SAT Benchmark Performance in Connecticut in 2012-13

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Introduction

Our goal is to practice and develop our Exploratory Data Analysis(EDA) skills in R.

In this project we analyze the distributions of SAT Benchmark Performance among high schools in the state of Connecticut from 2012 to 2013, then try to find the relationship between the number of senior students and their SAT Benchmark Performance.

This project uses a primary dataset which(SAT_School_Participation_and_Performance___2012-2013.csv) has been downloaded from the link: https://catalog.data.gov/dataset/sat-school-participation-and-performance-2012-2013.

The SAT benchmarks are designed to measure the college readiness of high school students, using the SAT, a college entrance examination taken by nearly 1.45 million students in all 50 United States and the District of Columbia. The SAT benchmark determined in this study was 1550 for the composite. According to research conducted by the College Board, a score of 1550 indicates that a student will have a 65 percent or greater likelihood of achieving a B- average or higher during the first year of college. (College Board. 250 Vesey Street, New York, NY 10281. Tel: 212-713-8000; e-mail: research@collegeboard.org; Web site: http://research.collegeboard.org)

The primary dataset provided SAT Benchmark Meeting and participation rate, but it did not exactly show how many senior students reach the Benchmark, and the Percent among the total number of senior students in the schools. Therefore, we created a new index called BMR(Benchmark Meeting Rate),which comes through the number of Benchmark-Meeting seniors divided by the number of total seniors in the same school. We use BMR to evaluate SAT Benchmark Performance among high schools in Connecticut in 2012 and 2013.

Questions and Findings

What is the relationship between a school's senior population and the school's benchmark-meeting rate?

```
data <- read_csv("C:/Users/alex/Documents/SAT-Benchmark-Group-Report/SAT_School_Participation_and_Perfo
```

```
## 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()
## )
```

```
df <- data %>%
  select(-1, -6, -9, -12) %>%
  rename(district = "District", school = "School", t_takes2012 = "Test-takers: 2012", t_takes2013 = "Te
df <- df %>%
  dplyr::filter(!(is.na(t_takes2012) | is.na(t_takes2013) | is.na(part_rate2012) | is.na(part_rate2013)
```

```
#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
#BMR is calculated as such:
#bmr = number of meeting Benchmark / number of total seniors = (t_takes*perc_mb) / (t_takes/part_rate)
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)
```

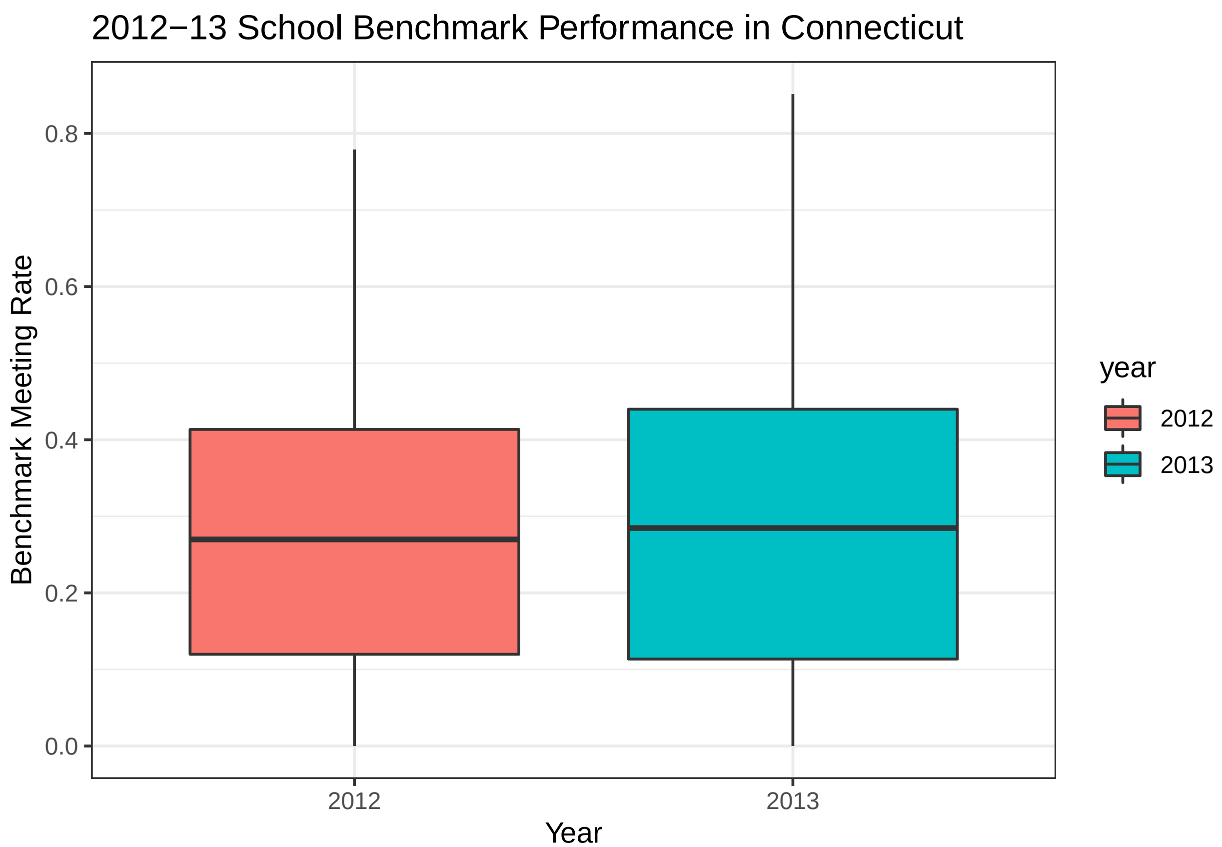
First we'll get the senior population for each school (denoted as pop)

```
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
```

