R Notebook

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 is calculated as such:

bmr = number of meeting Benchmark / number of total seniors

= (t_takes*perc_mb) / (t_takes/part_rate)

= pec_mb*part_rate

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.

Questions and Findings

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

```
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()
## )
```

```
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)
```

```r
#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)
```

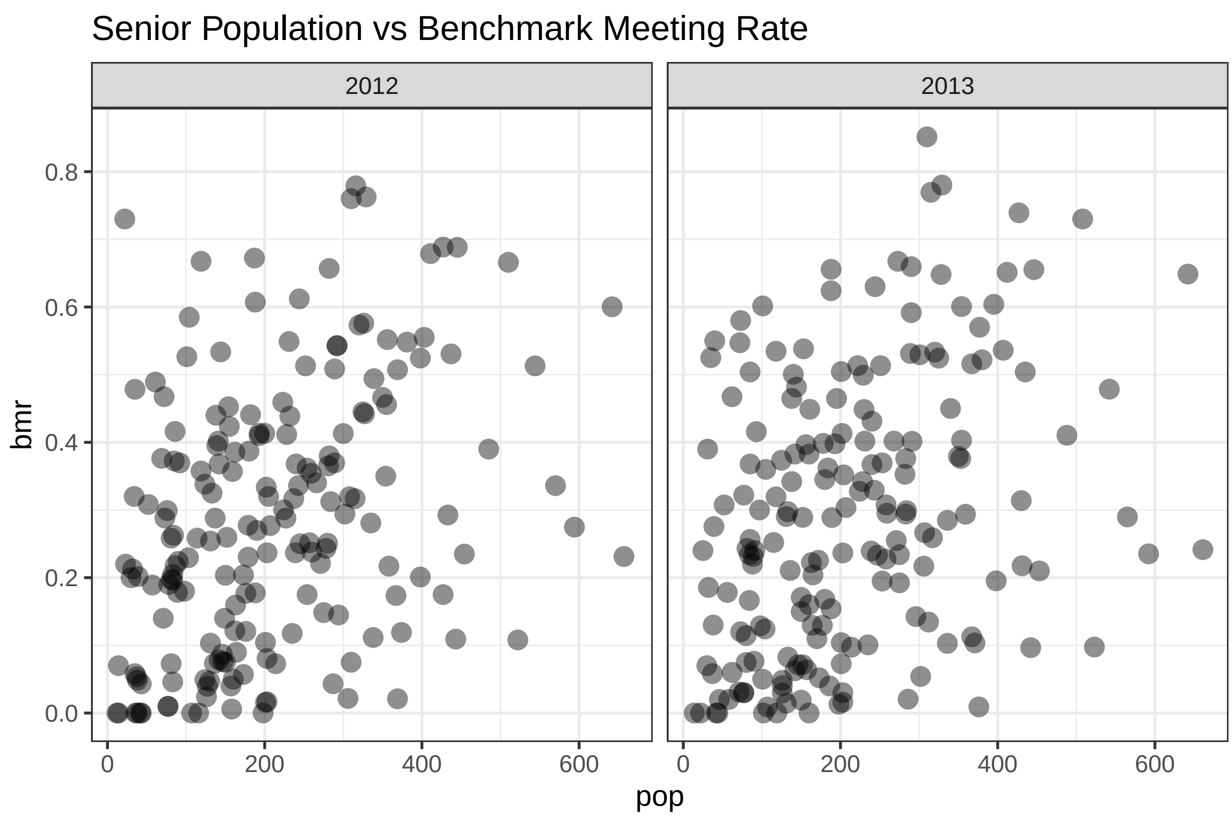
First we'll get the senior population for each school (denoted as pop)

```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
```

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

```r
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
```

