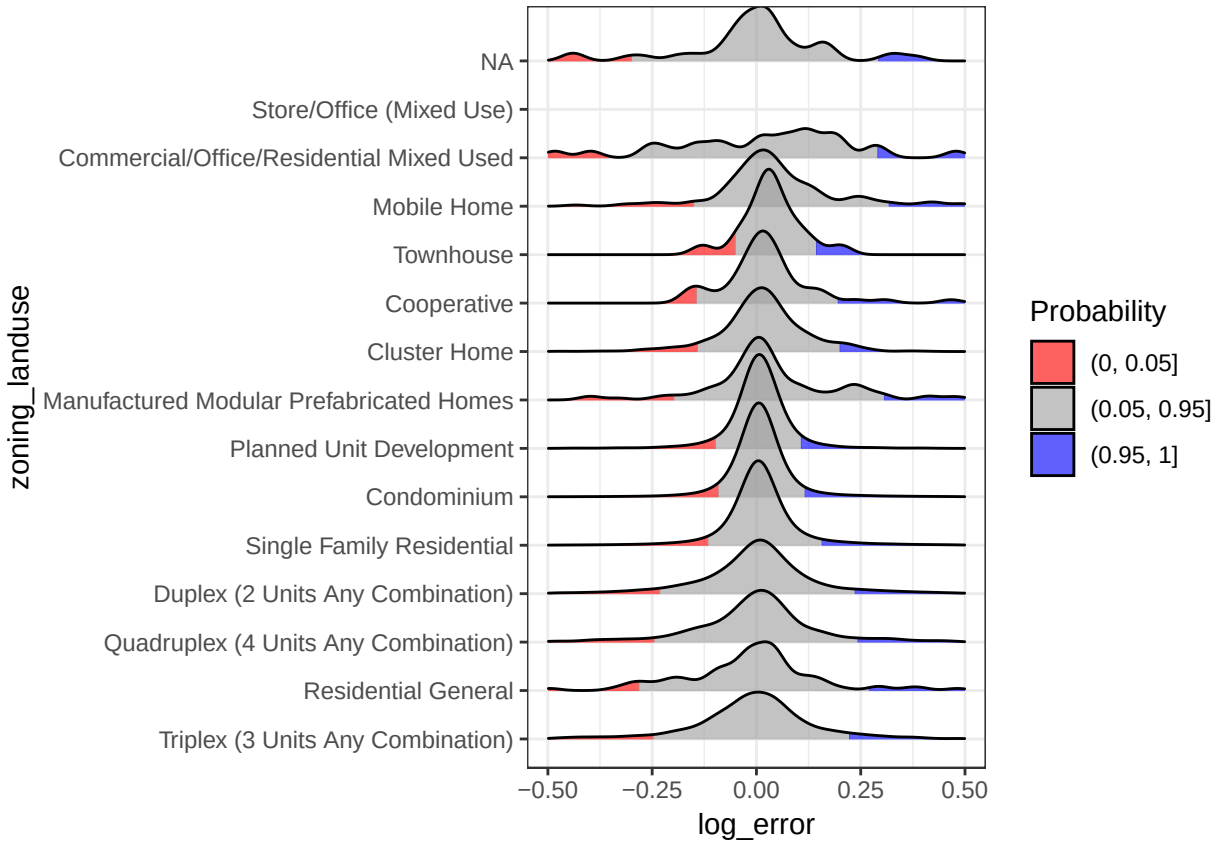



Figure 3.17: Distribution of Log Error Across Zoning Feature

```
  id_parcel,
  zoning_landuse
) %>%
right_join(trans, by = "id_parcel") %>%
ggplot(aes(x = log_error, y = fct_reorder(zoning_landuse, log_error), fill = factor(..quantile..))) +
stat_density_ridges(
  geom = "density_ridges_gradient",
  calc_ecdf = TRUE,
  quantiles = c(0.05, 0.95)
  ) +
scale_fill_manual(
  name = "Probability",
  values = c("#FF0000A0", "#A0A0A0A0", "#0000FFA0"),
  labels = c("(0, 0.05]", "(0.05, 0.95]", "(0.95, 1]")
  ) +
xlim(c(-0.5, 0.5)) +
theme_bw() +
labs(
  y = "zoning_landuse"
)
```

Since the distributions of `log_error` within each category seems well behaved, we will recode them based on number of observations

```
properties <- properties %>%
  mutate(
    str_heating = fct_lump(str_heating, n = 6),
    zoning_landuse = fct_lump(zoning_landuse, n = 8),
    str_heating = fct_recode(str_heating,
      "Central" = "2",
      "Floor/Wall" = "7",
      "Solar" = "20",
      "Forced Air" = "6",
      "Yes - Type Unknown" = "24",
      "None" = "13"
    )
  )
```

## 3.3 Exploring log_error A little More

Now let's join the properties and properties_geo tables to our trans table of tranactions and their log_error's and explore those

```
trans_prop <- read_feather("data/properties_geo_only.feather") %>%
  right_join(trans, by = "id_parcel") %>%
  left_join(properties, by = "id_parcel")
```

```
trans_prop %>%
  group_by(id_geo_bg_fips, id_geo_county_name) %>%
  summarise(
    n = n(),
    mean_abs_error = mean(abs_log_error)
    ) %>%
  ungroup() %>%
  mutate(
    trans_pert = cut(n, breaks = c(seq(0, 100, 10), 350))
    ) %>%
  ggplot(aes(x = trans_pert, y = mean_abs_error, colour = id_geo_county_name)) +
  geom_boxplot(outlier.size = 1.5, outlier.alpha = 1/3) +
  theme_bw() +
  labs(
    subtitle = "Block Group Average Mean Absolute Error",
    colour = NULL,
    x = "Number of Total Transactions per Block Group",
    y = "Mean Absolute Log Error"
  )
```

It looks like Los Angeles is largerly the only county that has information populated for str_qaulity

```
trans_prop %>%
  ggplot(aes(x = str_quality, y = log_error, colour = id_geo_county_name)) +
  geom_boxplot(outlier.size = 1.5, outlier.alpha = 1/3) +
  theme_bw() +
  labs(
    colour = NULL
  )
```

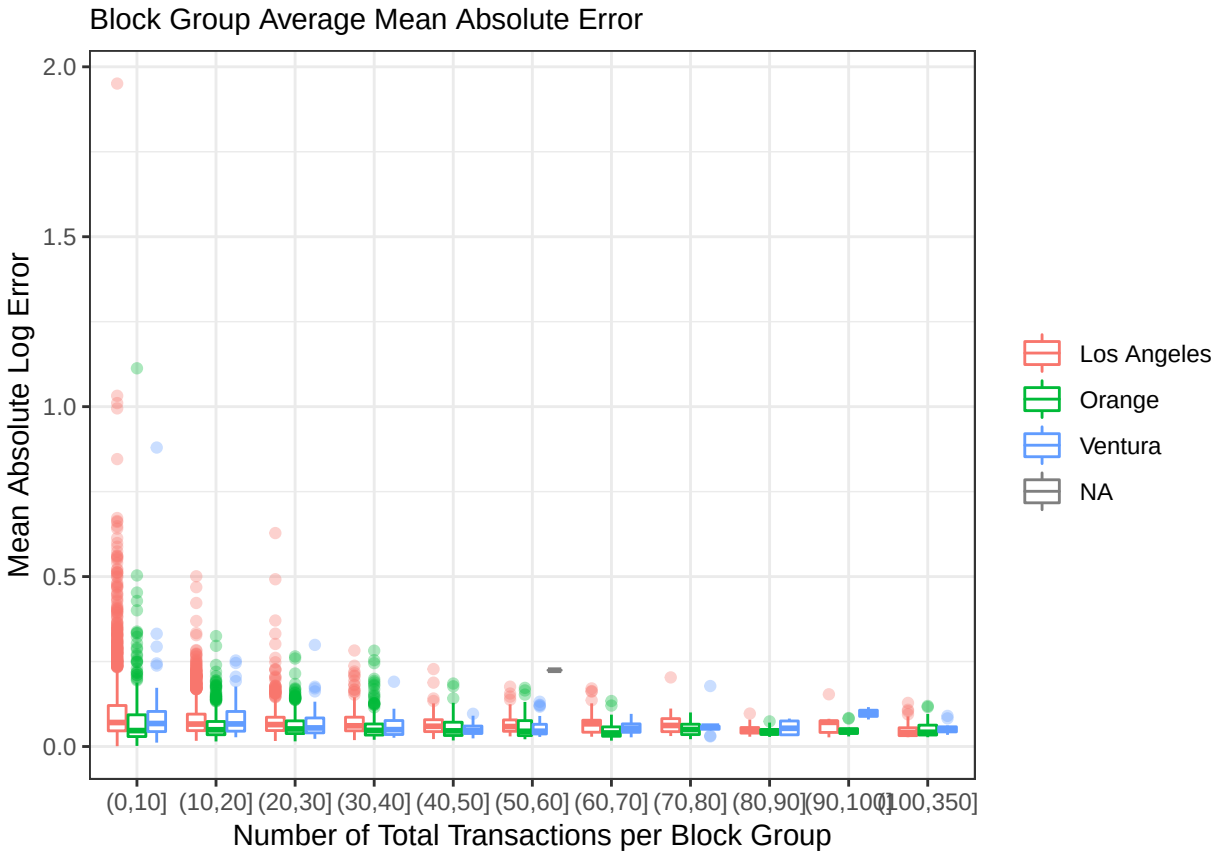



Figure 3.18: Outliers and Variability of Mean Absolute Error Dreceases When Neighborhood Sales Increase