Let's see the trend of bmr vs year

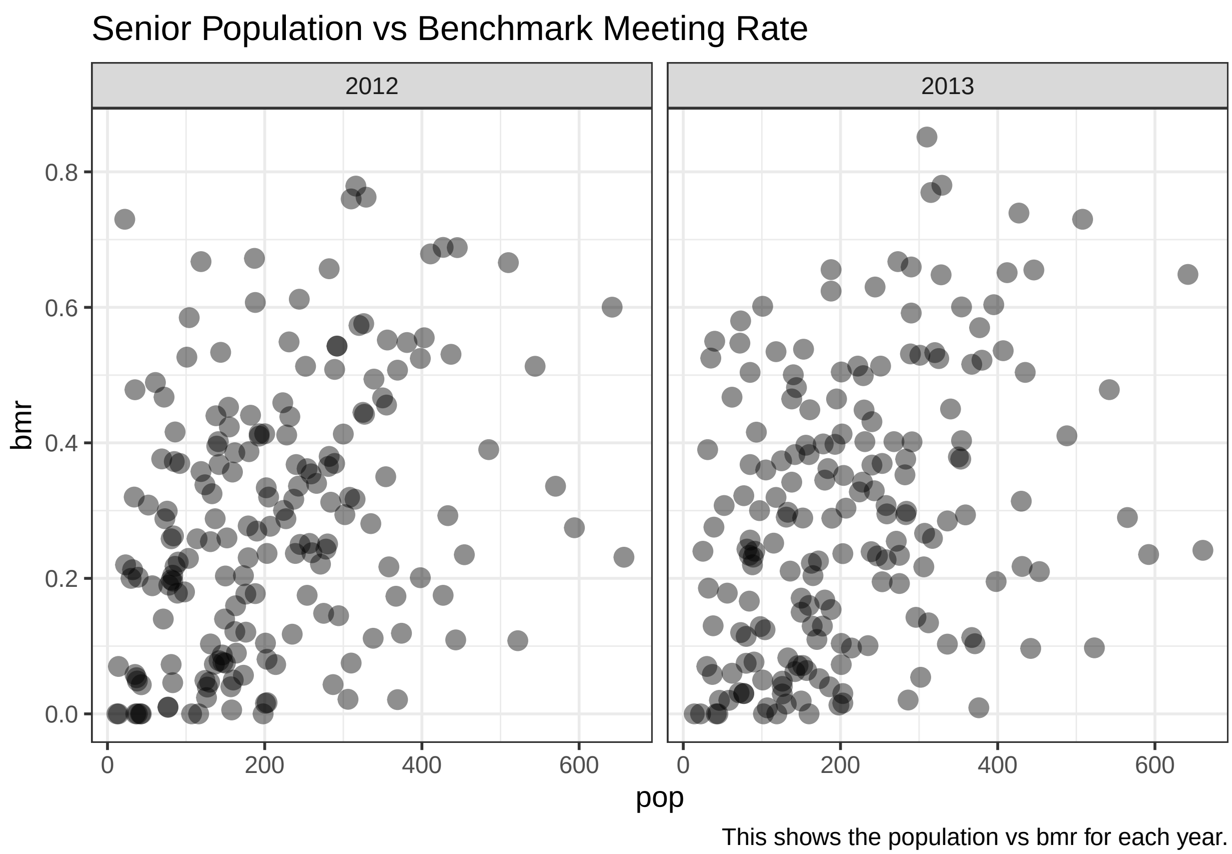
```
data %>%
  ggplot(aes(x = year, y = bmr, fill = year)) +
  geom_boxplot() + labs(
    title = "2012-13 School Benchmark Performance in Connecticut",
    y = "Benchmark Meeting Rate", x = "Year"
  ) + theme_bw()
```



From the graphic above , in 2012 the BMRs of Connecticut schools distributed from 0 to 80 percent, but in 2013 the rate went up a little bit, a couple of schools' numbers almost over 80 percent.