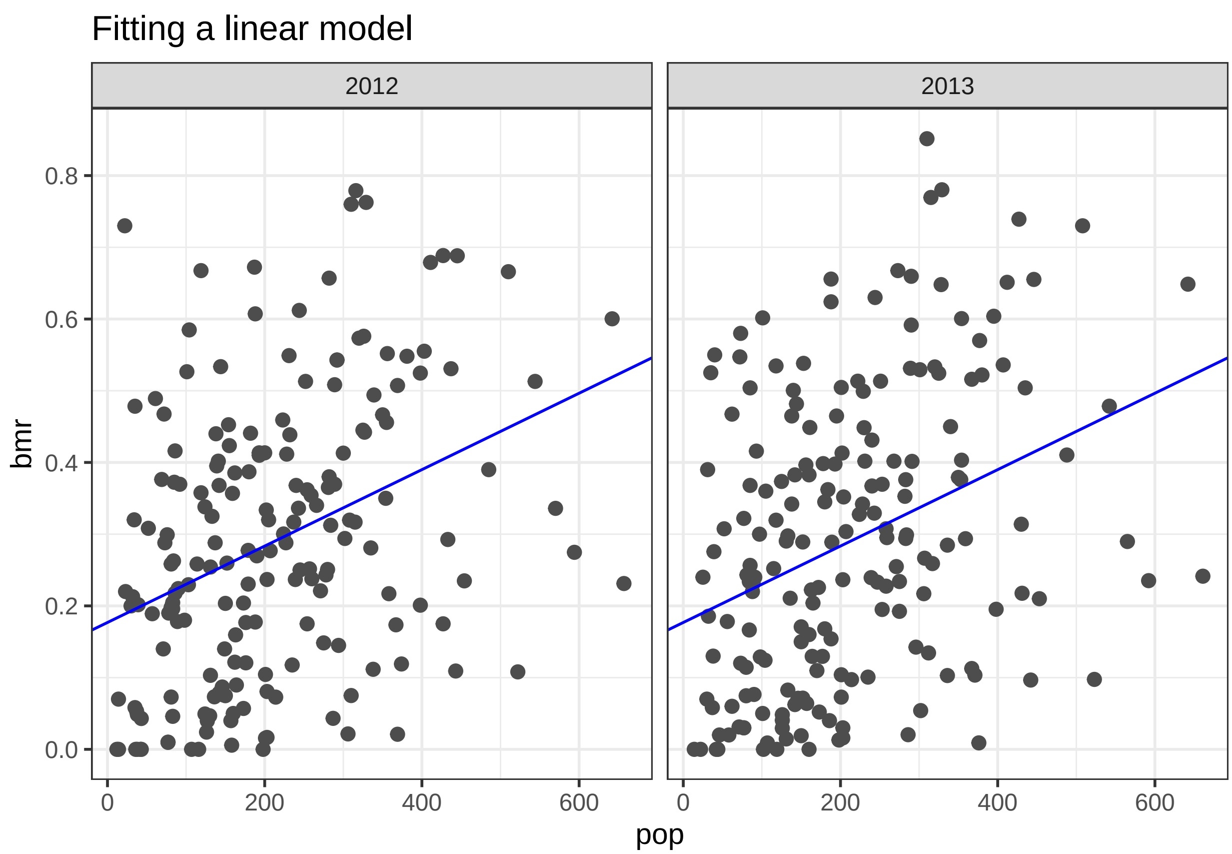


This shows the population vs bmr for each year.