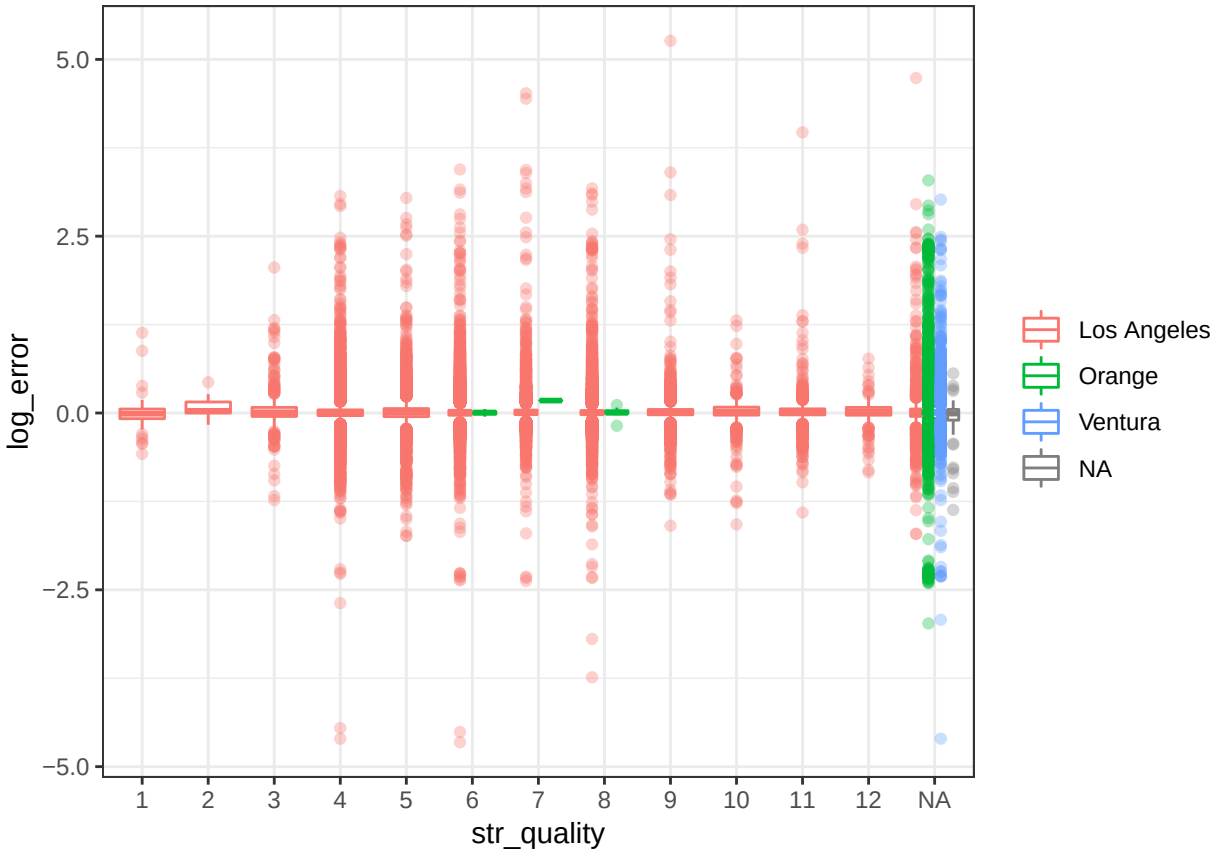



Figure 3.19: Log Error by Structure Quality

```
library(ggmap)

trans_prop_tmp <- trans_prop %>%
  filter(!is.na(id_geo_county_name)) %>%
  group_by(
    id_parcel,
    id_geo_county_name
    ) %>%
  mutate(
    log_error_parcel_avg = mean(log_error)
    ) %>%
  ungroup() %>%
  mutate(
    outlier = ifelse(log_error < quantile(log_error, probs  = .1) |
                     log_error > quantile(log_error, probs  = .9),
                     "Outlier", "Normal")
    )

error_map <- get_map(location = "Los Angeles, CA",
                     color="bw",
                     crop = FALSE,
                     zoom = 9)

ggmap(error_map) +
  stat_density2d(
    data = trans_prop_tmp,
    aes(x = lon, y = lat,
        fill = ..level..,
        alpha = ..level..),
    geom = "polygon",
    size = 0.001,
    bins = 100
    ) +
  scale_fill_viridis_c() +
  scale_alpha(range = c(0.05, 0.95), guide = FALSE) +
  facet_wrap(~outlier)
```

Now lets look at the spatiotemporal distribution of `log_error` outliers

```
trans_prop %>%
  filter(
    !is.na(lat),
    (
      log_error <= quantile(log_error, probs  = .1) |
      log_error >= quantile(log_error, probs  = .9)
      )
    ) %>%
  mutate(
    lon = round(lon/0.5, digits = 1) * 0.5,
    lat = round(lat/0.5, digits = 1) * 0.5
  ) %>%
  group_by(lon, lat, month_year) %>%
  summarise(
    n = n()
```

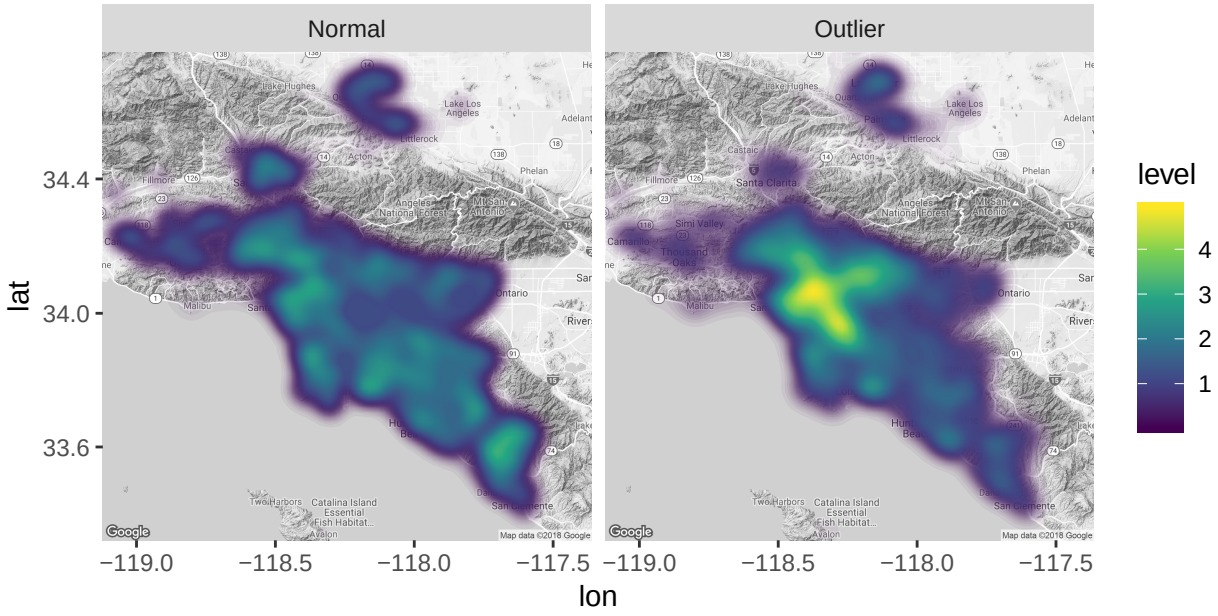



Figure 3.20: Spatial Distribution of Log Error Outliers

```
  ) %>%
ggplot(aes(lon, lat)) +
  geom_raster(aes(fill = n)) +
  scale_fill_viridis_c() +
  facet_wrap(~month_year, ncol = 3) +
  coord_quickmap() +
  theme_dark() +
  labs(
    subtitle = "Downtown Los Angeles looks to be consistently bad",
    fill = "Count"
  ) +
  theme(
    axis.text = element_text(size = 5)
    )
```

At first glance there looks to be a strong spatial and temporal correlation to `log_error`. Let's look more into the spatial correlation.

Moran's I and its variant Local Moran's I, provide a useful measure of the amount of spatial autocorrelation in a variable.

```
library(spatstat)
library(spdep)

d <- trans_prop %>%
  filter(
    !is.na(lat),
    (
      log_error <= quantile(log_error, probs  = .1) |
      log_error >= quantile(log_error, probs  = .9)
      )
    ) %>%
  mutate(
    lon = round(lon/0.1, digits = 1) * 0.1,
    lat = round(lat/0.1, digits = 1) * 0.1
  ) %>%
  group_by(lon, lat) %>%
  summarise(
    n = n()
  )

coordinates(d) <- ~lon + lat
w <- knn2nb(knearneigh(d, k = 10, longlat = TRUE))
moran.test(d$n, nb2listw(w))
```

```
##
##  Moran I test under randomisation
##
## data:  d$n
## weights: nb2listw(w)
##
## Moran I statistic standard deviate = 71.112, p-value < 2.2e-16
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
```

