LM_prediction

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Load packages

```
library(tidyverse)
library(lubridate)
library(readr)
library("ggplot2")
library("dplyr")
library(xts)
library("lubridate")
library("RColorBrewer")
library("ggthemes")
library("gridExtra")
library("leaflet")
library("highcharter")
library(scales)
library(leaflet.extras)
library(modelr)
rats_raw <- read.csv("./Rat_Sightings.csv", na = c("", "NA", "N/A", "Unspecified")) %>%
  janitor::clean_names() %>%
  mutate(created_date = mdy_hms(created_date)) %>%
  mutate(sighting_year = year(created_date),
         sighting_month_num = month(created_date),
         sighting_month = month(created_date, label = TRUE, abbr = FALSE),
         sighting_day = day(created_date),
         sighting_weekday = wday(created_date, label = TRUE, abbr = FALSE))
```

Clean data set more on the predictor variables that were googled through research to have the most effect on rat sightings, keeping borough and location type.

```
cleaner_rats <-
  rats_raw %>%
  drop_na(descriptor, location_type, incident_address, incident_zip,street_name, borough, latitude, long
  select(unique_key, agency, descriptor, location_type, incident_address, incident_zip, street_name, bo
  drop_na() %>%
  janitor::clean_names()

cleaner_rats <- as.data.frame(unclass(cleaner_rats),stringsAsFactors=TRUE)
cleaner_rats
sample_1 <- cleaner_rats[sample(nrow(cleaner_rats), 500), ]
```

Run a linear model on the cleaner data set to be able to see which predictor variables had the most impact on the model by looking at their P values.

```
model1 <-  lm(latitude ~ borough + location_type + incident_zip + street_name, data = sample_1)
model2 <-  lm(longitude ~ borough + location_type + incident_zip + street_name, data = sample_1)
summary(model1)
summary(model2)
```

Simply run a kfold technique to have a training and testing data set, run a new linear regression model to see the effect on latitude using

```
set.seed(23)
cleaner_rats1 <-
  sample_1 %>%
  select(location_type, borough,incident_zip, street_name, latitude)

rats_folds <- crossv_kfold(cleaner_rats1, k = 10)

rats_folds <- rats_folds %>% mutate(model4 = map(train, ~ lm(latitude ~ ., data = .)))

rats_folds$model4[[1]] %>% summary()
```

```
set.seed(23)
cleaner_rats2 <-
  sample_1 %>%
  select(location_type, borough, street_name, incident_zip, longitude)

rats_folds2 <- crossv_kfold(cleaner_rats2, k = 10)

rats_folds2 <- rats_folds2 %>% mutate(model = map(train, ~ lm(longitude ~ ., data = .)))

rats_folds2$model[[1]] %>% summary()
```

This is the longitude prediciton

```
library(broom)
```

```
##
## Attaching package: 'broom'
```

```
## The following object is masked from 'package:modelr':
##
##     bootstrap
```

```
prediction <-
  rats_folds2 %>%
  mutate(predicted = map2(model, train, ~ augment(.x, newdata = .y))) %>%
  unnest(predicted)
```

```
## Warning: There were 10 warnings in `mutate()`.
## The first warning was:
## i In argument: `predicted = map2(model, train, ~augment(.x, newdata = .y))`.
## Caused by warning in `predict.lm()`:
## ! prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases
## i Run `dplyr::last_dplyr_warnings()` to see the 9 remaining warnings.
```