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

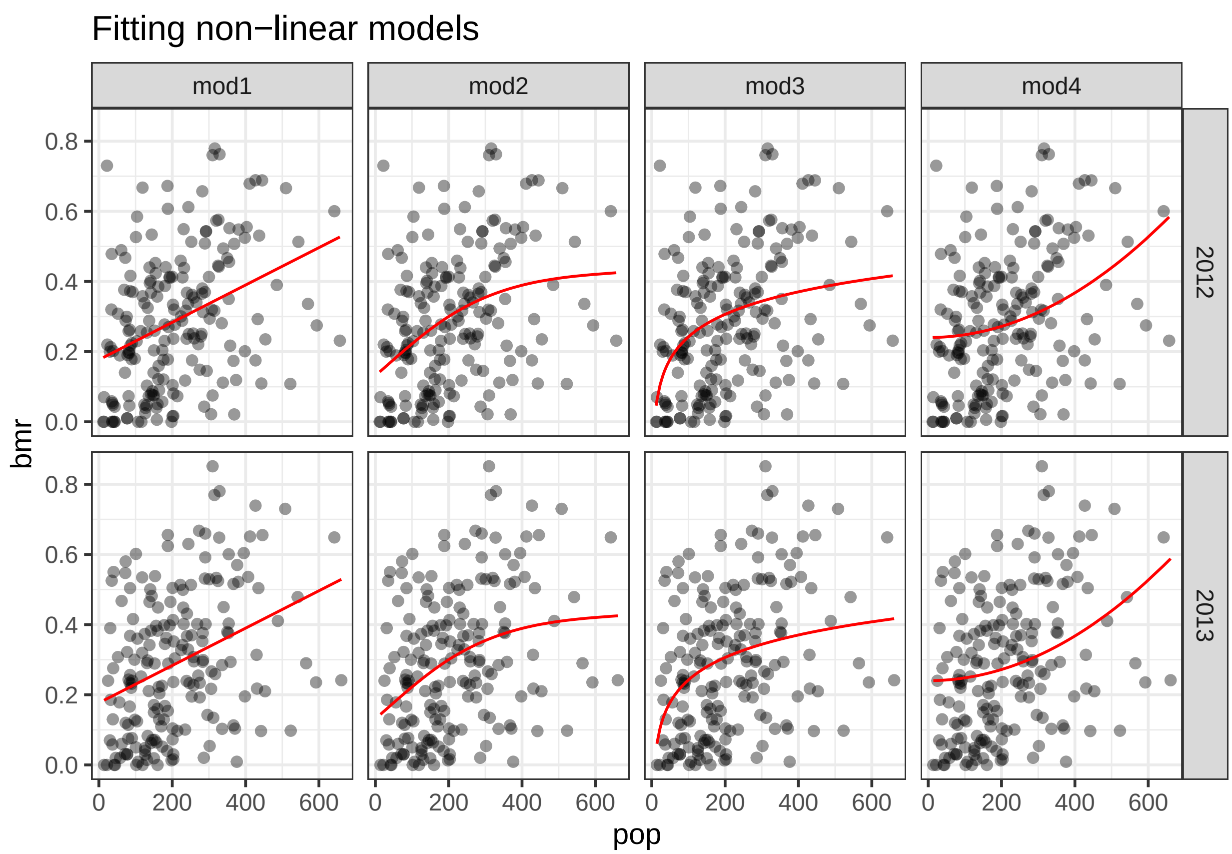
We can create a linear model using root mean squared residuals.

```
#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)
```



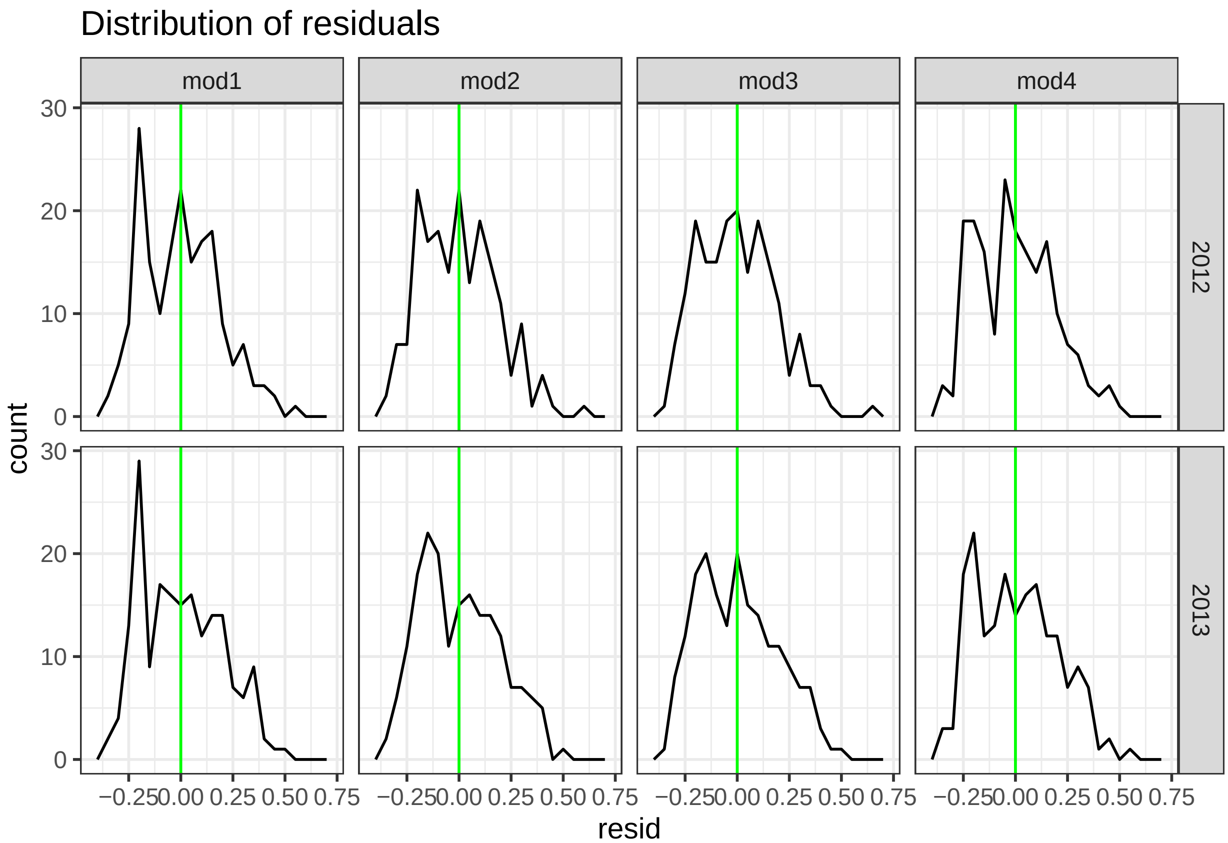
However, there's still many points in the data that are far from our linear model. Let's try out some nonlinear models to see if it can fit the data any better.

```
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")
```