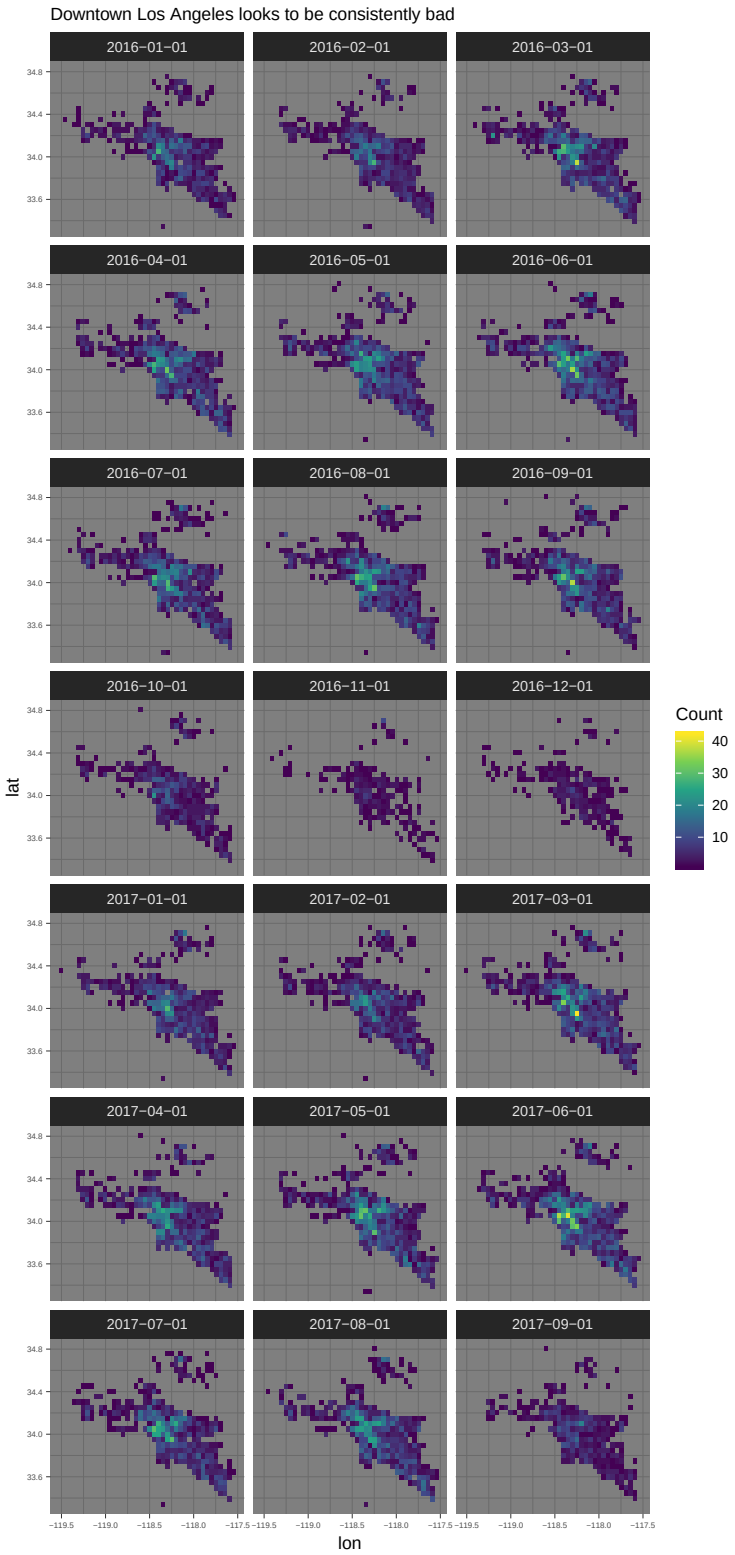



Figure 3.21: SpatioTemporal Distribution of Log Error Outliers

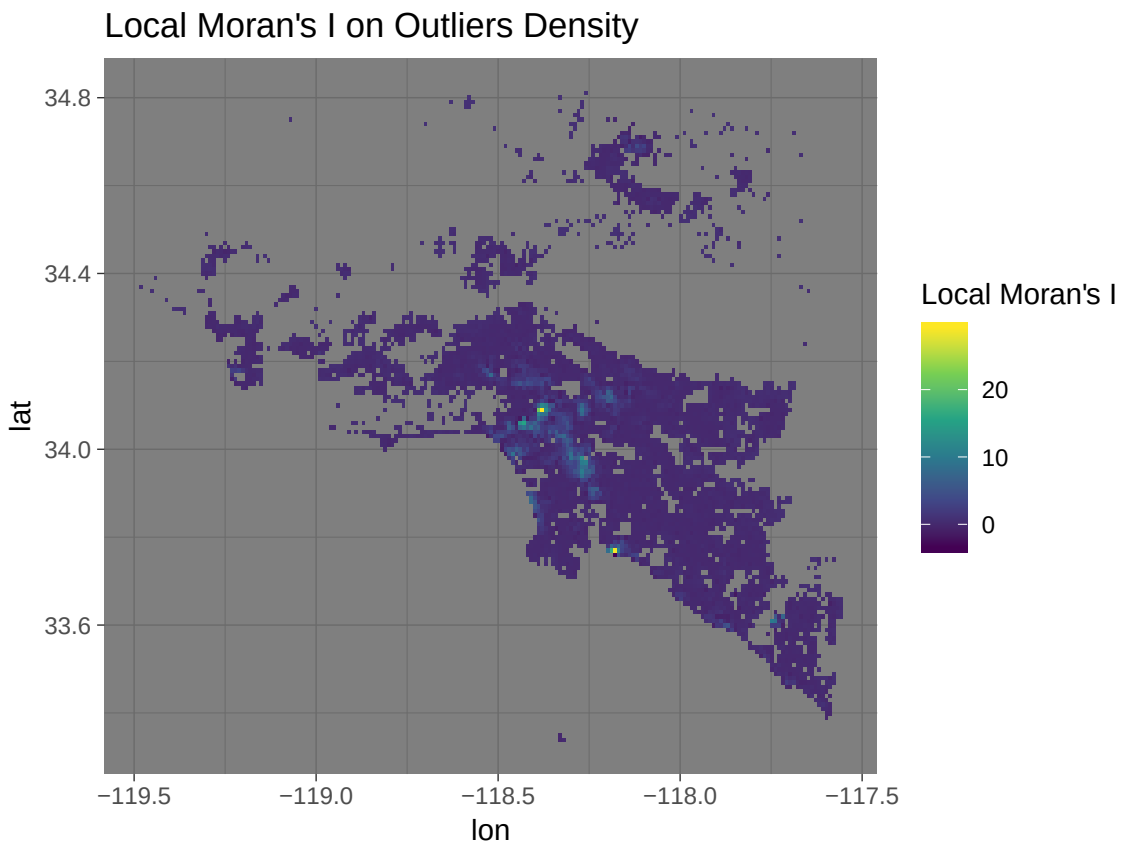



Figure 3.22: Spatial Autocorrelation of Log Error Outliers

```
##      4.308120e-01     -1.952362e-04      3.673489e-05
```

```
local_moran <- as.data.frame(localmoran(d$n, nb2listw(w)))

d %>%
  as.data.frame() %>%
  cbind(local_moran) %>%
  ggplot(aes(lon, lat)) +
  geom_raster(aes(fill = Ii)) +
  scale_fill_viridis_c() +
  coord_quickmap() +
  theme_dark() +
  labs(
    title = "Local Moran's I on Outliers Density",
    fill = "Local Moran's I"
  )
```

Let's save our pared down `properties` table and then get into feature engineering

```
write_feather(properties, "data/properties_17_filtered.feather")
```

# Chapter 4

# Feature Engineering

After we have done an intital EDA of our data we can start doing some feature engineering, this is where we can create new features such as interaction variables, apply transformations such as centering and scaling, choice how we want to encode our categorical features, and also bring in new external information.

Just as in Chapter 3, throughout this section we will progressively updating our `properties` data to include new and transformed features that we are going to continue with into the next stages.

## 4.1 Creating New Features

> "Everything is related to everything else, but near things are more related than distant things."
>
> — Waldo Tobler

This "First Law of Geography" is something we can take advantage of for creating new features based on our existing ones. In this section we will create based on both data from the Kaggle competition and also examples of external sources as well

### 4.1.1 Internal Features

Since we have the neighborhood, as defined by `id_geo_bg_fips`, that each parcel is apart of, we can use this to create neighborhood average features.

There are many ways one could define neighborhood for the purposes of using near by parcels, knn for example. Perhaps a more rigourous and certainly more computationly intensive approach would be to estimate the radius at which the spatial autocorrelation of `log_error` is no longer statistically significant using something such as a bootstrapped spline correlogram such as the function `spline.correlog()` provided by the `ncf` package

```
ncf::spline.correlog(x = lon, y = lat, z = log_error)
```

For now we will stick with defining our neighborhood by the census block group (`id_geo_bg_fips`) that each parcel is apart of

#### 4.1.1.1 Neigborhood Average `properties` Features

```
bg_avg_features <- properties %>%
  group_by(id_geo_bg_fips) %>%
  select(-id_parcel) %>%
  select_if(is.numeric) %>%
  summarise_all(mean, na.rm = TRUE) %>%
  filter(
    !is.na(id_geo_bg_fips)
    )

names(bg_avg_features) <- paste0("bg_avg_", names(bg_avg_features))
names(bg_avg_features)[1] <- "id_geo_bg_fips"

# update the properties table
properties <- properties %>%
  left_join(bg_avg_features, by = "id_geo_bg_fips")
```

#### 4.1.1.2 Rolling Local Average `log_error`

There is a strong spatial and temporal autocorrelation to our response variable `log_error`. To take advantage of this, let's create a few new features based on the rolling average of the local `log_error` values.

Because these features will have values for every day from `min(trans$date)` to `max(trans$date)` we won't join them to our data yet.

```
library(tibbletime)

trans_prop <- properties_geo %>%
  right_join(trans, by = "id_parcel") %>%
  select(
    id_parcel,
    id_geo_bg_fips,
    id_geo_tract_fips,
    date,
    log_error
  )

# create rolling functions ------------------------------------------------

rolling_sum_7 <- rollify(~sum(.x, na.rm = TRUE), window = 7)
rolling_sum_28 <- rollify(~sum(.x, na.rm = TRUE), window = 28)

# by block group ----------------------------------------------------------

roll_bg <- create_series(min(trans_prop$date) ~ max(trans_prop$date),
                         'daily', class = "Date") %>%
  tidyr::expand(
    date,
    id_geo_bg_fips = unique(trans_prop$id_geo_bg_fips)
  ) %>%
  full_join(trans_prop) %>%
  group_by(id_geo_bg_fips, date) %>%
  summarise(
    sum_log_error = sum(log_error, na.rm = TRUE),
```

```
    sales_total = sum(!is.na(log_error))
    ) %>%
  ungroup() %>%
  group_by(id_geo_bg_fips) %>%
  mutate(
    sum_log_error_7days = rolling_sum_7(sum_log_error),
    sum_log_error_28days  =  rolling_sum_28(sum_log_error),
    roll_bg_trans_total_7days = rolling_sum_7(sales_total),
    roll_bg_trans_total_28days  =  rolling_sum_28(sales_total),
    roll_bg_avg_log_error_7days = sum_log_error_7days / roll_bg_trans_total_7days,
    roll_bg_avg_log_error_28days = sum_log_error_28days / roll_bg_trans_total_28days,
    date = date + lubridate::days(1) # to not include the current day in avg
  ) %>%
  select(
    id_geo_bg_fips,
    date,
    roll_bg_trans_total_7days,
    roll_bg_trans_total_28days,
    roll_bg_avg_log_error_7days,
    roll_bg_avg_log_error_28days
  ) %>%
  mutate(
    roll_bg_trans_total_7days = ifelse(is.na(roll_bg_trans_total_7days),
                                       0, roll_bg_trans_total_7days),
    roll_bg_trans_total_28days = ifelse(is.na(roll_bg_trans_total_28days),
                                        0, roll_bg_trans_total_28days),
    roll_bg_avg_log_error_7days = ifelse(is.nan(roll_bg_avg_log_error_7days),
                                         0, roll_bg_avg_log_error_7days),
    roll_bg_avg_log_error_28days = ifelse(is.nan(roll_bg_avg_log_error_28days),
                                          0, roll_bg_avg_log_error_28days),
    roll_bg_avg_log_error_7days = as.numeric(forecast::na.interp(roll_bg_avg_log_error_7days)),
    roll_bg_avg_log_error_28days = as.numeric(forecast::na.interp(roll_bg_avg_log_error_28days))
  )

# by tract ------------------------------------------------------------------

roll_tract <- create_series(min(trans_prop$date) ~ max(trans_prop$date),
                            'daily', class = "Date") %>%
  tidyr::expand(
    date,
    id_geo_tract_fips = unique(trans_prop$id_geo_tract_fips)
  ) %>%
  full_join(trans_prop) %>%
  group_by(id_geo_tract_fips, date) %>%
  summarise(
    sum_log_error = sum(log_error, na.rm = TRUE),
    sales_total = sum(!is.na(log_error))
  ) %>%
  ungroup() %>%
  group_by(id_geo_tract_fips) %>%
  mutate(
    sum_log_error_7days = rolling_sum_7(sum_log_error),
    sum_log_error_28days  =  rolling_sum_28(sum_log_error),
```

```
    roll_tract_trans_total_7days = rolling_sum_7(sales_total),
    roll_tract_trans_total_28days  =  rolling_sum_28(sales_total),
    roll_tract_avg_log_error_7days = sum_log_error_7days / roll_tract_trans_total_7days,
    roll_tract_avg_log_error_28days = sum_log_error_28days / roll_tract_trans_total_28days,
    date = date + lubridate::days(1) # to not include the current day in avg
  ) %>%
  select(
    id_geo_tract_fips,
    date,
    roll_tract_trans_total_7days,
    roll_tract_trans_total_28days,
    roll_tract_avg_log_error_7days,
    roll_tract_avg_log_error_28days
  ) %>%
  mutate(
    roll_tract_trans_total_7days = ifelse(is.na(roll_tract_trans_total_7days),
                                          0, roll_tract_trans_total_7days),
    roll_tract_trans_total_28days = ifelse(is.na(roll_tract_trans_total_28days),
                                           0, roll_tract_trans_total_28days),
    roll_tract_avg_log_error_7days = ifelse(is.nan(roll_tract_avg_log_error_7days),
                                            0, roll_tract_avg_log_error_7days),
    roll_tract_avg_log_error_28days = ifelse(is.nan(roll_tract_avg_log_error_28days),
                                             0, roll_tract_avg_log_error_28days),
    roll_tract_avg_log_error_7days = as.numeric(forecast::na.interp(roll_tract_avg_log_error_7days)),
    roll_tract_avg_log_error_28days = as.numeric(forecast::na.interp(roll_tract_avg_log_error_28days))
  )

prop_geo_ids <- properties_geo %>%
  select(
    id_parcel,
    id_geo_bg_fips,
    id_geo_tract_fips
  )

write_feather(roll_bg, "data/external-features/roll_features_blockgroup.feather")
write_feather(roll_tract, "data/external-features/roll_features_tract.feather")
```