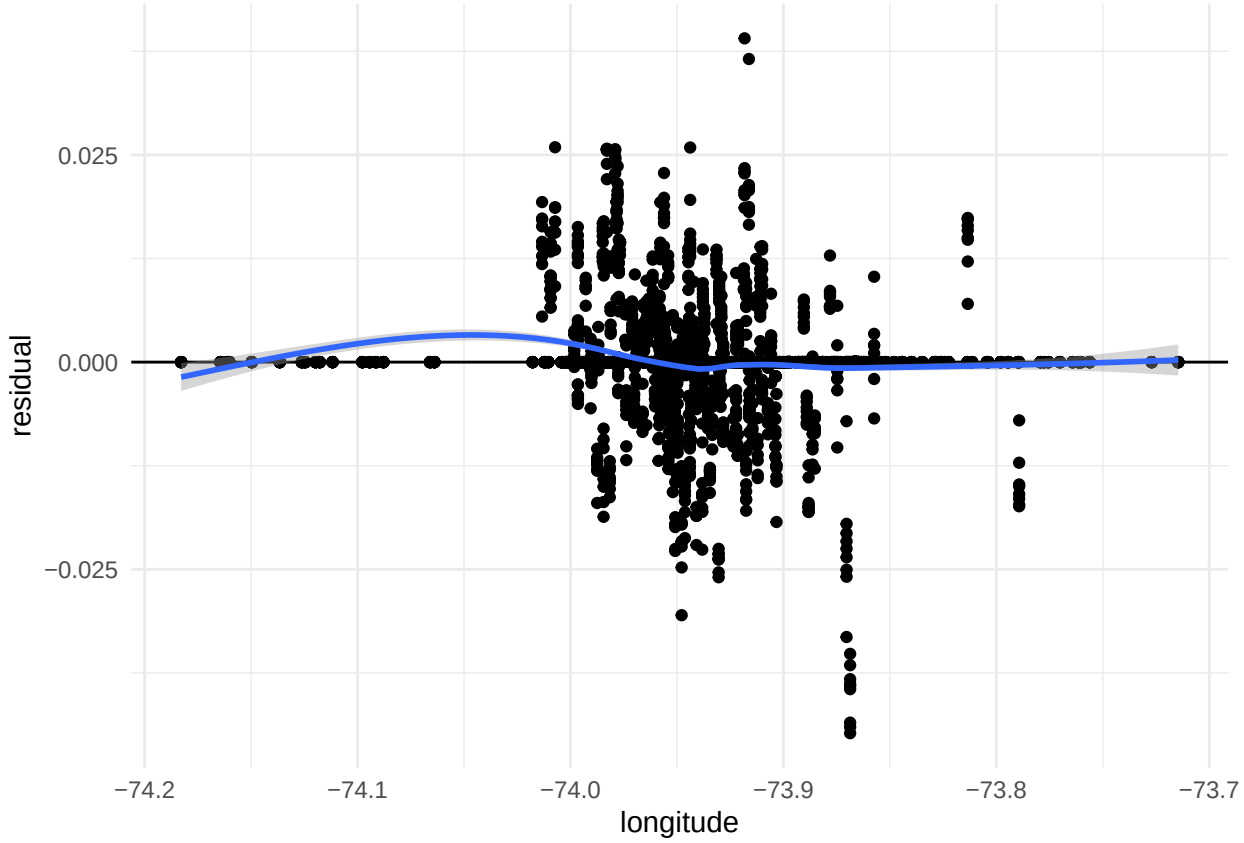
```
prediction
```

We compare by looking to residual

```r
prediction <- prediction %>%
  mutate(residual = .fitted - longitude)

prediction%>%
  ggplot(aes(longitude, residual)) +
    geom_hline(yintercept = 0) +
    geom_point() +
    stat_smooth(method = "loess") +
    theme_minimal()
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

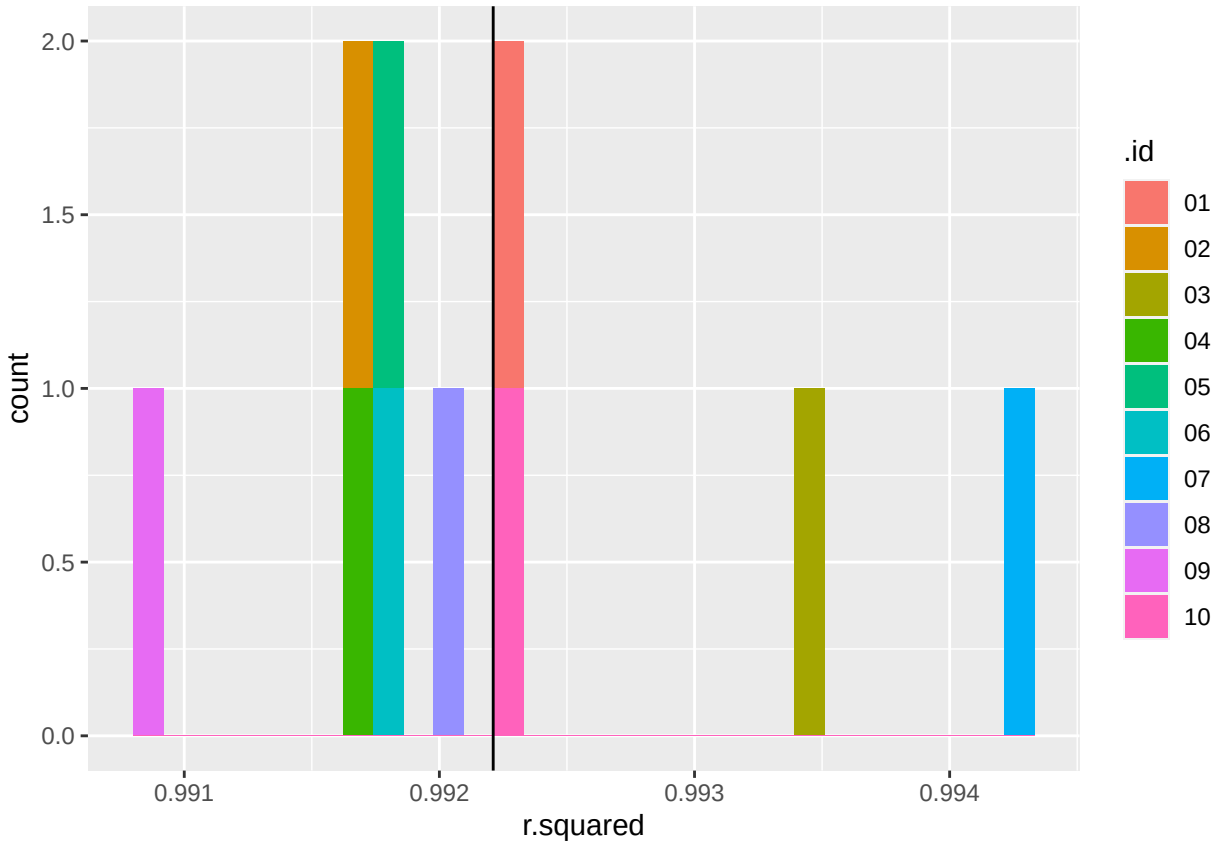


We compare the R^2 and look at the residuals

```r
rs <- prediction %>%
  group_by(.id) %>%
  summarise(
    sst = sum((longitude - mean(longitude)) ^ 2), # Sum of Squares Total
    sse = sum(residual ^ 2),           # Sum of Squares Residual/Error
    r.squared = 1 - sse / sst          # Proportion of variance accounted for
    )

rs %>%
  ggplot(aes(r.squared, fill  = .id)) +
    geom_histogram() +
    geom_vline(aes(xintercept = mean(r.squared)))
```

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



Same process as above for the latitude

```
library(broom)