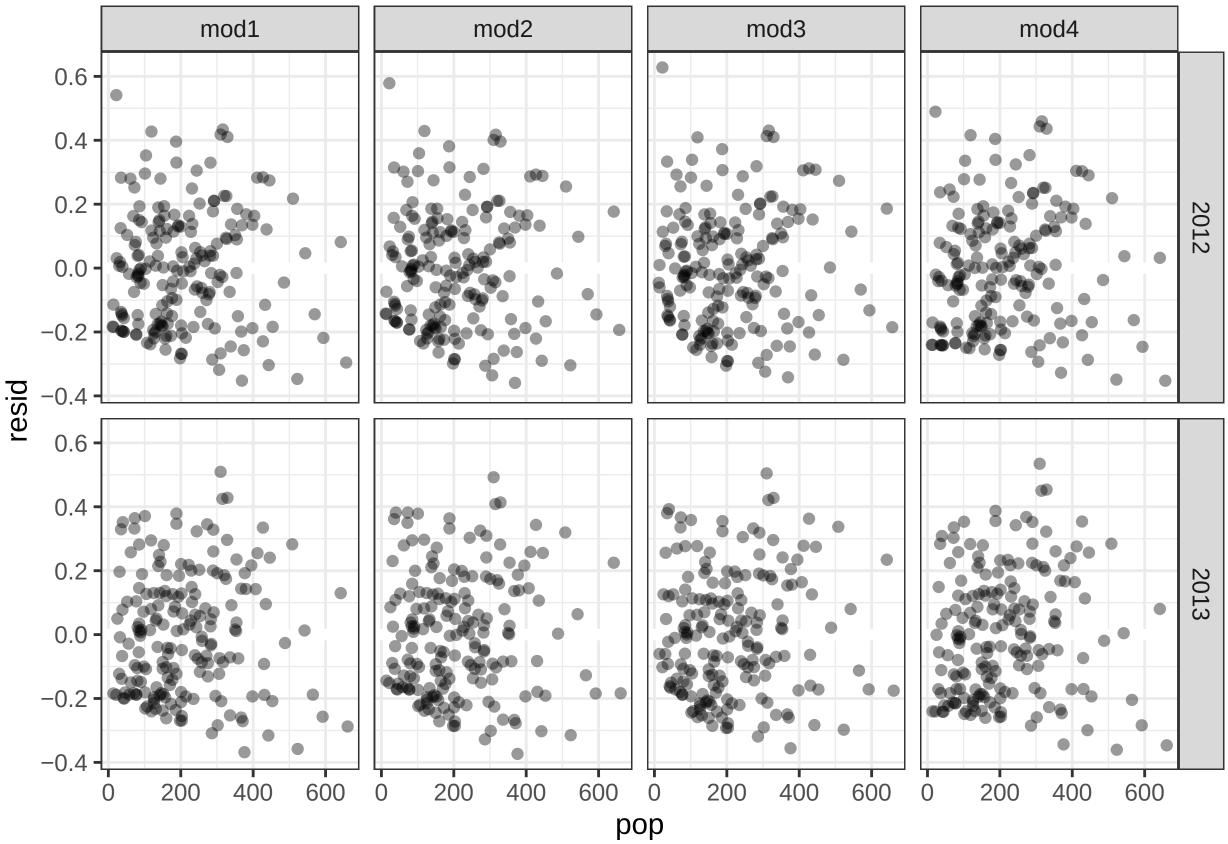
None of these models appear very satisfactory since many data points are still ommitted. But we can't conclude that a model isn't good just by appearance, we also have to examine other factors of the models to check how good it is. Let's check the residuals for any patterns.

```
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 is good.

