R Notebook

```
data <- read_csv("SAT_School_Participation_and_Performance__2012-2013.csv")
```

```
## Parsed with column specification:
## cols(
##   `District Number` = col_double(),
##   District = col_character(),
##   School = col_character(),
##   `Test-takers: 2012` = col_double(),
##   `Test-takers: 2013` = col_double(),
##   `Test-takers: Change%` = col_double(),
##   `Participation Rate (estimate): 2012` = col_double(),
##   `Participation Rate (estimate): 2013` = col_double(),
##   `Participation Rate (estimate): Change%` = col_double(),
##   `Percent Meeting Benchmark: 2012` = col_double(),
##   `Percent Meeting Benchmark: 2013` = col_double(),
##   `Percent Meeting Benchmark: Change%` = col_double()
## )
```

```
#Alex's contribution: Tidying up the data
df <- data %>% select(-1, -6, -9, -12) %>% rename(district = "District", school = "School", t_takes2012
df <- df %>% dplyr::filter(!(is.na(t_takes2012) | is.na(t_takes2013) | is.na(part_rate2012) | is.na(par
df
```

```
## # A tibble: 187 x 8
##    district school t_takes2012 t_takes2013 part_rate2012 part_rate2013
##    <chr>    <chr>        <dbl>       <dbl>         <dbl>         <dbl>
##  1 Ansonia  Anson~         118         104            67            61
##  2 Avon     Avon ~         254         243            90            89
##  3 Berlin   Berli~         216         220            81            82
##  4 Bethel   Bethe~         200         190            86            82
##  5 Bloomfi~ Bloom~         116         130            79            89
##  6 Bloomfi~ Big P~          14          30           100           100
##  7 Bolton   Bolto~          62          70            85            96
##  8 Branford Branf~         196         213            77            84
##  9 Bridgep~ Bassi~         105         122            52            60
## 10 Bridgep~ Centr~         346         305            78            69
## # ... with 177 more rows, and 2 more variables: perc_mb2012 <dbl>,
## #   perc_mb2013 <dbl>
```

Introduction In this project, the dataset provides Benchmark Meeting and participation rate, but it did not show what exactly how many people reach the Benchmark in that year, and the Percent Meeting Benchmark of the total number of test takers. Therefore, we created a new index call BMR(Benchmark Meeting Rate),we find all the seniors in a school fist, then calculate BMR through Benchmark-meeting seniors divided by the number of total seniors. We use BMR to evaluate the quality of education in the districts. This report we will analyze the distribution of Benchmark Performance in 2012 and 2013.

bmr = number of meeting Benchmark / number of total seniors = (t_takes*perc_mb) / (t_takes/part_rate) = pec_mb*part_rate bmr = perc_mb*part_rate*0.0001

We use bmr because it's a better measurement for comparing how well schools do. If 2 schools have the same percentage meeting benchmark, but one of them has a higher participation rate then the one with the higher participation rate is the better school.

```r
#Alex's contribution: creating BMR formula
#df1 is for testtakers for each school+year
df1 <- df %>%
  select(1:4) %>%
  rename(`2012` = t_takes2012, `2013` = t_takes2013) %>%
  gather(3,4,key = "year", value = "t_takes") %>%
  arrange(school)

#df2 is participation rate for each school+year
df2 <- df %>% select(1,2,5,6) %>%
  rename(`2012` = part_rate2012, `2013` = part_rate2013) %>%
  gather(3,4,key = "year", value = "part_rate")

#df3 is percentage meeting benchmark for each school+year
df3 <- df %>%
  select(1,2,7,8) %>%
  rename(`2012` = perc_mb2012, `2013` = perc_mb2013) %>%
  gather(3,4,key = "year", value = "perc_mb")

#df4 combines them all
df4 <- df1 %>%
  full_join(df2,by = c("district","school","year")) %>%
  full_join(df3,by = c("district","school","year"))
df4 <- df4 %>%
  mutate(bmr = perc_mb*part_rate*1e-4)
```