prediction2 <-
  rats_folds %>%
  mutate(predicted = map2(model4, train, ~ augment(.x, newdata = .y))) %>%
  unnest(predicted)
```

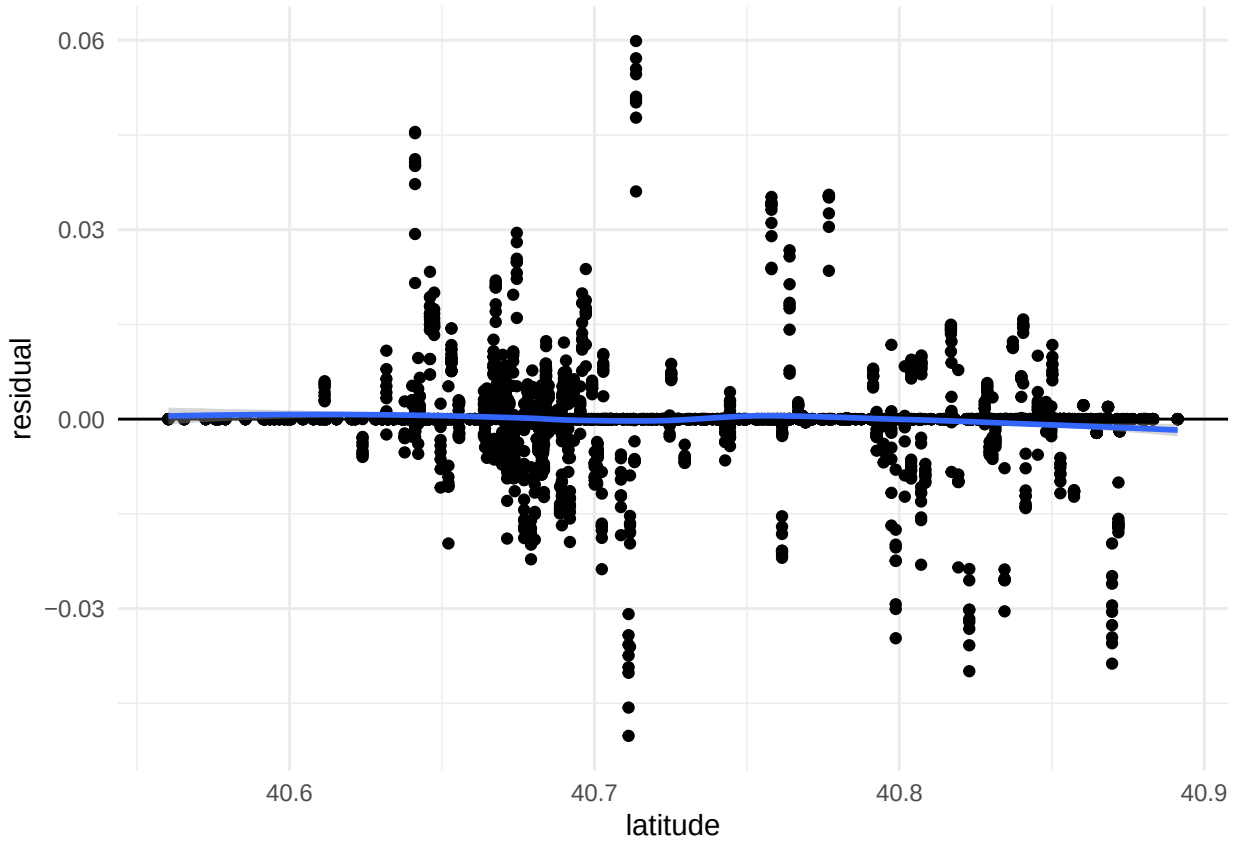
```
## Warning: There were 10 warnings in `mutate()`.
## The first warning was:
## i In argument: `predicted = map2(model4, train, ~augment(.x, newdata = .y))`.
## Caused by warning in `predict.lm()`:
## ! prediction from rank-deficient fit; attr(*, "non-estim") has doubtful cases
## i Run `dplyr::last_dplyr_warnings()` to see the 9 remaining warnings.
```

