

Quality of NYC Schools - Survey Analysis

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1 Introduction

This is a TLDR. Enjoy!

- Do student, teacher and parent perceptions of NYC school quality appear to be related to demographic and academic success metrics?
- Do students, teachers, and parents have similar perceptions of NYC school quality?

2 Data Cleansing

2.1 Initial Remarks on Raw Data

In `data\raw-data` 5 files are available: **combined.csv**, **masterfile11_gened_final.txt**, **masterfile11_gened_final.xlsx**, **masterfile11_d75_final.txt** and **masterfile11_d75_final.xlsx**.

These files have been downloaded from the following links:

- <https://data.cityofnewyork.us/Education/2011-NYC-School-Survey/mnz3-dyi8> [last visited July 7th, 2022]
- <https://data.world/dataquest/nyc-schools-data/workspace/file?filename=combined.csv> [last visited July 13th, 2022]

From the *Survey-Data-Dictionary* file in `data\metadata` we can notice that **masterfile11_gened_final** and **masterfile11_d75_final** differ by a small aspect: **gened** contains information on all community schools, while **d75** from all District 75 schools, that is schools designed to teach and help students with disabilities. As the Dictionary states, “these files display one line of information for each school, by DBN, that includes the response rate for each school, the number of surveys submitted, the size of the eligible survey population at each school, question scores, the percentage of responses selected, and the count of responses selected”.

Both files come with two different formats: *.txt* and *.xlsx*. I decide to work working with *.txt*, because the Excel version requires paid software to be visualized (i.e. Microsoft Excel). Having a look at the *.txt* datasets, we can notice that they are actually saved as tsv (tab separated value) files.

The **combined** dataset has been pre-cleaned as an exercise and contains combined information on different NYC schools based on SAT, AP scores and geographical data.

2.2 Dataset Loading and Preview

Importing the **readr** package under **tidyverse**, I will save the datasets as **combined**, **general** and **district**, respectively for **combined.csv**, **masterfile11_gened_final.txt** and **masterfile11_d75_final.txt**.

```
dim(combined)
```

```
## [1] 479 30
```

```
dim(general)
```

```
## [1] 1646 1942
```

```
dim(district)
```

```
## [1] 56 1773
```

Looking at the Survey Dictionary we can notice that the first columns indicate some characteristics of the school (we'll get into that later). After that, there are some columns that contain aggregate data on the survey. We can identify three groups that responded to the survey:

- Students, encoded by **s**
- Teachers, encoded by **t**
- Parents, encoded by **p**

They were asked questions on 4 main categories:

- Safety and Respect, encoded by **saf**
- Communication, encoded by **com**
- Engagement, encoded by **eng**
- Academic expectations, encoded by **aca**

In addition those columns contain at the end a number: 11. We need to be aware of the fact that in the dictionary, that number is 10; so it might represent the year.

EXAMPLE: **eng_p_11** indicates the engagement score collected in 2011 based on the parent responses.

After the above described columns, we have thousands of columns on the precise survey question and answers.

As far as **combined** goes, we mainly have data on SAT scores with some other info on the different groups of people attending the school, the school's position, the class size, etc. Overall, all these pieces of information might come useful, so I decide to perform no cleaning.

2.3 Raw Data Cleaning

Since we don't really care about the specific survey responses that are present in pretty much all columns but the initial ones, I can say that we can exclude them. Moreover, since it would be great to match performance and perception of school quality to the SAT scores, we can exclude Elementary and Middle Schools from the dataset.

```
unique(general$schooltype)
```

```
## [1] "Elementary School"      "Elementary / Middle School"  
## [3] "Middle / High School"   "Middle School"  
## [5] "High School"           "Elementary / Middle / High School"  
## [7] "Early Childhood School" "YABC"
```

We are going to keep only "High School" rows.

In the d75 dataset the **schooltype** column has a unique value:

```
unique(district$schooltype)
```

```
## [1] "District 75 Special Education"
```

This value might refer to either elementary school or high school. In this case the `studentsurveyed` column can help us, because, as written in the dictionary, “This field indicates whether or not this school serves any students in grades 6-12”. The values that the column takes are the following:

```
unique(district$studentssurveyed)
```

```
## [1] "Yes" "No"
```

Therefore by keeping only the columns with value “Yes” we will only have high schools, which are what we are interested in.