We'll plot the data to see if we can recognize any patterns.

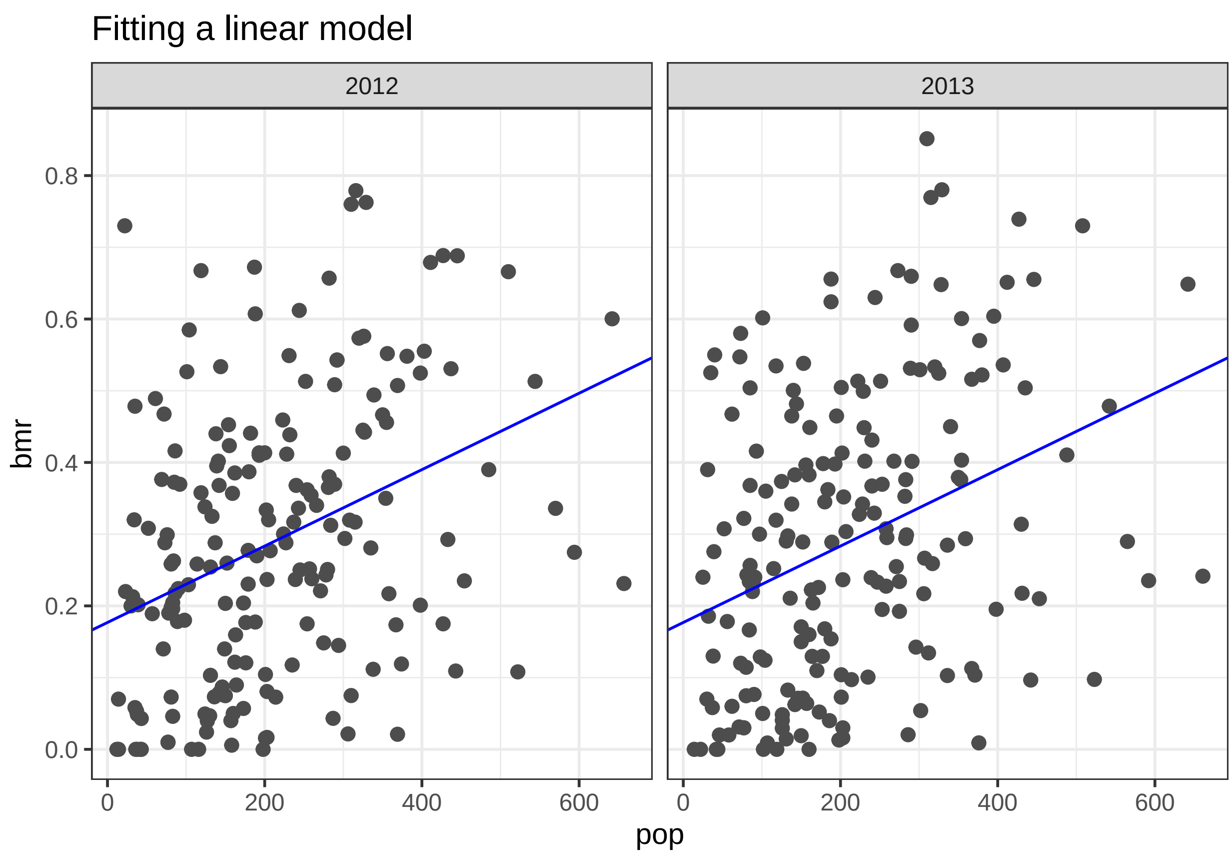
```
ggplot(data) +
  geom_point(aes(pop,bmr),alpha=4/9,size=3) +
  facet_wrap(~year) +
  theme_bw() +
  labs(title="Senior Population vs Benchmark Meeting Rate",caption="This shows the population vs bmr fo
```