### 4.1.2 External Features

Breaking from the rules of the actual Kaggle competition, we're going to add in some external features as an example of bringing in other information

#### 4.1.2.1 American Community Survey

The American Community Survey is a great source of demographic and household data. As an example of using this data let's bring in a few features related to our area of interest.

In our example here, we are completely ignoring the margin or error for each feature, given more time investigating the information contained in these fields is most likely worth your while.

There are literally thousands you can explore in the ACS. For our example, we are going to use a few

```
library(tidycensus)

api_key <- Sys.getenv("CENSUS_API_KEY")
census_api_key(api_key)

acs_var_list <- load_variables(2016, "acs5", cache = TRUE)

acs_bg_vars <- c("B25034_001E", "B25034_002E", "B25034_003E",
                 "B25034_004E", "B25034_005E", "B25034_006E",
                 "B25034_007E", "B25034_008E", "B25034_009E",
                 "B25034_010E", "B25034_011E", "B25076_001E",
                 "B25077_001E", "B25078_001E", "B25056_001E",
                 "B25002_001E", "B25002_003E", "B25001_001E")

acs_bg_home_value <- acs_var_list %>%
  filter(grepl("B25075_", x = name))

acs_bg_home_value_vars <- acs_bg_home_value$name

acs_bg_vars <- c(acs_bg_vars, acs_bg_home_value_vars)

acs_bg_data <- get_acs(
  geography = "block group",
  variables = acs_bg_vars,
  state = "CA",
  county = c("Los Angeles", "Orange", "Ventura"),
  output = "wide",
  geometry = FALSE,
  keep_geo_vars = TRUE
)

acs_bg_data1 <- acs_bg_data %>%
  select(
    id_geo_bg_fips = GEOID,
    acs_str_yr_total = B25034_001E,
    acs_str_yr_2014_later = B25034_002E,
    acs_str_yr_2010_2013 = B25034_003E,
    acs_str_yr_2000_2009 = B25034_004E,
    acs_str_yr_1990_1999 = B25034_005E,
    acs_str_yr_1980_1989 = B25034_006E,
    acs_str_yr_1970_1979 = B25034_007E,
    acs_str_yr_1960_1969 = B25034_008E,
    acs_str_yr_1950_1959 = B25034_009E,
    acs_str_yr_1940_1949 = B25034_010E,
    acs_str_yr_1939_earlier = B25034_011E,
    acs_home_value_lwr = B25076_001E,
    acs_home_value_med = B25077_001E,
    acs_home_value_upr = B25078_001E,
    acs_num_of_renters_total = B25056_001E,
    acs_num_of_house_units = B25001_001E,
    acs_occ_status_total = B25002_001E,
    acs_occ_status_vacant = B25002_003E,
    acs_home_value_cnt_total = B25075_001E,
```

```
    acs_home_value_cnt_less_10k = B25075_002E,
    acs_home_value_cnt_10k_15k = B25075_003E,
    acs_home_value_cnt_15k_20k = B25075_004E,
    acs_home_value_cnt_20k_25k = B25075_005E,
    acs_home_value_cnt_25k_30k = B25075_006E,
    acs_home_value_cnt_30k_35k = B25075_007E,
    acs_home_value_cnt_35k_40k = B25075_008E,
    acs_home_value_cnt_40k_50k = B25075_009E,
    acs_home_value_cnt_50k_60k = B25075_010E,
    acs_home_value_cnt_60k_70k = B25075_011E,
    acs_home_value_cnt_70k_80k = B25075_012E,
    acs_home_value_cnt_80k_90k = B25075_013E,
    acs_home_value_cnt_90k_100k = B25075_014E,
    acs_home_value_cnt_100k_125k = B25075_015E,
    acs_home_value_cnt_125k_150k = B25075_016E,
    acs_home_value_cnt_150k_175k = B25075_017E,
    acs_home_value_cnt_175k_200k = B25075_018E,
    acs_home_value_cnt_200k_250k = B25075_019E,
    acs_home_value_cnt_250k_300k = B25075_020E,
    acs_home_value_cnt_300k_400k = B25075_021E,
    acs_home_value_cnt_400k_500k = B25075_022E,
    acs_home_value_cnt_500k_750k = B25075_023E,
    acs_home_value_cnt_750k_1000k = B25075_024E,
    acs_home_value_cnt_1000k_1500k = B25075_025E,
    acs_home_value_cnt_1500k_2000k = B25075_026E,
    acs_home_value_cnt_2000k_more = B25075_027E
  ) %>%
  mutate_at(
    vars(starts_with("acs_home_value_cnt")), function(x) round(x / .$acs_home_value_cnt_total, digits =
    ) %>%
  mutate_at(
    vars(starts_with("acs_str_yr")), function(x) round(x / .$acs_str_yr_total, digits = 5)
  ) %>%
  mutate(
    acs_per_renters = round(acs_num_of_renters_total / acs_num_of_house_units, digits = 5),
    acs_per_vacant = round(acs_occ_status_vacant / acs_occ_status_total, digits = 5)
  ) %>%
  select(
    -acs_occ_status_total,
    -acs_home_value_cnt_total,
    -acs_str_yr_total
    )

acs_features <- properties_geo %>%
  select(
    id_parcel,
    id_geo_bg_fips
    ) %>%
  left_join(acs_bg_data1, by = "id_geo_bg_fips") %>%
  select(-id_geo_bg_fips)

properties <- properties %>%
  left_join(acs_features, by = "id_parcel")
```

#### 4.1.2.2 Economic Indicators

The value of a home is not only influenced by itself and its neighbors, but also larger economic trends. To help account for this in our model we are going to add in the following economic indicators

- 30-Year Fixed Rate Mortgage Average in the United States
- S&P/Case-Shiller CA-Los Angeles Home Price Index
- Unemployment Rate in Los Angeles County, CA

```
library(alfred)

# 30-Year Fixed Rate Mortgage Average in the United States (weekly)
mort30 <- get_fred_series("MORTGAGE30US") %>%
  mutate(
    date_month = floor_date(date, unit = "month"),
    date_week = floor_date(date, unit = "week")
    )

# S&P/Case-Shiller CA-Los Angeles Home Price Index (monthly)
spcs <- get_fred_series("LXXRNSA")

# Unemployment Rate in Los Angeles County, CA (monthly)
unemployment <- get_fred_series("CALOSA7URN")

econ_features <- create_series(min(mort30$date) ~ max(mort30$date),
                               'daily', class = "Date") %>%
  mutate(date_week = floor_date(date, unit = "week")) %>%
  left_join(mort30, by = c("date_week" = "date_week")) %>%
  left_join(spcs, by = c("date_month" = "date")) %>%
  left_join(unemployment, by = c("date_month" = "date")) %>%
  select(
    date = date.x,
    econ_mort_30 = MORTGAGE30US,
    econ_case_shiller = LXXRNSA,
    econ_unemployment = CALOSA7URN
  ) %>%
  filter(
    date >= date("2015-12-01"),
    date <= date("2018-01-01")
    )

write_feather(econ_features, "data/external-features/econ_features.feather")
```

Ok, so a check in on where we are. We currently have 5 data frames of interest, our old friends `properties` which now contains new features from our `bg_avg_features` neighborhood data and the `acs_features` which contain a few indicators from the American Community Survey and `trans` which contains our response variable `log_error` as well as the transaction date and a few date based features.

The other 3 data frames we have are seperated from the `properties` and `trans` data currently because they contain features that have different values for each day and depending on what our transaction dates are for the partiuclar set of observations we will use filter those values down and join them at the time of training.

## 4.2 Handling Missing Data

There are many ways to handle missing data from simple mean or median imputation to more complex methods such as knn or multiple imputation or even constructing other predictive models for predicting missing features. We will not explore that topic in depth here and use a somewhat simple approach that takes advantage of the spatial relationships of our data.

We will use median (or modal for nominal features) imputation but instead of doing global median values for all observations, we are going to break our observations into subspaces based on `zoning_landuse`, `area_lot`, and increasingly larger neigborhood windows. The reasoning behind this choice is that the values for many of the other features can vary widely across these categories. For example it wouldn't make sense to include the `tax_building` values for mobile homes if we are imputing the `tax_building` value of a commercial office building. The is true for `area_lot` the tax burden on a large commercial office will be larger then the one of a smaller office.