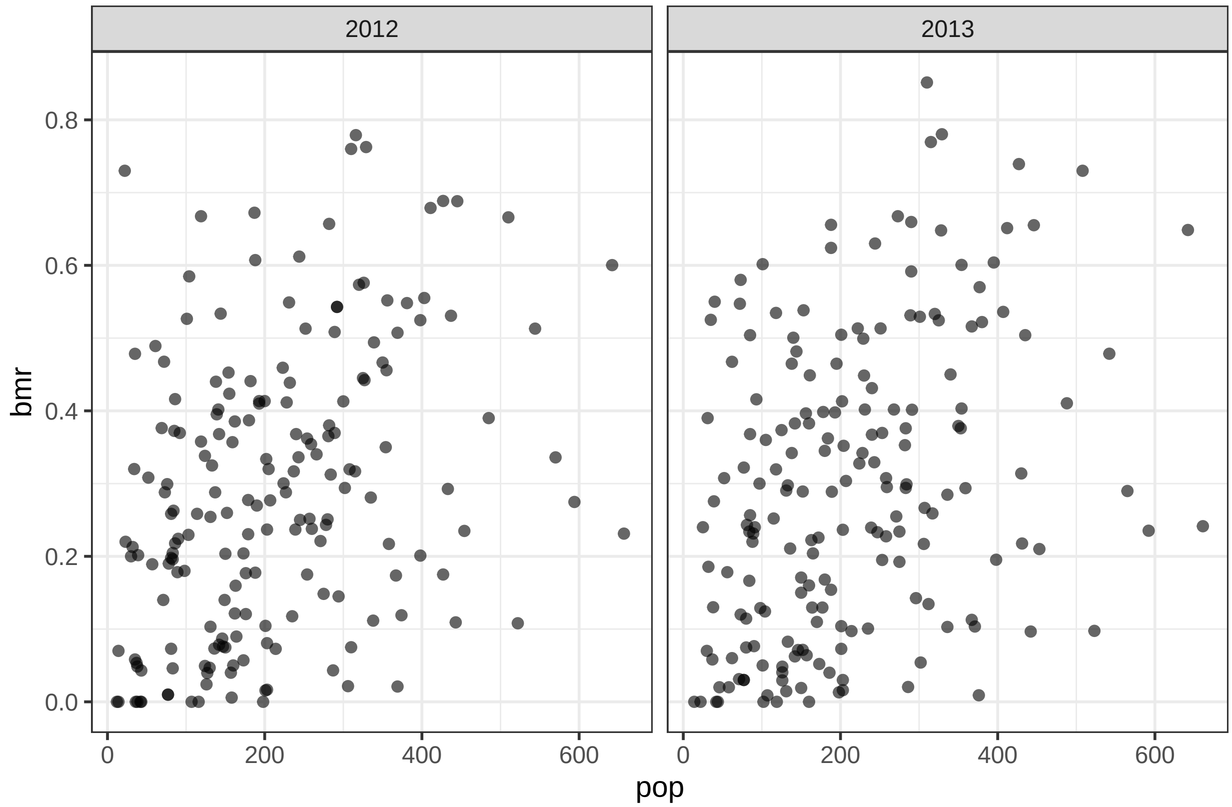
First we'll get the senior population for each school (denoted as pop)

```r
data <- df4 %>% mutate(pop = floor(1e2*t_takes / part_rate))
data
```

```
## # A tibble: 374 x 8
##    district        school       year  t_takes part_rate perc_mb    bmr   pop
##    <chr>           <chr>        <chr>   <dbl>     <dbl>   <dbl>  <dbl> <dbl>
##  1 Stamford        Academy of~ 2012      133        82      47 0.385    162
##  2 Stamford        Academy of~ 2013      142        88      51 0.449    161
##  3 Connecticut Te~ Albert I P~ 2012       92        58       1 0.0058   158
##  4 Connecticut Te~ Albert I P~ 2013       88        55       0 0        160
##  5 Amistad Academ~ Amistad Ac~ 2012       34       100      32 0.32      34
##  6 Amistad Academ~ Amistad Ac~ 2013       31       100      39 0.39      31
##  7 Regional 05     Amity Regi~ 2012      381        87      61 0.531    437
##  8 Regional 05     Amity Regi~ 2013      348        80      63 0.504    435
##  9 Ansonia         Ansonia Hi~ 2012      118        67      18 0.121    176
## 10 Ansonia         Ansonia Hi~ 2013      104        61      18 0.110    170
## # ... with 364 more rows
```