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

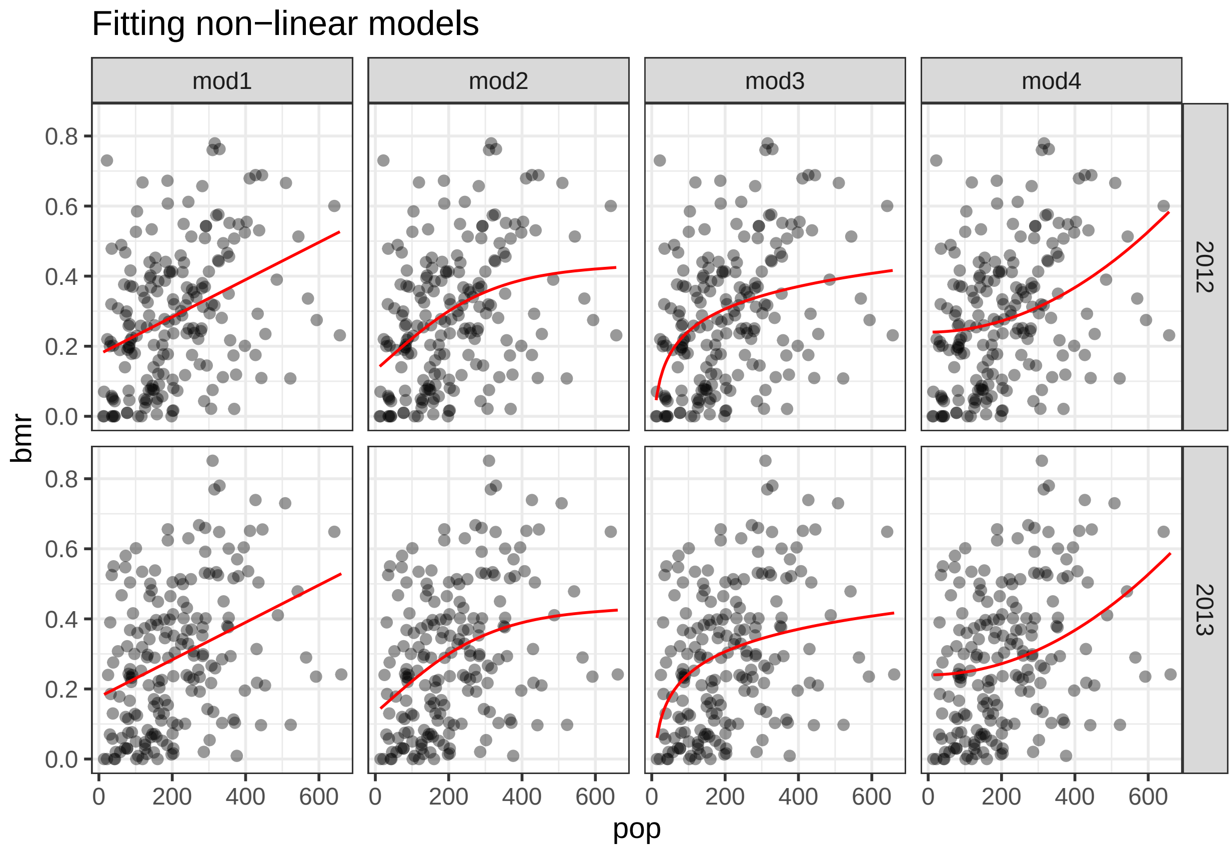
We can create a linear model using root mean squared residuals.

```
#root-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() +
  labs(title="Fitting a linear model") +
  facet_wrap(~year)
```



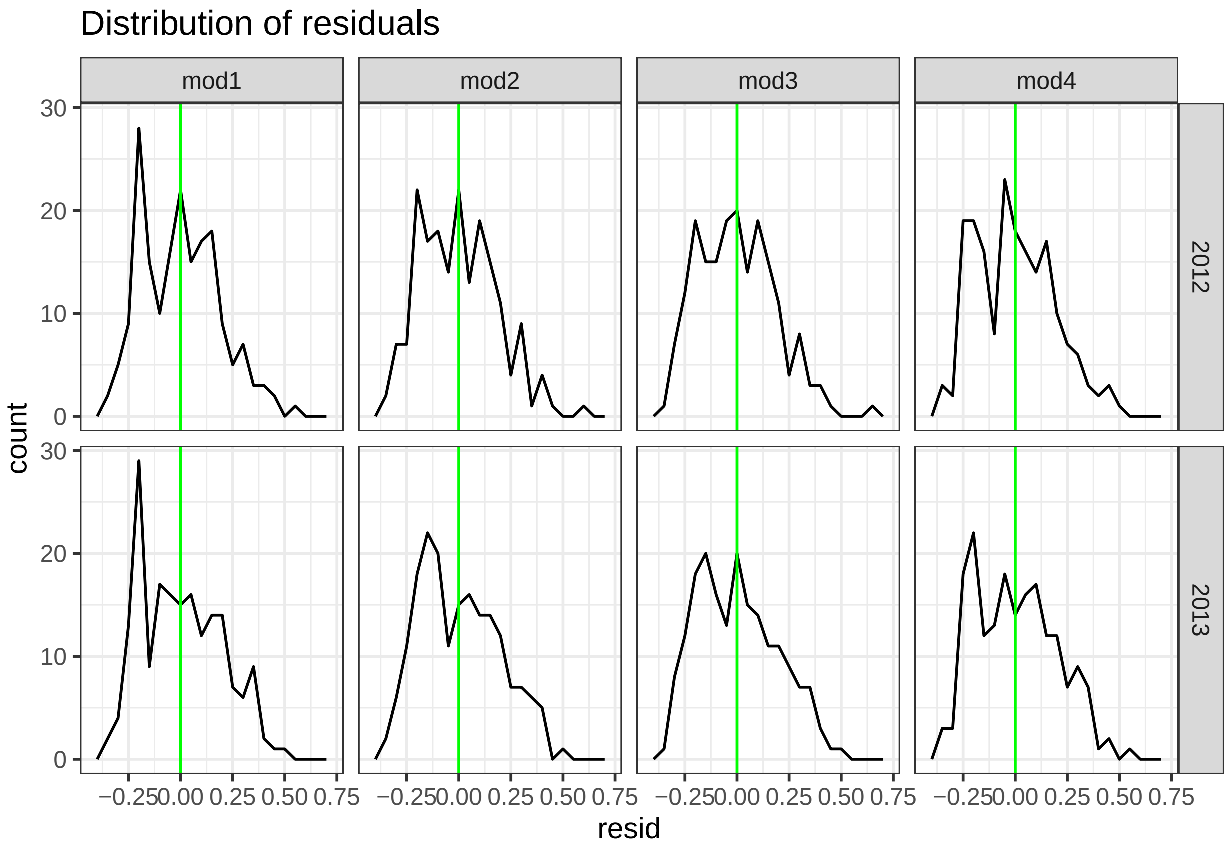
However, there's still many points in the data that are far from our linear model. Let's try out some nonlinear models to see if it can fit the data any better.

```
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() +
  labs(title="Fitting non-linear models")
```