So we will look at increaingly larger neighborhoods of `zoning_landuse` and (a discretized version of) `area_lot` combinations, if there are any none `NA` observations of that combination in the missing observations block group, fill its values with the block group median (mode), if there are no non-missing observations with that combination in that block group, then look at the tract level, if there are none at the tract look at the county level, and finally if there are no non-missing observations in the County that the parcel belongs to, an unlikely event, then use the "global" values to impute.

To do this we first need to impute the values for `zoning_landuse` and `area_lot`. For this we will just use the increasing neighborhood search for `zoning_landuse` and then use the increasing neighborhood search broken down by `zoning_landuse` to fill in `area_lot`

For some reason their are no built in functions for calculating the mode. Make a simple helper function to do so

```
# simple helper function to find the mode
fct_mode <- function(f) {

  f_no_na <- na.omit(f)
  fct_tab <- table(f_no_na)

  # if everything NA return NA
  if (length(fct_tab) == 0) return(NA)

  modal_fct <- names(fct_tab)[which(fct_tab == max(fct_tab))]
  modal_fct <- modal_fct[1] # in case of ties, go with first one

  modal_fct
}
```

Some parcels have no information at all including geographic ids. Randomly assign them a `id_geo_bg_fips` value based block group frequency

```
parcels_no_info <- properties %>%
  filter(
    is.na(id_geo_bg_fips)
    ) %>%
  select(id_parcel)

bg_probs <- table(properties$id_geo_bg_fips) %>%
  as.data.frame()

bg_assignments <- sample(bg_probs$Var1,
```

```
                          size = nrow(parcels_no_info),
                          replace = TRUE,
                          prob = bg_probs$Freq)

bg_assignments <- as.character(bg_assignments)

parcels_no_info_row_id <- properties$id_parcel %in% parcels_no_info$id_parcel

properties[parcels_no_info_row_id , "id_geo_bg_fips"] <- bg_assignments

# fill in the missing tract and county based on bg
properties <- properties %>%
  group_by(id_geo_bg_fips) %>%
  mutate(
    id_geo_tract_fips = fct_mode(id_geo_tract_fips)
    ) %>%
  ungroup() %>%
  group_by(id_geo_tract_fips) %>%
  mutate(
    id_geo_county_fips = fct_mode(id_geo_county_fips)
  ) %>%
  ungroup()
```

Now that all observations have at least geo id values we can impute `zoning_landuse` using the increasing neighborhood search

```
properties <- properties %>%
  group_by(id_geo_bg_fips) %>%
  mutate(
    zoning_landuse = replace_na(zoning_landuse, fct_mode(zoning_landuse))
  ) %>%
  ungroup() %>%
  group_by(id_geo_tract_fips) %>%
  mutate(
    zoning_landuse = replace_na(zoning_landuse, fct_mode(zoning_landuse))
  ) %>%
  ungroup() %>%
  group_by(id_geo_county_fips) %>%
  mutate(
    zoning_landuse = replace_na(zoning_landuse, fct_mode(zoning_landuse))
  ) %>%
  ungroup()
```

Now for `area_lot`

```
properties <- properties %>%
  group_by(
    id_geo_bg_fips,
    zoning_landuse
    ) %>%
  mutate(
    area_lot = replace_na(area_lot, median(area_lot, na.rm = TRUE))
  ) %>%
  ungroup() %>%
  group_by(
```

```
    id_geo_tract_fips,
    zoning_landuse
    ) %>%
  mutate(
    area_lot = replace_na(area_lot, median(area_lot, na.rm = TRUE))
  ) %>%
  ungroup() %>%
  group_by(
    id_geo_county_fips,
    zoning_landuse
    ) %>%
  mutate(
    area_lot = replace_na(area_lot, median(area_lot, na.rm = TRUE))
  ) %>%
  ungroup()
```

OK, now for the rest of them. Becasue we used `median()` to fill in `area_lot` the `quantile()` are not unique, so add a little bit of noise `area_lot_jitter` and base the breaks on those.

```
# impute all other features based on neighborhood, zoning_landuse, and area_lot
properties <- properties %>%
  mutate(
    area_lot_jitter = area_lot + runif(n = n(), min = -1, max = 1),
    area_lot_quantile = cut(area_lot_jitter,
                            breaks = quantile(area_lot_jitter, probs = seq(0, 1, 0.1), na.rm = TRUE))
    ) %>%
  group_by(
    id_geo_bg_fips,
    zoning_landuse,
    area_lot_quantile
  ) %>%
  mutate_if(
    is.numeric, .funs = function(x) replace_na(x, median(x, na.rm = TRUE))
    ) %>%
  mutate_if(
    is.factor, .funs = function(x) replace_na(x, fct_mode(x))
  ) %>%
  ungroup() %>%
  group_by(
    id_geo_tract_fips,
    zoning_landuse,
    area_lot_quantile
  ) %>%
  mutate_if(
    is.numeric, .funs = function(x) replace_na(x, median(x, na.rm = TRUE))
  ) %>%
  mutate_if(
    is.factor, .funs = function(x) replace_na(x, fct_mode(x))
  ) %>%
  ungroup() %>%
  group_by(
    id_geo_county_fips,
    zoning_landuse,
    area_lot_quantile
```

```
  ) %>%
  mutate_if(
    is.numeric, .funs = function(x) replace_na(x, median(x, na.rm = TRUE))
  ) %>%
  mutate_if(
    is.factor, .funs = function(x) replace_na(x, fct_mode(x))
  ) %>%
  ungroup() %>%
  group_by(
    zoning_landuse,
    area_lot_quantile
  ) %>%
  mutate_if(
    is.numeric, .funs = function(x) replace_na(x, median(x, na.rm = TRUE))
  ) %>%
  mutate_if(
    is.factor, .funs = function(x) replace_na(x, fct_mode(x))
  ) %>%
  ungroup()
```

At this point we now have all the original features we are going to use and have filled in all missing values. The next step is to transform our features, create interaction features, and then move unto feature selection.

## 4.3 Feature Transformation

Combine all of our data and remove a handful of features that we aren't going to use

```
# have to remove id_geo after joins because of time features
d <- trans %>%
  left_join(properties, by = "id_parcel") %>%
  left_join(econ_features, by = "date") %>%
  left_join(roll_bg, by = c("id_geo_bg_fips", "date")) %>%
  left_join(roll_tract, by = c("id_geo_tract_fips", "date")) %>%
  select(
    -id_parcel,
    -abs_log_error,
    -week,
    -region_city,
    -region_zip,
    -area_lot_jitter,
    -area_lot_quantile,
    -lat, # we have other lat/lon features
    -lon,
    -starts_with("id_geo")
  ) %>%
  mutate(
    date = as.numeric(date),
    year = factor(year, levels = sort(unique(year)), ordered = TRUE),
    month_year = factor(
      as.character(month_year),
      levels = as.character(unique(sort(month_year))),
      ordered = TRUE),
```

```
    str_quality = factor(str_quality, levels = 12:1, ordered = TRUE)
  )
```

Here we are going to use the `recipes` package to handle all of our feature transformations. The main transformations we are going to apply are as follows

1. Apply a Box-Cox transformation on the features that were highly skewed
2. Creating dummy variables using one hot encoding for non ordered factors and polynomial spline for ordered factors
3. Create interaction features from all of the `tax_*` and `area_*` features
4. Center and Scale all the predictors
5. Transform the several `acs_home_value_cnt_*` features using PCA. Keep only 5
6. Remove any Features that have zero variance

```
library(recipes)

rec <- recipe(d) %>%
  add_role(log_error, new_role = 'outcome') %>%
  add_role(-log_error, new_role = 'predictor') %>%
  step_meanimpute(starts_with("roll_")) %>%
  step_zv(all_numeric()) %>%
  step_BoxCox(
    starts_with("num_"),
    starts_with("area_"),
    starts_with("tax_"),
    starts_with("bg_avg_num_"),
    starts_with("bg_avg_area_"),
    starts_with("bg_avg_tax_")
  ) %>%
  step_dummy(all_nominal(), one_hot = TRUE) %>%
  step_interact(~starts_with("tax_"):starts_with("area_")) %>%
  step_center(all_numeric(), -all_outcomes()) %>%
  step_scale(all_numeric(), -all_outcomes()) %>%
  step_pca(starts_with("acs_home_value_cnt"), prefix = "acs_home_value_cnt_PC") %>%
  step_zv(all_numeric())

rec_prepped <- prep(rec, training = d)
```

# Chapter 5

# Feature Selection

Now that we created a boat load of features, how do we decide which ones we want to use? As typical, there are many ways of performing feature selection. Here we will perform just one.

Based on the data frame we created in `d` and the transformation recipe we made we are going to do some initital analysis on which features we want to keep or drop. The `xgboost` package provides a function, `xgb.importance()` that gives a summary of how important each feature was in a model estimated by `xgb.train()`. We will use this to help guide our selection of features to carry forward. However, we want to make sure that we don't mistakenly remove a feature that is actually important, so instead of running the `xgb.importance()` function just once on all of our traning data, we will use v fold cross validation to create mutliple sub samples and run the `xgb.importance()` function for each one.

## 5.1 Generate Importance Helper Function

```
library(broom)
library(purrr)
library(xgboost)

importance_results <- function(splits) {

  x <- bake(rec_prepped, newdata = analysis(splits))
  y <- x$log_error

  d <- model.matrix(log_error ~., data = x)
  d <- xgb.DMatrix(d, label = y)

  mdl <- xgb.train(data = d, label = y, nrounds = 1000, nthread = 4)
  print(summary(mdl))

  mdl_importance <- as.data.frame(xgb.importance(model = mdl))

  mdl_importance
}
```

## 5.2 V-Fold Cross Validation Resampling

Create the resampling, run the models and summarize the results

```
library(rsample)

resamples <- vfold_cv(d, v = 10, repeats = 5)

resamples$results <- map(resamples$splits,
                         importance_results)


importance_df <- bind_rows(resamples$results)

feature_avg <- importance_df %>%
  group_by(Feature) %>%
  summarise(
    mean = mean(Gain),
    sd = sd(Gain),
    n = n()
    )
```

## 5.3 Inspect Importance Results

```
feature_avg %>%
  ggplot(aes(x = forcats::fct_reorder(Feature, mean), y = mean)) +
  geom_hline(aes(yintercept = 0.001), colour = "red", size = 1, alpha = 0.5) +
  geom_point(size = 1) +
  geom_errorbar(aes(ymin = mean - sd * 2, ymax = mean + sd * 2)) +
  coord_flip() +
  theme_bw() +
  theme(
    axis.text=element_text(size = 6)
    ) +
  labs(
    x = "Feature",
    y = "Mean Gain"
  )
```