Now lets plot it

```r
ggplot(data) +
  geom_point(aes(pop,bmr),alpha=3/5) +
  facet_wrap(~year) +
  theme_bw() +
  labs(caption="This shows the population vs bmr for each year.")
```

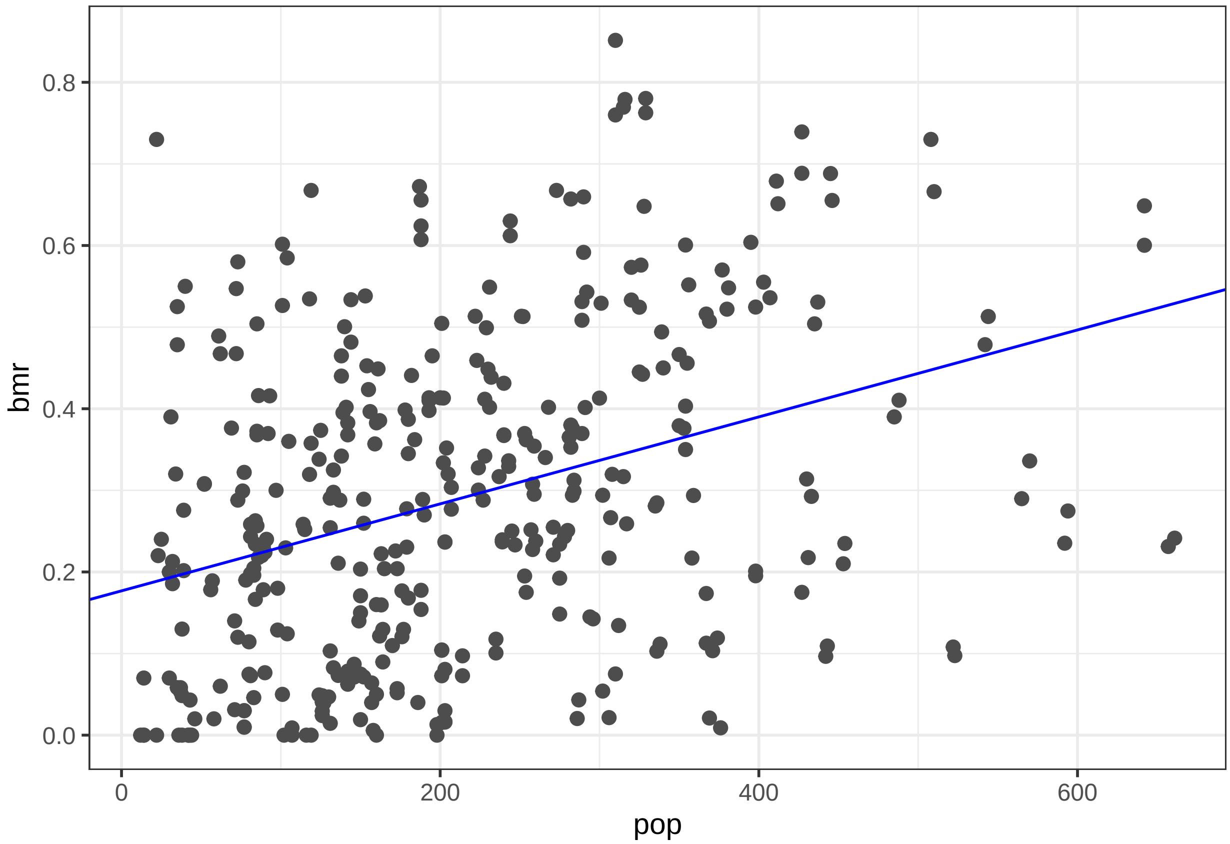


This shows the population vs bmr for each year.