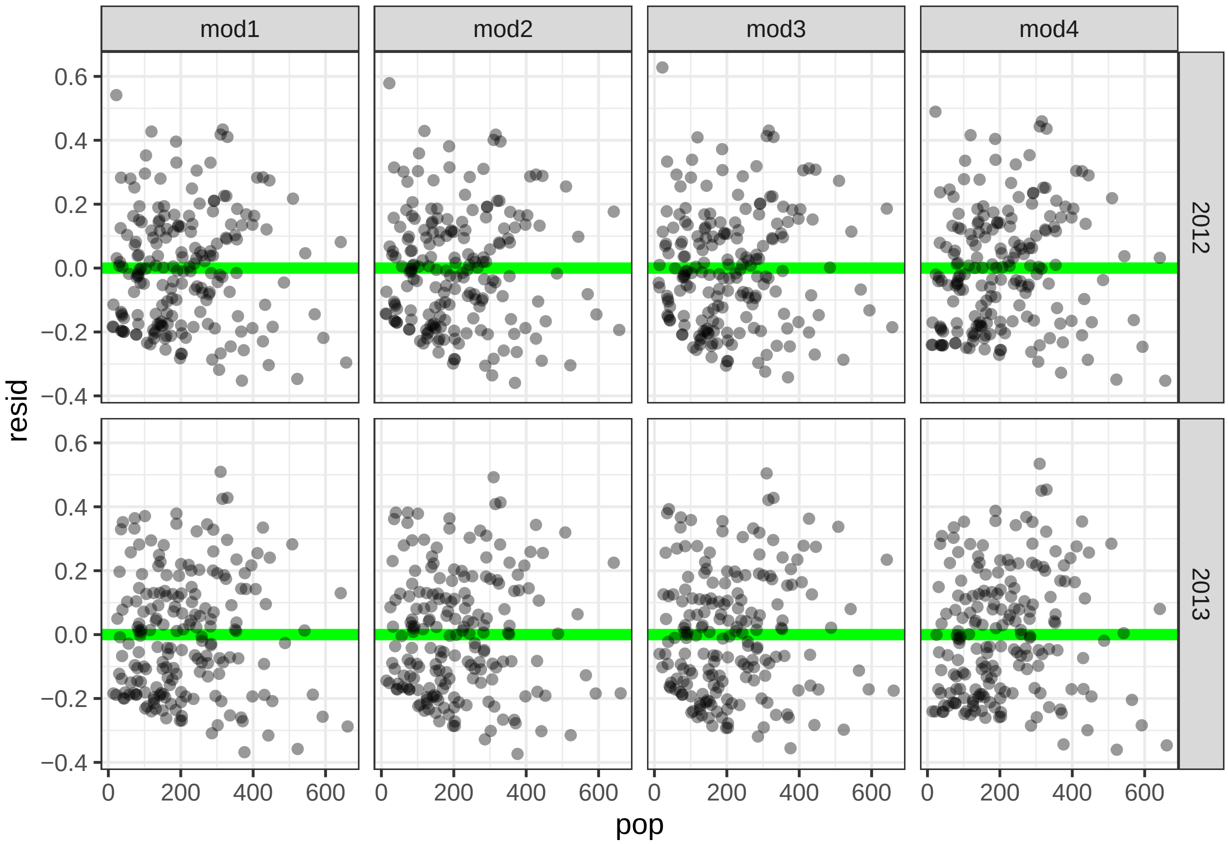
None of these models appear very satisfactory since many data points are still ommitted. But we can't conclude that a model isn't good just by appearance, we also have to examine other factors of the models to check how good it is. Let's check the residuals for any patterns.

```
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) +
  theme_bw() +
  labs(title="Distribution of residuals")
```



Except the first model, all the other residuals have an approximately normal distribution around 0, which are good.