To reduce the complexity and computation time our of modeling, we are going to remove the feature that consistantly did not provide much value by cutting off the number of features we'll use at a mean gain at `0.001` (red line).

```
features_to_use <- feature_avg %>%
  filter(mean >= 0.001) %>%
  .$Feature
```

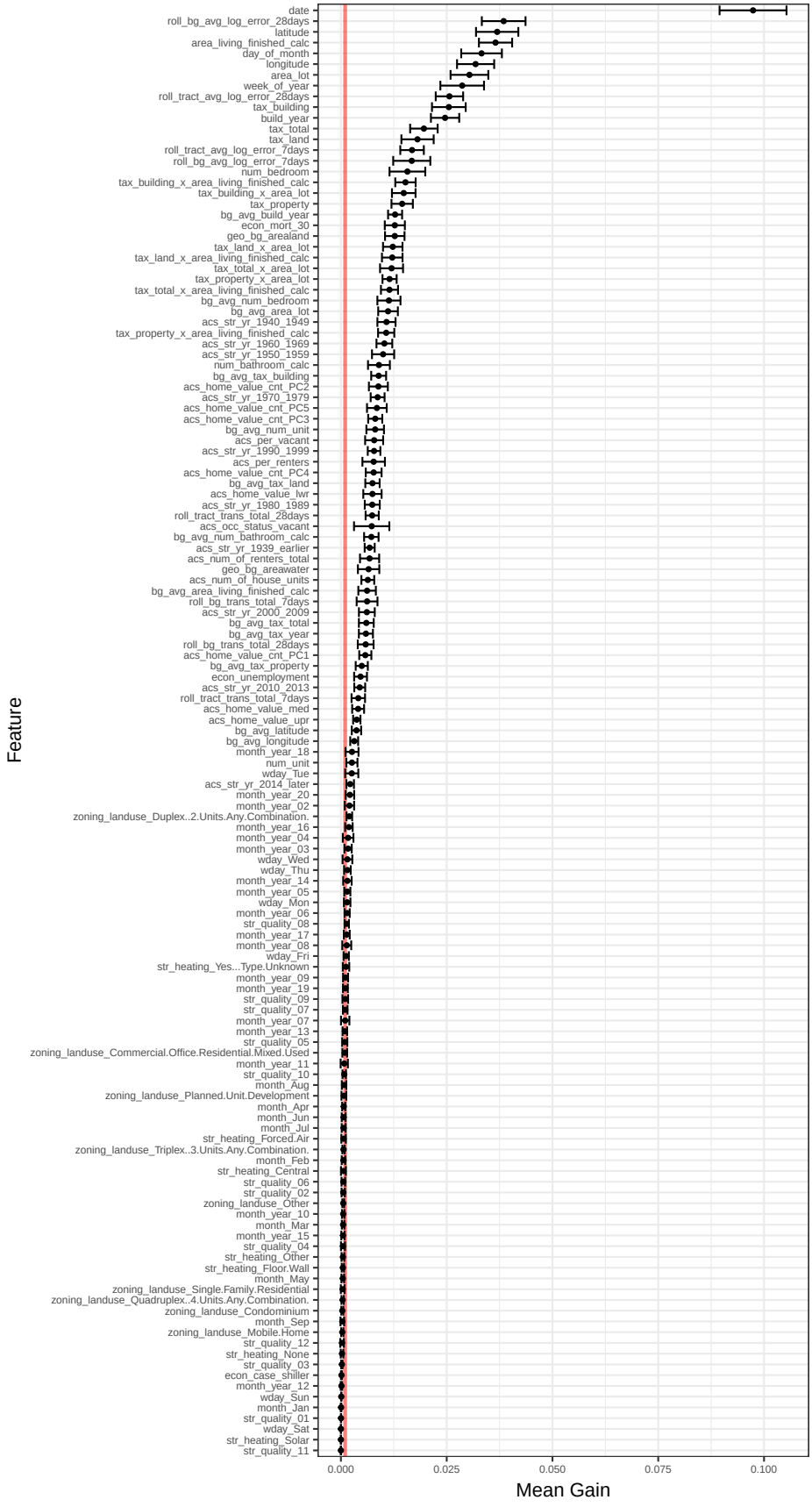



Figure 5.1: Mean Feature Importance Based on Cross Validation Using Basic XGBoost Model

# Chapter 6

# Modeling

For our first pass a submission, we are going to use the XGBoost model. This model has seen much success in Kaggle competitions and wide use across industry and academia due to its flexiblity, speed, and range of modeling tasks it can be applied to. We'll start by creating a base line model and then try our hand at tuning a few of the XGBoost parameters to see how of performance changes.

## 6.1 XGBoost

XGBoost, which stands for eXtreme Gradient Boosting, is a highly optimized and flexible implementation of gradient boosted decision trees. At a high level boosted trees work by creating ensembles of decision trees and uses gradient boosting (additive training) to combine each of the tree's predictions into one strong prediction by optimizing over any differentiable loss function. In practice a regularization penalty is added to the loss function to help control complexity.

Decision trees, particularly XGBoost is widely used for several reasons such as its flexibilty to be used for numerous problem types across both regression and classification, it's invariance to scaling inputs, and it's ability to scale to handle large amounts of data.

For more information about XGBoost see Chen & Guestrin[1] and Gradient Boosting in general, Fridmean (1999)[2]

## 6.2 Our Recipe for Success

As a reminder our recipe for our transformations are stored in `rec` that we created in Chapter 4. It's looks like this

```
rec
```

```
## Data Recipe
##
## Inputs:
##
##       role #variables
##    outcome          1
##  predictor         98
```

[1] XGBoost: A Scalable Tree Boosting System https://arxiv.org/abs/1603.02754

[2] Greedy Function Approximation: A Gradient Boosting Machine http://statweb.stanford.edu/~jhf/ftp/trebst.pdf

```
##
## Operations:
##
## Mean Imputation for starts_with("roll_")
## Zero variance filter on all_numeric()
## Box-Cox transformation on 6 items
## Dummy variables from all_nominal()
## Interactions with starts_with("tax_"):starts_with("area_")
## Centering for all_numeric(), -all_outcomes()
## Scaling for all_numeric(), -all_outcomes()
## PCA extraction with starts_with("acs_home_value_cnt")
## Zero variance filter on all_numeric()
```

## 6.3 Base Line Model

> Alice: "Would you tell me, please, which way I ought to go from here?"
>
> The Cheshire Cat: "That depends a good deal on where you want to get to."
>
> Alice: "I don't much care where."
>
> The Cheshire Cat: "Then it doesn't matter which way you go."
>
> — The Adventures of Alice in Wonderland, on the need for base line models in machine learning (that's my interpretation at least)

Making Predictive models is an iterative process, a process in which it is easy to get pulled in wrong directions by needless complexity, fruitless tweaks, and soul crushingly poor performing ideas you thought might actually work.

To help tether ourselves to reality, it is useful to generate a base line model to compare all other models against before we get into any of the more complex tasks like parameter tuning. This will help guide what direction we should take next so we don't end up like Alice.

Kaggle competitions have done wonders for our collective obession for improving predictive accuracy with wild disregard for the time and effort it took to achieve that improvement. In a typical business or scientific academic application, improvement in predictive accuracy has to be balanced with the cost of acheiving it. A base line model can help use measure these diminishing returns.

For our base line model, we will use the top 20 features returned from our feature selection process in an xgboost model with default parameter settings and with `nrounds`, the maximum number of boosting iterations, set to 1000

```
features_to_use_baseline <- feature_avg %>%
  arrange(desc(mean)) %>%
  head(20) %>%
  .$Feature

d_prepped <- prep(rec)

train_df <- bake(d_prepped, newdata = d)

x_train <- train_df %>%
  select(features_to_use_baseline) %>%
  as.matrix()

y_train <- train_df$log_error
```

```
xgb_train_data <- xgb.DMatrix(x_train, label = y_train)

base_model <- xgb.train(data = xgb_train_data,
                        objective = 'reg:linear',
                        verbose = FALSE,
                        nrounds = 1000,
                        nthread = 20)
```

### 6.3.1 Making Predictions with Base Line Model

Now we finally get to make our first predictions! Since we'll be doing this again and potentially many times, let's make a helper function `predict_date()` to do this. This function will take, the parcels (`parcel_id`) and the dates (`predict_date`) we wish to predict, along with the model (`mdl`) and features we want to use to (`features_to_use`) to do the predictions

```
predict_date <- function(parcel_id, predict_date, mdl, features_to_use) {

d_predict_ids <- properties %>%
  filter(id_parcel %in% parcel_id) %>%
  crossing(date = predict_date)

d_predict <- d_predict_ids %>%
  mutate(
    year = year(date),
    month_year = make_date(year(date), month(date)),
    month = month(date, label = TRUE),
    week = floor_date(date, unit = "week"),
    week_of_year = week(date),
    week_since_start = (min(date) %--% date %/% dweeks()) + 1,
    wday = wday(date, label = TRUE),
    day_of_month = day(date)
  ) %>%
  left_join(econ_features, by = "date") %>%
  left_join(roll_bg, by = c("id_geo_bg_fips", "date")) %>%
  left_join(roll_tract, by = c("id_geo_tract_fips", "date")) %>%
  select(
    -id_parcel,
    -week,
    -region_city,
    -region_zip,
    -area_lot_jitter,
    -area_lot_quantile,
    -lat, # we have other lat/lon features
    -lon,
    -starts_with("id_geo")
  ) %>%
  mutate(
    date = as.numeric(date),
    year = factor(year, levels = sort(unique(year)), ordered = TRUE),
    month_year = factor(
      as.character(month_year),
      levels = as.character(unique(sort(month_year))),
```

```
      ordered = TRUE),
    str_quality = factor(str_quality, levels = 12:1, ordered = TRUE)
  )

eval_df <- bake(d_prepped, newdata = d_predict)

x_eval <- eval_df %>%
  select(features_to_use) %>%
  as.matrix()

preds <- predict(mdl, x_eval)

properties_predict <- d_predict_ids %>%
  select(
    id_parcel,
    date
  ) %>%
  mutate(
    pred = preds
    ) %>%
  spread(date, pred)

names(properties_predict) <- c("ParcelId", "201610", "201611",
                               "201612", "201710", "201711", "201712")

properties_predict

}
```

The submission requires a prediction for Oct-Dec 2016 and Oct-Dec 2017. This means that the prediction is for any day in that month. For our example submissions, we are going to set the date to the first Wednesday in each month. This is completely arbitrary, but provides a simple starting point. Another approach would be to make predictions for every day in each month and submit the mean prediction for each month. We'll save this for later work.

```
# first wednesday in each month
predict_dates <- date(c("2016-10-06", "2016-11-02", "2016-12-07",
                        "2017-10-04", "2017-11-01", "2017-12-06"))

# split parcels to chunck our predictions
id_parcels <- properties$id_parcel
id_parcel_splits <- split(id_parcels, ceiling(seq_along(id_parcels) / 5000))
```

Now make the predictions with `base_model`

```
base_predict_list <- lapply(id_parcel_splits, function(i) {

  pred_df <- predict_date(
    parcel_id = i,
    predict_date = predict_dates,
    mdl = base_model,
    features_to_use = features_to_use_baseline
    )
  })
```

```
# they only evaluate to 4 decimcals so round to save space
# Convert ParcelId to integer to prevent Sci Notation that causes
# issues with submission
base_predict_df <- bind_rows(base_predict_list) %>%
  mutate_at(vars(`201610`:`201712`), round, digits = 4) %>%
  mutate(ParcelId = as.integer(ParcelId)) %>%
  as.data.frame()

write_csv(base_predict_df, "submissions/base_submit.csv")
```

The resulting MAE of this submission was `0.0789722` on the public leaderboard. Not that great, but hey at least we have room to improve.