You can find the code of the “reductions” in `src/00-data-processing.r` under the CLEANING comment.

```
dim(combined_reduced)
```

```
## [1] 479 27
```

```
dim(general_reduced)
```

```
## [1] 383 23
```

```
dim(district_reduced)
```

```
## [1] 55 23
```

Now we are dealing with a feasible number of variables and they are closer to what we really need. We can combine the data of the survey in a new dataframe, called `survey`.

```
glimpse(survey)
```

```
## Rows: 438
## Columns: 23
## $ dbn      <chr> "01M448", "01M458", "01M509", "01M515", "01M650", "01~
## $ bn       <chr> "M448", "M458", "M509", "M515", "M650", "M696", "M047~
## $ schoolname <chr> "University Neighborhood High School", "Forsyth Satel~
## $ d75      <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ studentssurveyed <chr> "Yes", "Yes", "Yes", "Yes", "Yes", "Yes", "Yes", "Yes~
## $ highschool <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
## $ schooltype <chr> "High School", "High School", "High School", "High Sc~
## $ saf_p_11  <dbl> 7.9, 8.1, 7.7, 8.3, 9.0, 8.8, 8.9, 7.6, 8.7, 8.0, 7.5~
## $ com_p_11  <dbl> 7.4, 7.0, 7.4, 7.2, 8.4, 8.2, 7.7, 7.0, 8.1, 7.3, 7.1~
## $ eng_p_11  <dbl> 7.2, 6.7, 7.2, 7.4, 8.1, 8.3, 7.9, 6.9, 7.9, 7.1, 6.9~
## $ aca_p_11  <dbl> 7.3, 7.6, 7.3, 7.5, 8.6, 9.1, 8.1, 7.6, 8.3, 7.5, 7.5~
## $ saf_t_11  <dbl> 6.6, 8.5, 6.4, 9.1, 7.6, 8.2, 8.1, 7.3, 8.0, 8.6, 6.6~
## $ com_t_11  <dbl> 5.8, 8.2, 5.3, 7.3, 7.5, 7.4, 6.1, 7.1, 7.7, 8.1, 6.3~
```

```
## $ eng_t_11      <dbl> 6.6, 8.9, 6.1, 8.7, 8.3, 7.5, 7.7, 7.8, 7.9, 8.7, 6.8~
## $ aca_t_11      <dbl> 7.3, 8.9, 6.8, 9.1, 8.7, 8.3, 7.2, 7.7, 8.9, 8.9, 7.1~
## $ saf_s_11      <dbl> 6.0, 6.8, 6.4, 8.0, 8.1, 8.3, 7.3, 6.2, 7.4, 7.1, 6.6~
## $ com_s_11      <dbl> 5.7, 6.1, 5.9, 6.3, 6.9, 7.3, 6.3, 5.7, 6.5, 6.5, 6.2~
## $ eng_s_11      <dbl> 6.3, 6.1, 6.4, 7.0, 7.9, 8.0, 7.0, 6.1, 7.3, 7.0, 6.7~
## $ aca_s_11      <dbl> 7.0, 6.8, 7.0, 7.3, 8.4, 8.9, 7.5, 7.2, 7.6, 7.4, 7.5~
## $ saf_tot_11    <dbl> 6.8, 7.8, 6.9, 8.5, 8.3, 8.5, 8.1, 7.0, 7.9, 7.9, 6.9~
## $ com_tot_11    <dbl> 6.3, 7.1, 6.2, 7.0, 7.6, 7.6, 6.7, 6.6, 7.3, 7.3, 6.6~
## $ eng_tot_11    <dbl> 6.7, 7.2, 6.6, 7.7, 8.1, 8.0, 7.5, 6.9, 7.7, 7.6, 6.8~
## $ aca_tot_11    <dbl> 7.2, 7.8, 7.0, 8.0, 8.6, 8.7, 7.6, 7.5, 8.2, 8.0, 7.4~
```