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



There appears to be no pattern in our residual plot for all of the models, which is also a good thing. The last thing we need to check is the coefficient of determination.

```r
print(str_c("r^2 of 1-degree of freedom cubic spline model: ", round(summary(mod1)$r.squared,3)  ))
```

```
## [1] "r^2 of 1-degree of freedom cubic spline model: 0.126"
```

```r
print(str_c("r^2 of 2-degrees of freedom cubic spline model: ", round(summary(mod2)$r.squared,3)  ))
```

```
## [1] "r^2 of 2-degrees of freedom cubic spline model: 0.138"
```

```r
print(str_c("r^2 of logarithmic model: ", round(summary(mod3)$r.squared,3)  ))
```

```
## [1] "r^2 of logarithmic model: 0.125"
```

```r
print(str_c("r^2 of 2nd-degree polynomial model: ", round(summary(mod4)$r.squared,3)  ))
```

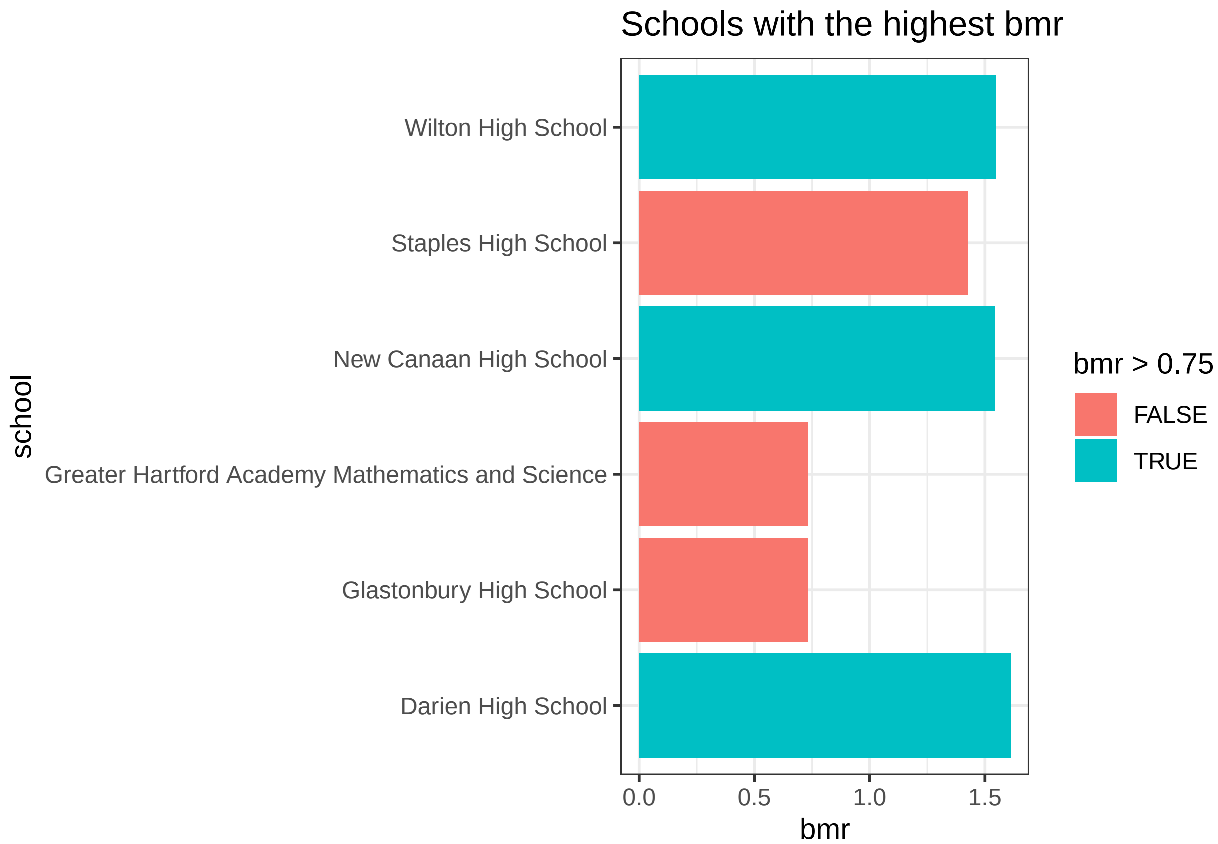
```
## [1] "r^2 of 2nd-degree polynomial model: 0.09"
```

These coefficients are pretty low overall, which are not good. The model with highest coefficient of determination is mod2, the 2-degrees of freedom cubic spline model, so this is the best model we have so far. When predicting a school's benchmark meeting rate based on its population, we can use this model, and be correct about 13.8% of the time.