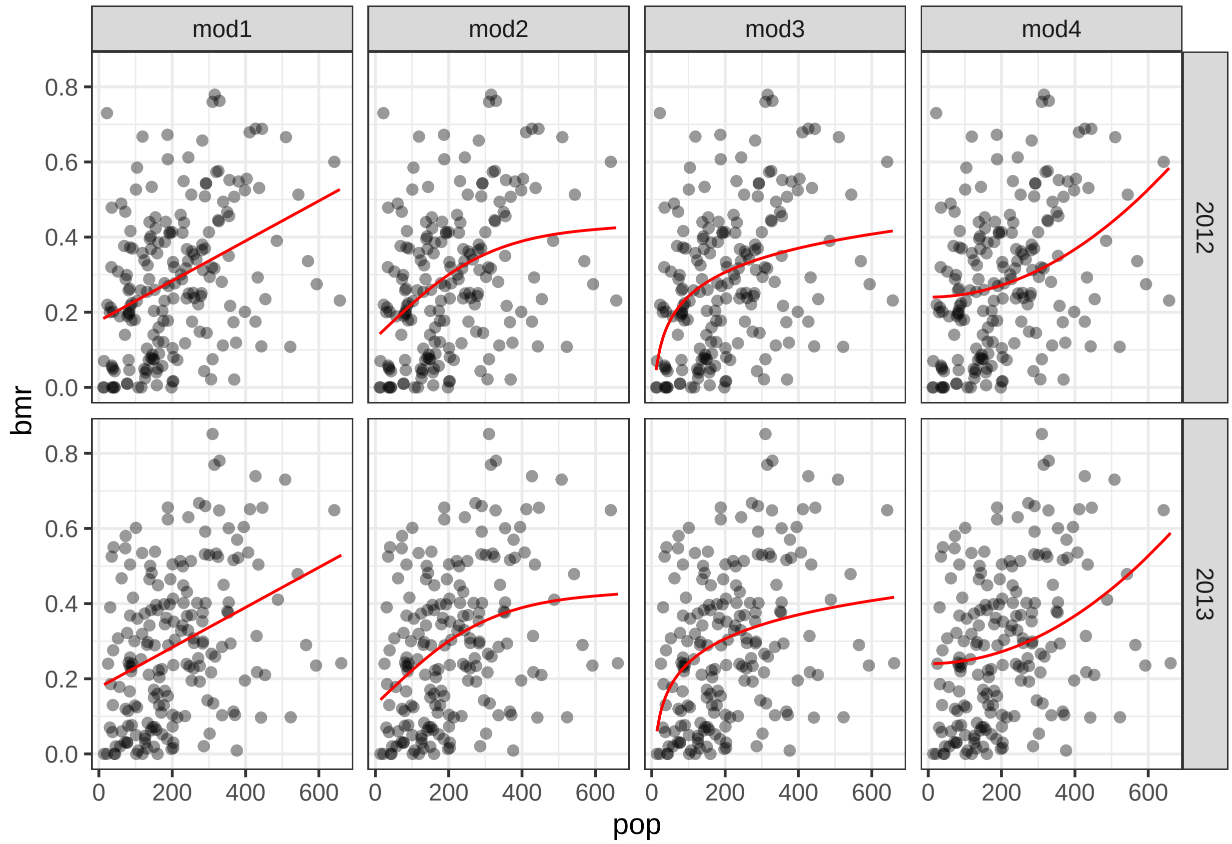
The data is relatively scattered, but we can see a weak positive linear trend.