```
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) +
  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.

```
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"
```

```
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"
```

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

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

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

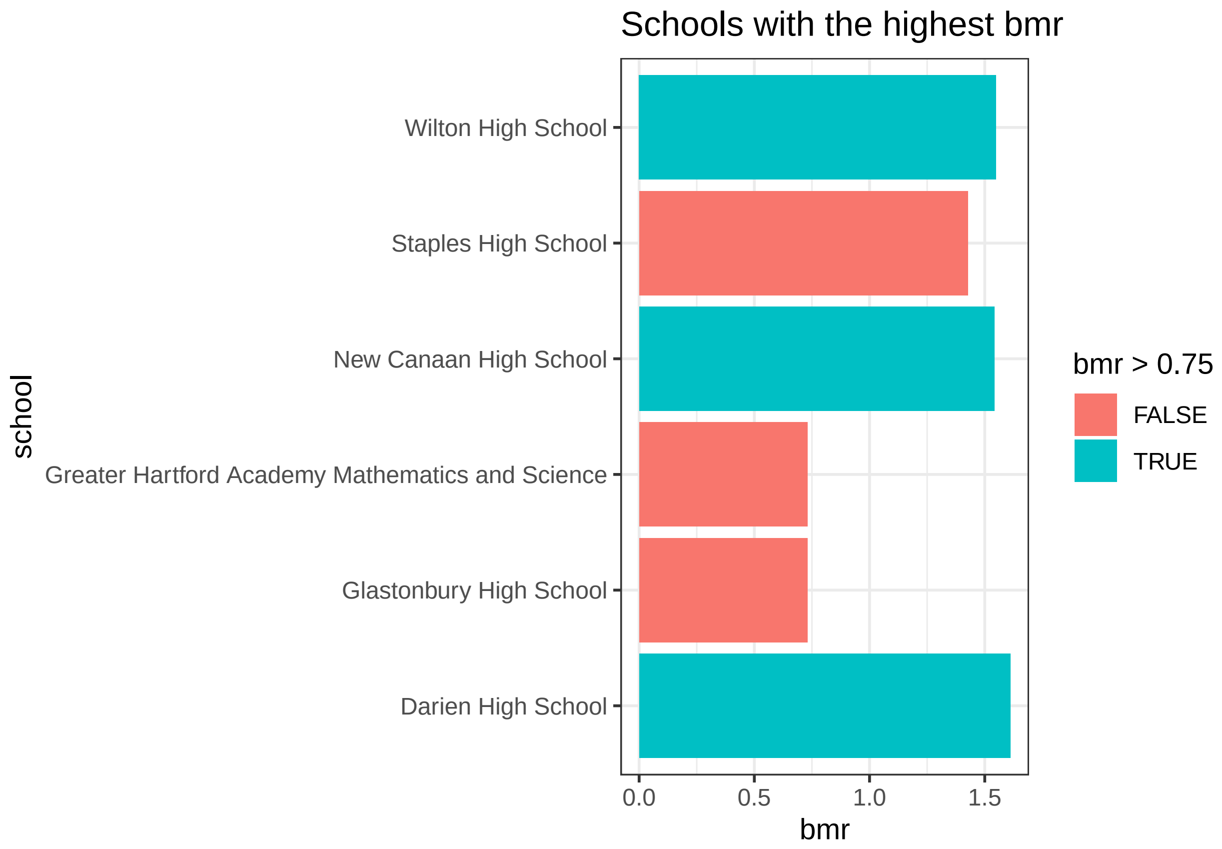
```
## [1] "r^2 of 2nd-degree polynomial model: 0.09"
```