Save this value for comparison

```
base_mae <- 0.0789722
```

Let's see if tuning the parameters of the XGBoost model can help improve that.

## 6.4 Hyperparameter Optimization

The double edged sword of the XGBoost model is how widely varying the predictions it generates can be depending on what the models hyperparameters are set to. The good is that it allows us to be very flexible across many different datasets, the bad is it almost always requires us to perform some type of hyperparameter optimization to fine tune its' performance. The ugly is the code needed to perform this.

Our parameter optimization strategy is as follows

1. Create a scoring function to capture model performance using MAE
2. Use 5-fold cross validation to resample our training data
3. Randomly generate intital parameter combinations.
4. Using step 3 as an intital input, use a surrogate Random Forest model to progressively zoom into parameter space based on the average performance of parameter sets across the resampled data on our scoring function. We will set this to 4 runs for now, zooming further down each time.

### 6.4.1 Creating Our Scoring Function

To assess our parameter tuning performance we will create the function `xgboost_regress_score()` that will capture the MAE of each resample and parameter combination of our data

```
# create scoring function ------------------------------------------------

xgboost_regress_score <- function(train_df, target_var, params, eval_df, ...) {

    X_train <- train_df %>%
      select(features_to_use) %>%
      as.matrix()

    y_train <- train_df[[target_var]]
    xgb_train_data <- xgb.DMatrix(X_train, label = y_train)

    X_eval <- eval_df %>%
      select(features_to_use) %>%
```

```
    as.matrix()

  y_eval <- eval_df[[target_var]]

  xgb_eval_data <- xgb.DMatrix(X_eval, label = y_eval)

  model <- xgb.train(params = params,
                     data = xgb_train_data,
                     watchlist = list(train = xgb_train_data, eval = xgb_eval_data),
                     objective = 'reg:linear',
                     verbose = FALSE,
                     nthread = 20,
                     ...)

  preds <- predict(model, xgb_eval_data)

  list(mae = MAE(preds, y_eval))

}
```

### 6.4.2 Parameter Search Space

We will use the following parameters

- `eta` [default=0.3, alias: `learning_rate`]
  - Step size shrinkage used in update to prevents overfitting. After each boosting step, we can directly get the weights of new features, and eta shrinks the feature weights to make the boosting process more conservative.
  - range: [0, 1]
- `gamma` [default=0, alias: `min_split_loss`]
  - Minimum loss reduction required to make a further partition on a leaf node of the tree. The larger `gamma` is, the more conservative the algorithm will be.
  - range[0, `Inf`]
- `max_depth` [default=6]
  - Maximum depth of a tree. Increasing this value will make the model more complex and more likely to overfit. 0 indicates no limit.
  - range: [0, `Inf`]
- `min_child_weight` [default=1]
  - Minimum sum of instance weight (hessian) needed in a child. If the tree partition step results in a leaf node with the sum of instance weight less than `min_child_weight`, then the building process will give up further partitioning. In linear regression task, this simply corresponds to minimum number of instances needed to be in each node. The larger `min_child_weight` is, the more conservative the algorithm will be.
  - range: [0, `Inf`]
- `subsample` [default=1]
  - Subsample ratio of the training instances. Setting it to 0.5 means that XGBoost would randomly sample half of the training data prior to growing trees. and this will prevent overfitting. Subsampling will occur once in every boosting iteration.
  - range: (0, 1]
- `colsample_bytree` [default=1]
  - Subsample ratio of columns when constructing each tree. Subsampling will occur once in every boosting iteration.
  - range: (0, 1]

Based on the performance of these optimizations other parameters could be included later. I set the ranges on these parameters with the idea that our base line model might be overfiting.

```
library(ParamHelpers)
# make parameter set ------------------------------------------------------
xgboost_random_params <-
  makeParamSet(
    makeIntegerParam('max_depth', lower = 1, upper = 15),
    makeNumericParam('eta', lower = 0.01, upper = 0.1),
    makeNumericParam('gamma', lower = 0, upper = 5),
    makeIntegerParam('min_child_weight', lower = 1, upper = 100),
    makeNumericParam('subsample', lower = 0.25, upper = 0.9),
    makeNumericParam('colsample_bytree', lower = 0.25, upper = 0.9)
  )
```

### 6.4.3 5-fold Cross Validation

Set up our resampling via 5 fold cross validation

```
# create cv resampling ----------------------------------------------------
resamples <- vfold_cv(d, v = 5)
```

### 6.4.4 Random Forest Search of Parameter Space

All of the heavy lifting for the surrogate Random Forest model is contained in the `tidytune::surrogate_search()` function.

The progressive zoom into more promising parameter space is done by passing a vector to `n` and `n_canidates`. Higher values for `n_candidates` will restrict the search to better performing areas and lower values increase the randnomness (with `0` falling back on random search).`n` is the number of runs of the surrogate model that will run for each of our 5 folds.

`top_n` is set to 5, which tells the model out of the top `n_candidates` pass along the `top_n` to the next round.

We will do for runs of the surrogate Random Forest model, zooming into more performant parameter space each time.

```
library(MLmetrics)
library(xgboost)
library(tidytune)

# perform surrogate search over parameters --------------------------------
n <- c(10, 5, 3, 2)
# start with random and then zoom in
n_candidates <- c(0, 10, 100, 1000)

search_results <-
  surrogate_search(
    resamples = resamples,
    recipe = rec,
    param_set = xgboost_random_params,
    n = n,
    scoring_func = xgboost_regress_score,
    nrounds = 1000,
    early_stopping_rounds = 20,
```

```
    eval_metric = 'mae',
    input = NULL,
    surrogate_target = 'mae',
    n_candidates = n_candidates,
    top_n = 5
  )
```

```
search_summary <-
  search_results %>%
  group_by_at(getParamIds(xgboost_random_params)) %>%
  summarise(mae = mean(mae)) %>%
  arrange(mae)
```

| | max_depth | eta | gamma | min_child_weight | subsample | colsample_bytree | |
|---|---|---|---|---|---|---|---|
| 1 | 5 | 0.0753141567087732 | 2.00997113599442 | 100 | 0.882115679827984 | 0.528489873954095 | 0.0685 |
| 2 | 5 | 0.0254947707173415 | 2.04678243258968 | 38 | 0.842303937417455 | 0.55284611225361 | 0.0685 |
| 3 | 5 | 0.0119649214693345 | 2.05316238454543 | 26 | 0.866748715774156 | 0.553988792502787 | 0.0685 |
| 4 | 5 | 0.0227248513093218 | 1.79130512056872 | 87 | 0.890362443809863 | 0.436710486758966 | 0.068 |
| 5 | 8 | 0.0179595448542386 | 2.05562060466036 | 93 | 0.891160581179429 | 0.521792834519874 | 0.068 |
| 6 | 6 | 0.0184877650788985 | 2.47866926947609 | 64 | 0.83313264483586 | 0.812140957009979 | 0.0686 |
| 7 | 6 | 0.0597224851348437 | 2.54486419609748 | 85 | 0.858863256021868 | 0.88247439750703 | 0.0686 |
| 8 | 5 | 0.0427106887870468 | 2.11250258260407 | 94 | 0.745799078559503 | 0.638513505784795 | 0.0686 |
| 9 | 5 | 0.0147431414970197 | 2.22801433177665 | 19 | 0.798432543617673 | 0.84205840973882 | 0.0686 |
| 10 | 3 | 0.0400677399151027 | 1.93769115372561 | 65 | 0.837546187068801 | 0.774923810071778 | 0.0686 |

### 6.4.5 Exploring Parameter Space

Let's explore the parameter space some, shall we?

```
search_results %>%
   group_by_at(
     c("surrogate_run",
       "surrogate_iteration",
       "param_id",
      getParamIds(xgboost_random_params)
       )
     ) %>%
   summarise(mae = mean(mae)) %>%
   ungroup() %>%
  mutate(surrogate_run = factor(surrogate_run)) %>%
ggplot(aes(x = subsample, y = gamma, size = mae)) +
  geom_point(aes(col = surrogate_run)) +
```