Let's use mean-square residuals

```
#mean-square residuals
measure_distance <- function(mod,data){
  diff <- data$bmr - (mod[1] + data$pop*mod[2])
  sqrt(mean(diff^2))
}

best <- optim(c(0, 0), measure_distance, data = data)

ggplot(data, aes(pop, bmr)) +
  geom_point(size = 2, colour = "grey30") +
  geom_abline(color="blue",intercept = best$par[1], slope = best$par[2]) +
  theme_bw()
```

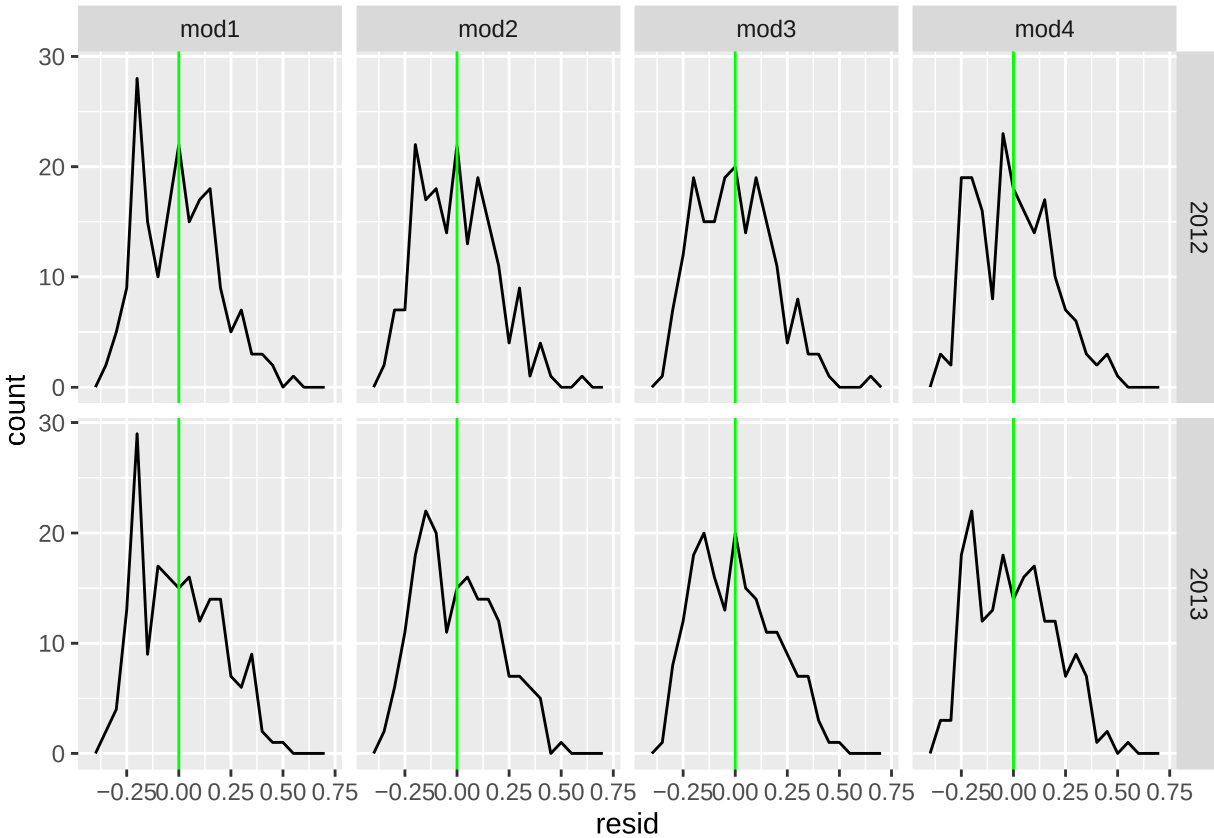



```
mod1 <- lm(bmr ~ ns(pop, 1), data = data)
mod2 <- lm(bmr ~ ns(pop, 2), data = data)
mod3 <- lm(bmr ~ log(pop, base = exp(1)), data = data)
mod4 <- lm(bmr ~ I(pop^2), data = data)

data %>%
  gather_predictions(mod1, mod2, mod3, mod4) %>%
  ggplot(aes(pop, bmr)) +
  geom_point(alpha=2/5) +
  geom_line(aes(pop,pred), colour = "red") +
  facet_grid(year~ model) +
  theme_bw()
```