These coefficients are pretty low overall, which isn't 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. 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?

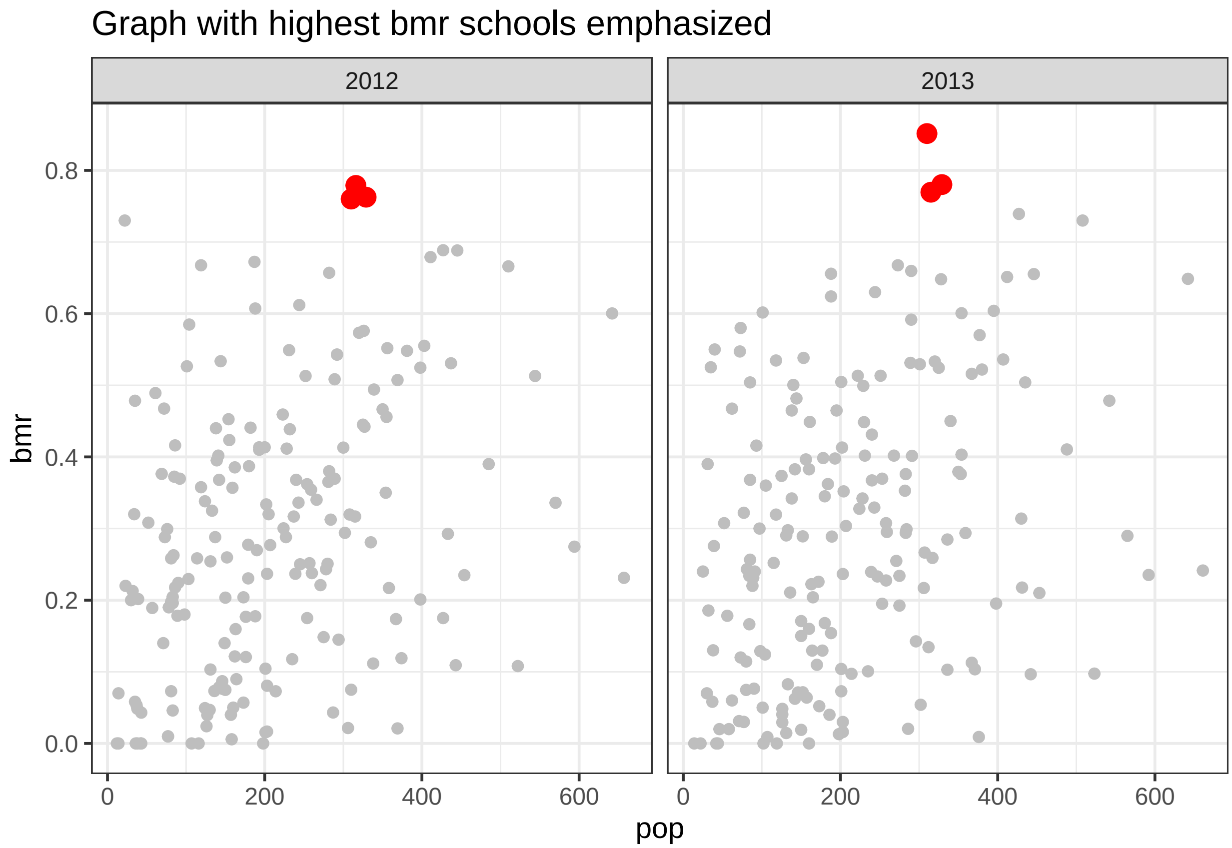
We find the schools with the highest bmr.

```
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")
```