2.4 NA Values Inspection

To better clean the data we can have a look at columns with NA values.

```
colSums(is.na(combined_reduced))
```

```
##                dbn                school_name
##                0                0
##      num.of.sat.test.takers      avg_sat_score
##                57                57
##      ap.test.takers      total.exams.taken
##                0                247
## number.of.exams.with.scores.3.4.or.5      exams_per_student
##                328                247
##      high_score_percent      avg_class_size
##                328                44
##      frl_percent      total_enrollment
##                41                41
##      ell_percent      sped_percent
##                41                41
##      selfcontained_num      asian_per
##                51                41
##      black_per      hispanic_per
##                41                41
##      white_per      male_per
##                41                41
##      female_per      total.cohort
##                41                89
##      grads_percent      dropout_percent
##                111                111
##      boro      lat
##                109                109
##      long
##                109
```

```
colSums(is.na(survey))
```

```
##      dbn      bn      schoolname      d75
##      0      0      0      0
## studentssurveyed      highschool      schooltype      saf_p_11
##      0      424      0      0
```

```
##      com_p_11      eng_p_11      aca_p_11      saf_t_11
##          0          0          0          0
##      com_t_11      eng_t_11      aca_t_11      saf_s_11
##          0          0          0          3
##      com_s_11      eng_s_11      aca_s_11      saf_tot_11
##          3          3          3          0
##      com_tot_11      eng_tot_11      aca_tot_11
##          0          0          0
```

The first thing that we can notice is that the `highschool` column in the survey dataframe has 424 NA values, out of 438 observations. This means that that column is pretty much unusable, so we will delete it.

In addition, `combined_reduced` has `number.of.exams.with.scores.3.4.or.5` and `high_score_percent` with 328 NA values, which is more than half of the rows in the dataset. So, it is safe to say that those columns are useless and we will delete them.

The final dimensions of the cleaned datasets are the following:

```
dim(combined_reduced_2)
```

```
## [1] 479 26
```

```
dim(survey_2)
```

```
## [1] 438 22
```

2.5 Joining the Datasets

Now that the necessary cleaning has been done, we can finally join `survey` and `combined_reduced` into one dataset, that we are going to be using for the analysis.

We are going to apply a `left_join` to `combined_reduced` so that we will have all values for schools of which we have SAT data. We will save it as `school_data_raw`. These are the initial dimensions:

```
dim(school_data_raw)
```

```
## [1] 479 47
```

We can eliminate some redundant columns, such as `bn` and `schoolname`. In addition, we now know that we are dealing with high schools, so we can drop `schooltype` and `studentssurveyed`.

We can also notice that there is a duplicated value in the schools

```
sum(duplicated(school_data_raw$dbn))
```

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

So we will remove that duplicate as well.