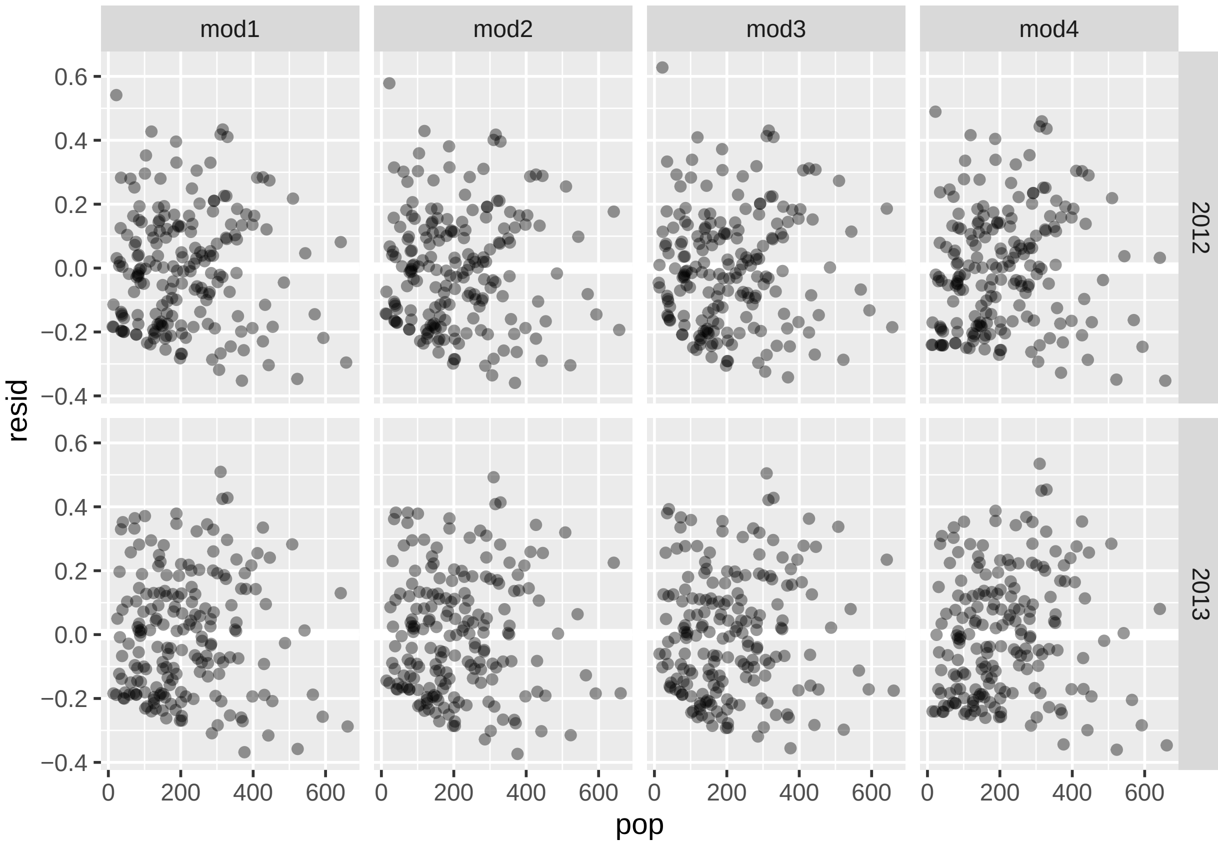
Let's check the residuals for any patterns

```
data %>%
  gather_residuals(mod1,mod2,mod3,mod4) %>%
  ggplot(aes(resid)) +
  geom_freqpoly(binwidth = 0.05) +
  geom_vline(xintercept = 0, colour = "Green", size=0.5) +
  facet_grid(year ~ model)
```