What's significant about the schools with the highest bmr?

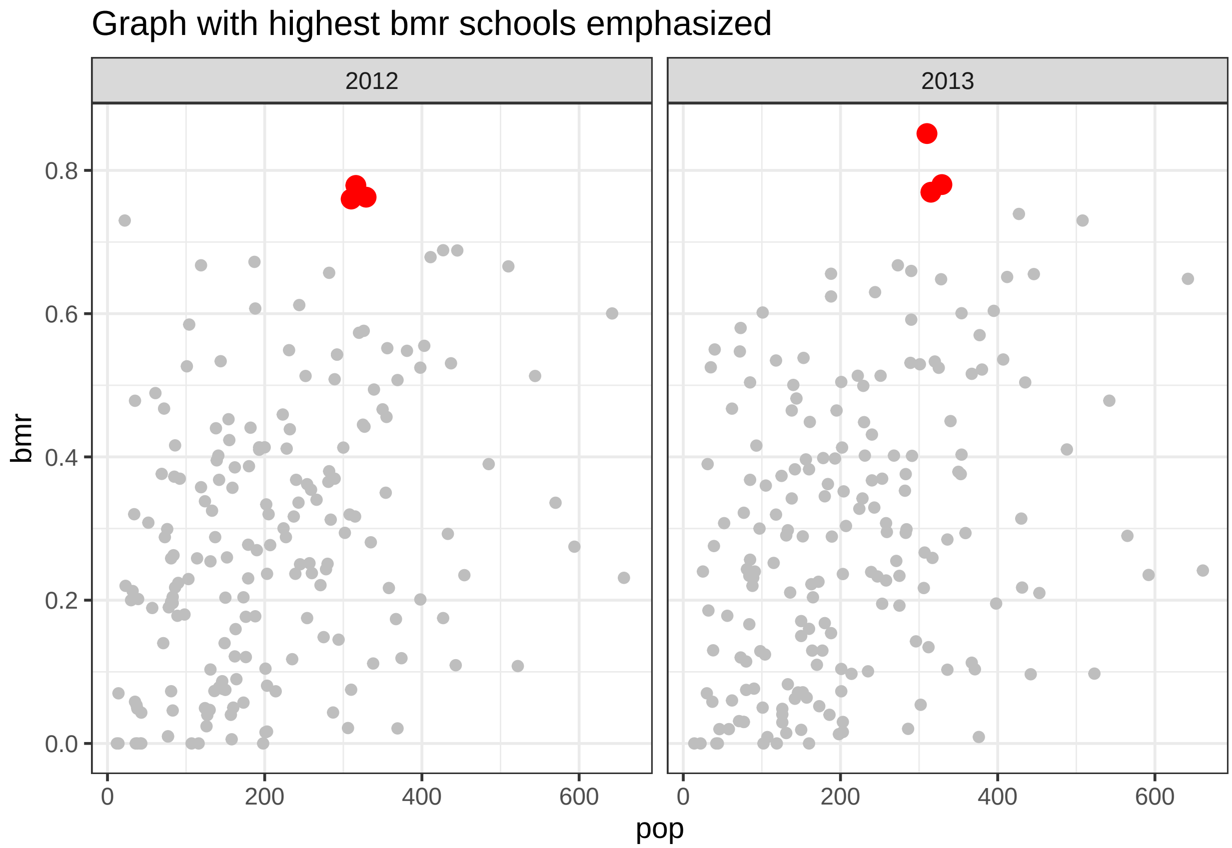
We find the schools with the highest bmr.

```
df4 %>%
  arrange(desc(bmr)) %>%
  head(10) %>%
  ggplot() +
  geom_bar(aes(school,bmr,fill = bmr>0.75),stat="identity") +
  coord_flip() +
  theme_bw() +
  labs(title="Schools with the highest bmr")
```