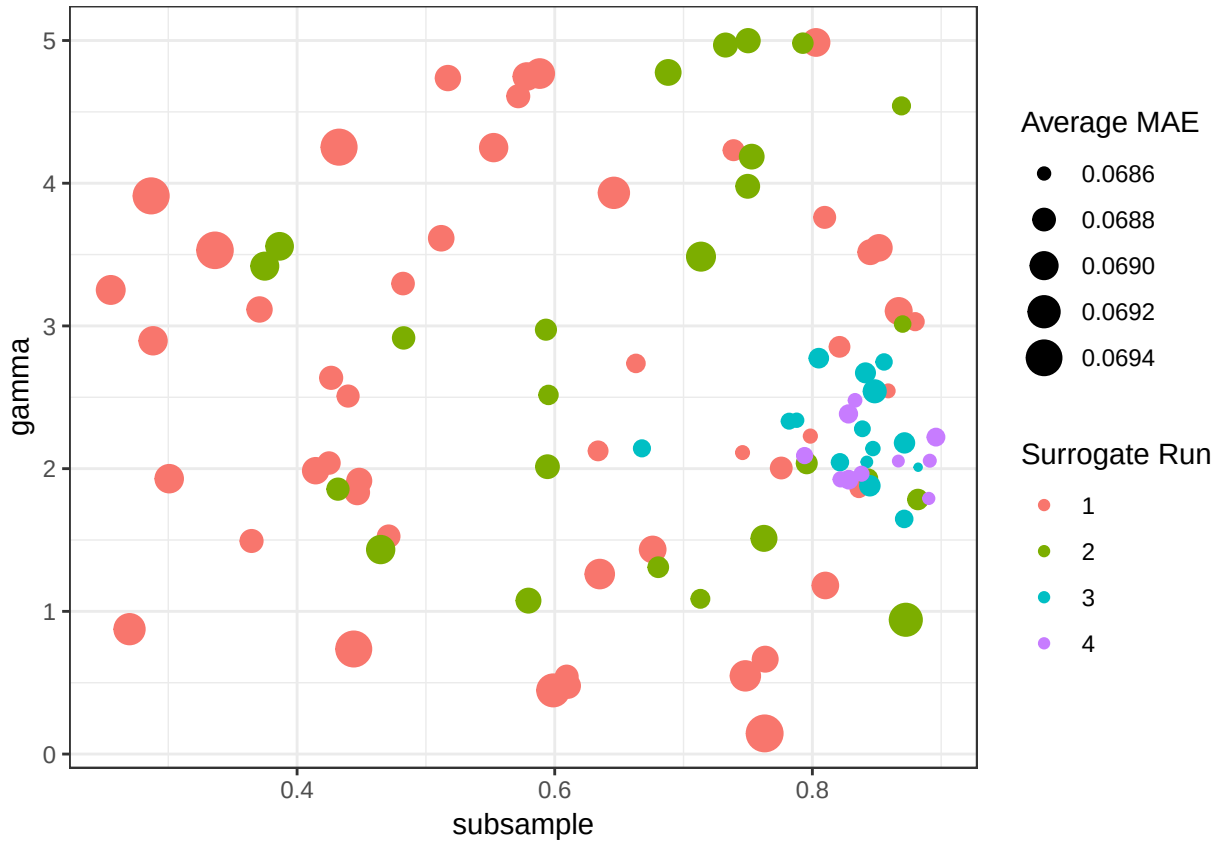



Figure 6.1: Gamma and subsample parameters converging with each surrogate run

```
  theme_bw() +
  labs(
    y = "gamma",
    x = "subsample",
    col = "Surrogate Run",
    size = "Average MAE"
  )
```

How does performance increase with each iteration?

```
search_results %>%
  group_by_at(
    c("surrogate_run",
      "surrogate_iteration",
      "param_id",
       getParamIds(xgboost_random_params)
      )
    ) %>%
  summarise(mae = mean(mae)) %>%
  ungroup() %>%
  mutate(surrogate_run = factor(surrogate_run)) %>%
  arrange(
    surrogate_run,
```

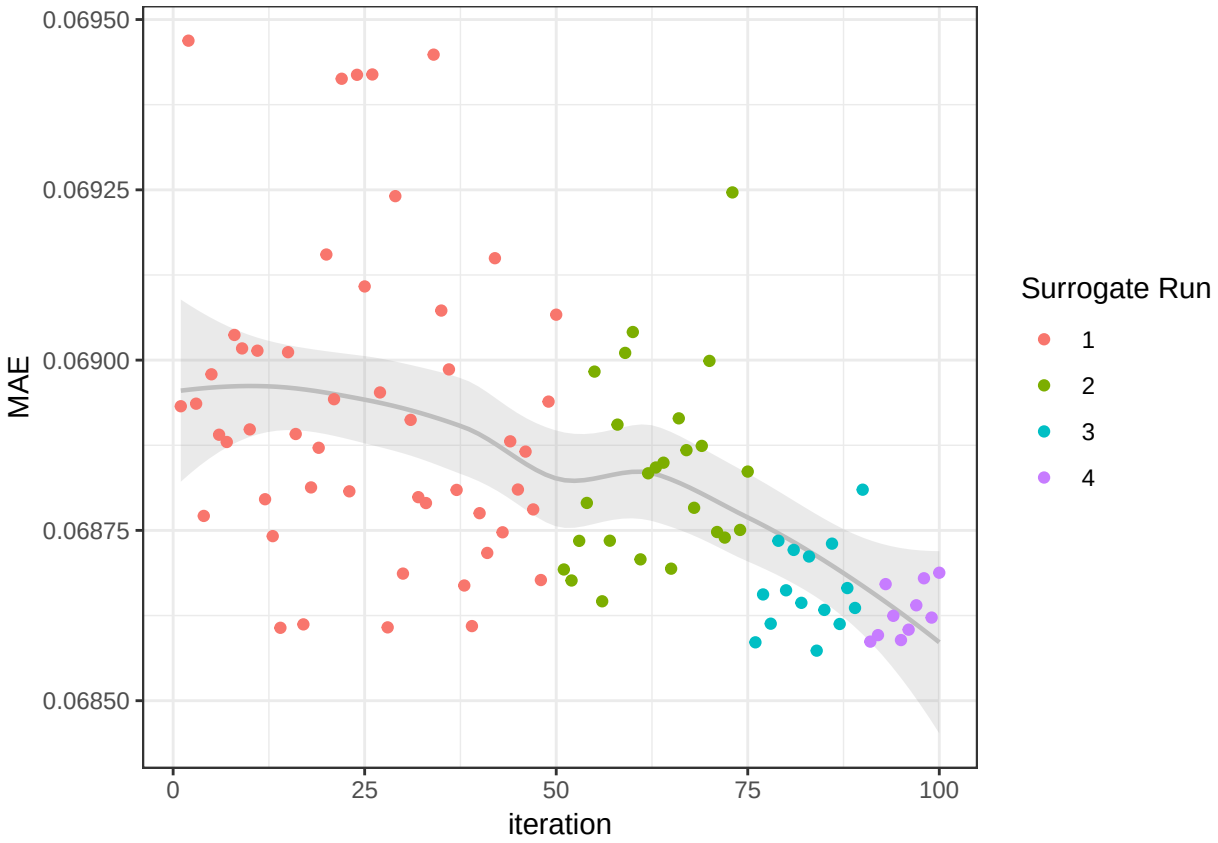



Figure 6.2: Mean Absolute Error Progressively Decreasing with Each Surrogate Run

```
    surrogate_iteration
  ) %>%
  mutate(
    iteration = row_number()
  ) %>%
ggplot(aes(x = iteration, y = mae)) +
    geom_smooth(alpha = 0.2, size = 0.8, colour = "grey") +
  geom_point(aes(col = surrogate_run)) +
  theme_bw() +
  labs(
    y = "MAE",
    x = "iteration",
    col = "Surrogate Run"
  )
```

## 6.5 Tuned Model

Get the parameter set with the lowest average `mae` across all folds

```
tuned_params <- search_summary %>%
  ungroup() %>%
```

```
  filter(mae == min(mae)) %>%
  select(getParamIds(xgboost_random_params)) %>%
  as.list()

tuned_params
```

```
## $max_depth
## [1] 5
##
## $eta
## [1] 0.07531416
##
## $gamma
## [1] 2.009971
##
## $min_child_weight
## [1] 100
##
## $subsample
## [1] 0.8821157
##
## $colsample_bytree
## [1] 0.5284899
```

Since we didn't save the actual models produced in our search, train a model with the tuned parameters

```
d_prepped <- prep(rec)

train_df <- bake(d_prepped, newdata = d)

x_train <- train_df %>%
  select(features_to_use) %>%
  as.matrix()

y_train <- train_df$log_error

xgb_train_data <- xgb.DMatrix(x_train, label = y_train)

tuned_model <- xgb.train(params = tuned_params,
                         data = xgb_train_data,
                         objective = 'reg:linear',
                         verbose = FALSE,
                         nthread = 20,
                         nrounds = 1000)
```

### 6.5.1 Making Predictions with Tuned Model

Since we already created our helper function `predict_dates()` we can apply it here with our new model

```
predict_list <- lapply(id_parcel_splits, function(i) {

  pred_df <- predict_date(
    parcel_id = i,
    predict_date = predict_dates,
```

```
    mdl = tuned_model,
    features_to_use = features_to_use
    )
  })


predict_df <- bind_rows(predict_list) %>%
  mutate_at(vars(`201610`:`201712`), round, digits = 4) %>%
  mutate(ParcelId = as.integer(ParcelId)) %>%
  as.data.frame()

write_csv(predict_df, "submissions/submit01.csv")
```

## 6.6 Model Comparison

This model produced a MAE of `0.0651839` on the public leaderboard.

```
tuned_mae <- 0.0651839

# how much did we improve?
(tuned_mae - base_mae) / base_mae
```

```
## [1] -0.1745969
```

Hey not bad! Our hyperparameter optimization process resulted in a 17.5% reduction in Mean Abosolute Error when compared to our base line model. While our absolute position on the leaderboard still isn't very high, it's a solid first submission that we can build upon and test new models against. With the top 10 finsishers on the public leaderboard all averaging 184 submissions each (highest being 449!) this empahsizes the iterative nature of predictive modeling. We aren't in 1$^{st}$ place with our first submission but we didn't expect to be.

At this point if we were competing the actual competition we would go back to the drawing board in start investigating what we could do differently to improve our score. In our specific case, things like not making the predicion date the first Wednesday of each month and looking at the average prediction across all days in the month would be the first thing I would check to se what kind of improvement resulted. Also based on @??fig:fig-mae-by-run) it looks like can could further shrink our parameter space to find more optimal hyperparameter combinations.

Other things like adding more interaction features or stacking our xgboost predictions as part of an ensemble of other models is an area to explore as well.

# Chapter 7

# Summary

Overall we went from basic preprocessing and exploratory analysis, to feature engineering, to complex parameter tuning. We found out alot about the data and alot about the modeling process in general.

Using a base line XGBoost model with a limited number of features, we were able to achieve a MAE of `0.0789722`, however when we used 5-fold cross validation and used a Random Forest surrogate model to optimatize the XGBoost parameters, we were able to achieve a submission MAE of `0.0651839`, a 17.46% reduction from our base line model. While the absolute quality of our prediction isn't high enough to take $1^{st}$ place just yet, we are set up well to continue to make improvements.

## 7.1 Key Findings

The main take away after exploring this dataset is that the spatial and temporal autocorrelation of features, especially that in the response variable `log_error` are extremely useful to take advantage of when making predictions. However, overfitting to our training data might cause our models so far to have a higher bias than we would like. This is something we could explore with future submissions.

## 7.2 Next Steps

- Keep exploring how tuning the model affects submission MAE
- Creating other features such as more interactions
- Try other models or ensembles of models
- If using external features, explore more geo-related information, such as
  - Proximity to Interstates,
  - The use of building footprints extracted from Imagery
  - School Zones
- Explore other imputation methods