Looks approximately normal for all.

```
data %>%
  gather_residuals(mod1,mod2,mod3,mod4) %>%
  ggplot(aes(pop, resid)) +
  geom_hline(yintercept = 0, colour = "white", size = 2) +
  geom_point(alpha=2/5) +
  facet_grid(year ~ model)
```



Coefficient of Determination (r^2)

```
summary(mod1)$r.squared
```

```
## [1] 0.1260082
```

```
summary(mod2)$r.squared
```

```
## [1] 0.137638
```

```
summary(mod3)$r.squared
```

```
## [1] 0.1248974
```

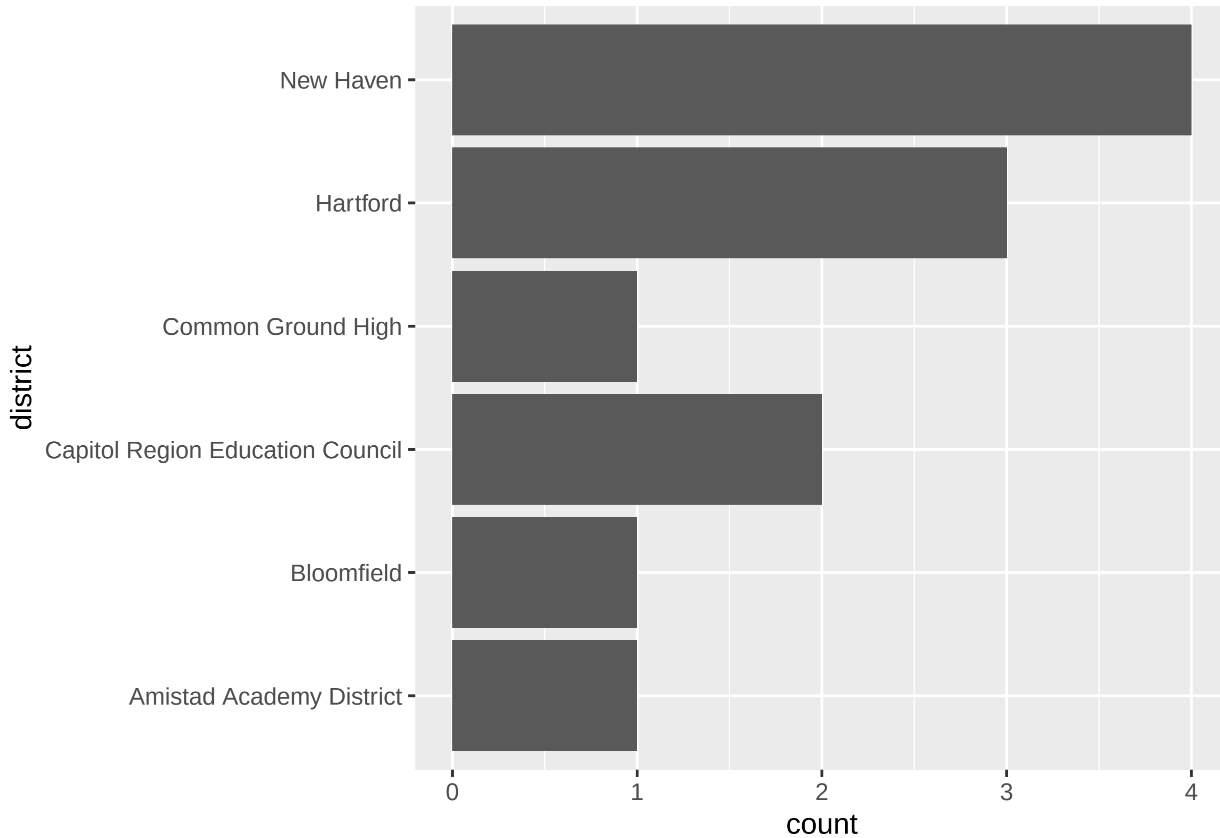
```
summary(mod4)$r.squared
```

```
## [1] 0.09041305
```