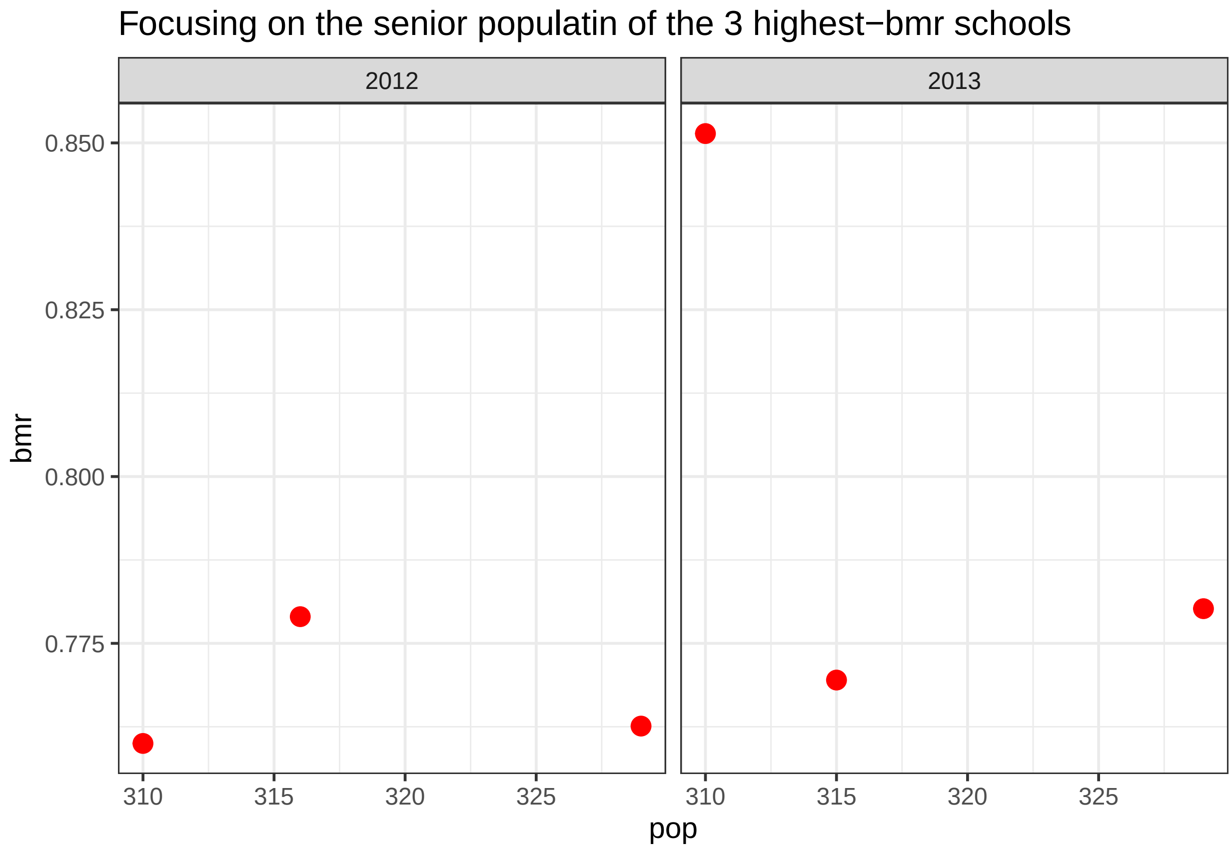
We'll focus on the top 3 schools: Darien High School, New Canaan High School, and Wilton High School.

```
Top3 <- data %>% dplyr::filter(school == "Darien High School" | school == "New Canaan High School" | sc
NotTop3 <- data %>% dplyr::filter(school != "Darien High School" & school != "New Canaan High School" &
ggplot() +
  geom_point(data=Top3,aes(pop,bmr), color = "Red", size=3) +
  geom_point(data=NotTop3,aes(pop,bmr), color="Gray") +
  facet_wrap(~year) +
  theme_bw() +
  labs(title="Graph with highest bmr schools emphasized")
```



If we were to zoom in those in those 3 schools,

```
ggplot() +
  geom_point(data=Top3,aes(pop,bmr), color = "Red", size=3) +
  facet_wrap(~year) +
  theme_bw() +
  labs(title="Focusing on the senior populatin of the 3 highest-bmr schools")
```



We can see that they fall around the 300-330 population range.

Conclusion

According to the graphs, we removed all the null values in both 2012 and 2013 from data of SAT School Participation and Performance informations in Connecticut state, there are around 170 schools remaining. From the graph of comparison of population and BMR, we find that students numbers in most school were less than 300, and most of them had BMR values lower than 0.5. SAT Benchmark Performance of 2013 increase a little bit than 2012, but it did not show big change overall. There are 3 schools from three districts have the highest BMR in both years, which are "Darien High School", "New canaan High School" and "Wilton High School". All three schools have student scale around 300. We concluded that in the state of Connecticut in 2012 and 2013, student scale around 300 can make best SAT Benchmark Performance.

Contributions

Alex - Created the formula for BMR, came up with the ideas on what to explain from our model, tidied the data frame, and proofread the project for any errors.

Michael - Created the models, analyzed each model, and made the plots looking pretty.

Hongyang - Wrote the Introduction, the Conlcusion, and added the graphs for the schools with the highest bmr.