```
prediction
```

```
prediction2 <- prediction2 %>%
  mutate(residual = .fitted - latitude)

prediction2%>%
  ggplot(aes(latitude, residual)) +
    geom_hline(yintercept = 0) +
    geom_point() +
    stat_smooth(method = "loess") +
    theme_minimal()
```

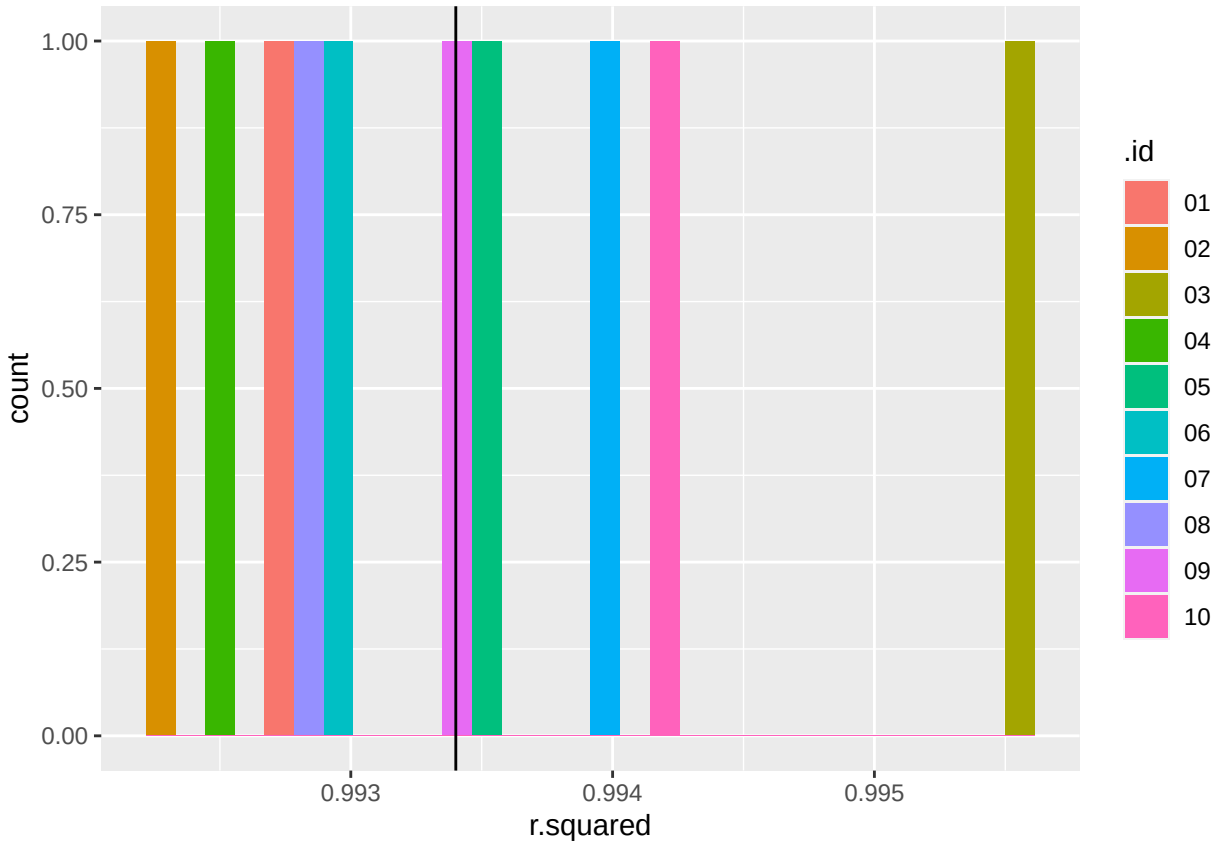
```
## `geom_smooth()` using formula = 'y ~ x'
```




```
rs2 <- prediction2 %>%
  group_by(.id) %>%
  summarise(
    sst = sum((latitude - mean(latitude)) ^ 2), # Sum of Squares Total
    sse = sum(residual ^ 2),           # Sum of Squares Residual/Error
    r.squared = 1 - sse / sst          # Proportion of variance accounted for
    )

rs2 %>%
  ggplot(aes(r.squared, fill  = .id)) +
    geom_histogram() +
    geom_vline(aes(xintercept = mean(r.squared)))
```

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


1.00
0.75
0.50
0.25
0.00
count
0.993
0.994
0.995
r.squared
.id
01
02
03
04
05
06
07
08
09
10