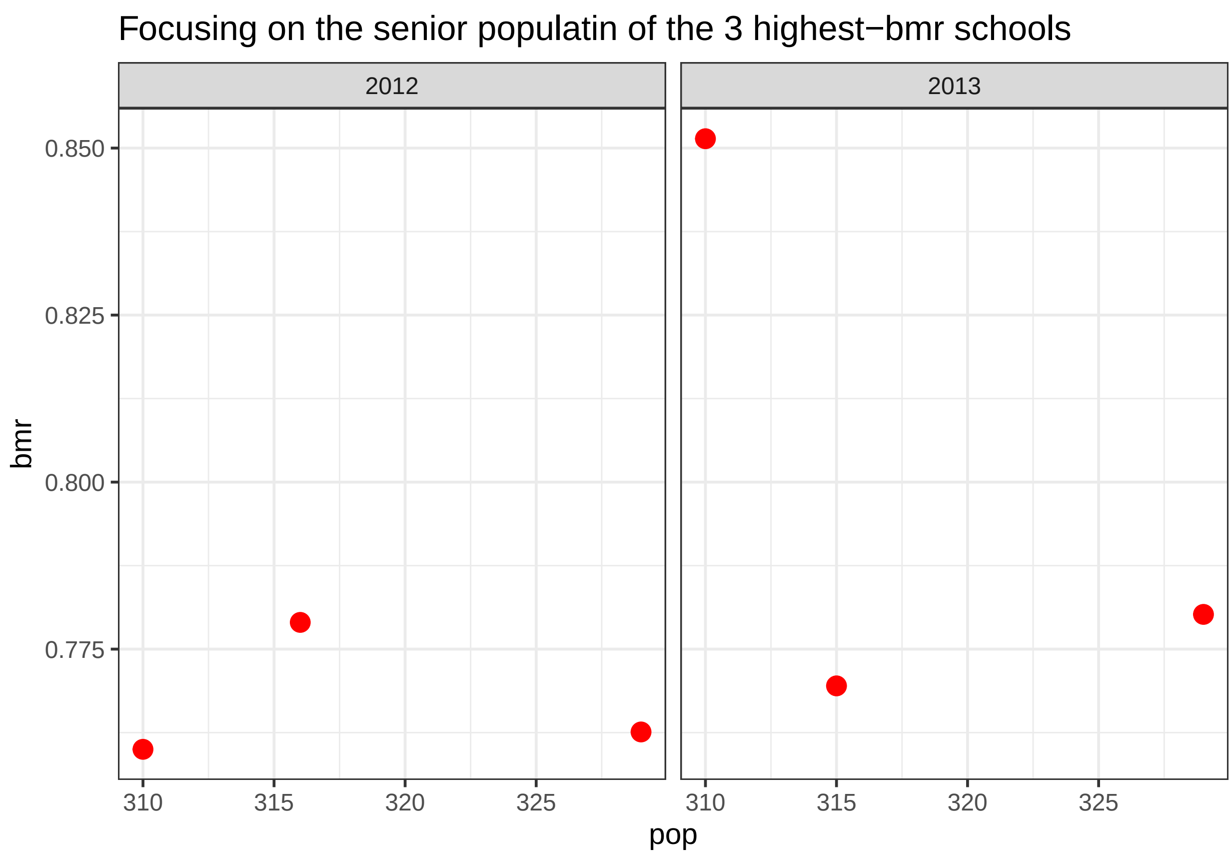
We'll focus on the top 3 schools: Darien High School, New Canaan High School, and Wilton High School.

```
Top3 <- data %>% dplyr::filter(school == "Darien High School" | school == "New Canaan High School" | scl
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 bull values in oth 2012 and 2013from data of SAT School Participation and Performance informations in Connecticut state, there are around 170 schools remaining. From the graph of compare to population and BMR, we find that students number in most school is less than 300, and most of them lower than 0.5 BMR. Population 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 is "Darien High School", "New canaan High School" and "Wilton High School". All three school have student scale around 300. We concluded that in the state of Connecticut, student scale around 300 can make best 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 look pretty.

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