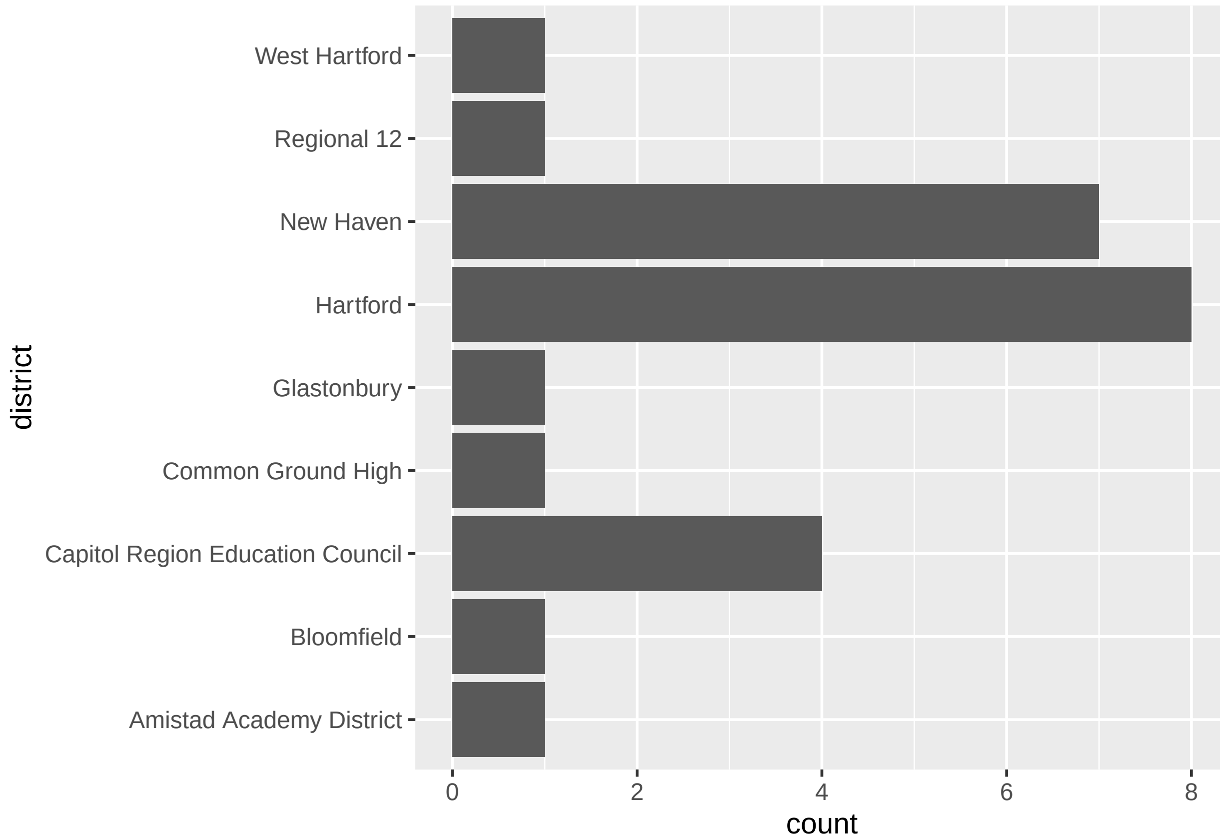
These coefficients SUCK

We find the highest participation rate of 2012 and 2013.

```r
pr2012_highest <- data %>%
    dplyr::filter(part_rate ==100, year == 2012) %>%
    select(district)
ggplot(pr2012_highest) +
  geom_bar(aes(district))+
coord_flip()
```




```r
pr2013_highest <- data %>%
    dplyr::filter(part_rate == 100, year == 2013) %>%
    select(district)

ggplot(pr2013_highest) +
  geom_bar(aes(district))+
coord_flip()
```


West Hartford
Regional 12
New Haven
Hartford
Glastonbury
Common Ground High
Capitol Region Education Council
Bloomfield
Amistad Academy District
district
0
2
4
6
8
count