2.6 Final Dataset

Therefore our final cleaned dataset, named `school_data` is the following:

```
glimpse(school_data)
```

```
## Rows: 478
## Columns: 44
## $ X                <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, ~
## $ dbn              <chr> "01M292", "01M448", "01M450", "01M458", "01M509~
## $ school_name      <chr> "HENRY STREET SCHOOL FOR INTERNATIONAL STUDIES"~
## $ num.of.sat.test.takers <int> 29, 91, 70, 7, 44, 112, 159, 18, 130, 16, 62, 5~
## $ avg_sat_score     <int> 1122, 1172, 1149, 1174, 1207, 1205, 1621, 1246, ~
## $ ap.test.takers    <dbl> 2.5, 39.0, 19.0, 2.5, 2.5, 24.0, 255.0, 2.5, 2.~
## $ total.exams.taken <int> NA, 49, 21, NA, NA, 26, 377, NA, NA, NA, NA, NA~
## $ exams_per_student <dbl> NA, 1.256410, 1.105263, NA, NA, 1.083333, 1.478~
## $ high_score_percent <dbl> NA, 20.408163, NA, NA, NA, 92.307692, 50.663130~
## $ avg_class_size    <int> 23, 22, 21, 23, 24, 23, 26, 22, 21, 16, 23, 15, ~
## $ frl_percent       <dbl> 88.6, 71.8, 71.8, 72.8, 80.7, NA, 23.0, 69.8, 1~
## $ total_enrollment <int> 422, 394, 598, 224, 367, NA, 1613, 218, 617, 17~
## $ ell_percent       <dbl> 22.3, 21.1, 5.0, 4.0, 11.2, NA, 0.2, 3.2, 0.2, ~
## $ sped_percent      <dbl> 24.9, 21.8, 26.4, 8.9, 25.9, NA, 2.7, 6.9, 0.8, ~
## $ selfcontained_num <int> 35, 10, 19, 0, 36, NA, 0, 0, 0, 10, 4, 2, 17, 3~
## $ asian_per         <dbl> 14.0, 29.2, 9.7, 2.2, 9.3, NA, 27.8, 0.5, 15.1, ~
## $ black_per         <dbl> 29.1, 22.6, 23.9, 34.4, 31.6, NA, 11.7, 45.4, 1~
## $ hispanic_per      <dbl> 53.8, 45.9, 55.4, 59.4, 56.9, NA, 14.2, 49.5, 1~
## $ white_per         <dbl> 1.7, 2.3, 10.4, 3.6, 1.6, NA, 44.9, 4.1, 49.8, ~
## $ male_per          <dbl> 61.4, 57.4, 54.7, 43.3, 46.3, NA, 49.2, 39.9, 3~
## $ female_per        <dbl> 38.6, 42.6, 45.3, 56.7, 53.7, NA, 50.8, 60.1, 6~
## $ total_cohort      <int> 78, 124, 90, NA, 84, 193, 46, 89, 139, 25, 102, ~
## $ grads_percent     <dbl> 55.1, 42.7, 77.8, NA, 56.0, 54.4, 100.0, 55.1, ~
## $ dropout_percent   <dbl> 14.1, 16.1, 5.6, NA, 6.0, 18.1, 0.0, 6.7, 0.7, ~
## $ boro              <chr> "Manhattan", "Manhattan", "Manhattan", NA, "Man~
## $ lat               <dbl> 40.71376, 40.71233, 40.72978, NA, 40.72057, NA, ~
## $ long              <dbl> -73.98526, -73.98480, -73.98304, NA, -73.98567, ~
## $ d75               <int> NA, 0, NA, 0, 0, 0, NA, 0, 0, 0, 0, 0, 0, 0, ~
## $ saf_p_11          <dbl> NA, 7.9, NA, 8.1, 7.7, 8.3, NA, 9.0, 8.8, 8.9, ~
## $ com_p_11          <dbl> NA, 7.4, NA, 7.0, 7.4, 7.2, NA, 8.4, 8.2, 7.7, ~
## $ eng_p_11          <dbl> NA, 7.2, NA, 6.7, 7.2, 7.4, NA, 8.1, 8.3, 7.9, ~
## $ aca_p_11          <dbl> NA, 7.3, NA, 7.6, 7.3, 7.5, NA, 8.6, 9.1, 8.1, ~
## $ saf_t_11          <dbl> NA, 6.6, NA, 8.5, 6.4, 9.1, NA, 7.6, 8.2, 8.1, ~
## $ com_t_11          <dbl> NA, 5.8, NA, 8.2, 5.3, 7.3, NA, 7.5, 7.4, 6.1, ~
## $ eng_t_11          <dbl> NA, 6.6, NA, 8.9, 6.1, 8.7, NA, 8.3, 7.5, 7.7, ~
## $ aca_t_11          <dbl> NA, 7.3, NA, 8.9, 6.8, 9.1, NA, 8.7, 8.3, 7.2, ~
## $ saf_s_11          <dbl> NA, 6.0, NA, 6.8, 6.4, 8.0, NA, 8.1, 8.3, 7.3, ~
## $ com_s_11          <dbl> NA, 5.7, NA, 6.1, 5.9, 6.3, NA, 6.9, 7.3, 6.3, ~
## $ eng_s_11          <dbl> NA, 6.3, NA, 6.1, 6.4, 7.0, NA, 7.9, 8.0, 7.0, ~
## $ aca_s_11          <dbl> NA, 7.0, NA, 6.8, 7.0, 7.3, NA, 8.4, 8.9, 7.5, ~
## $ saf_tot_11        <dbl> NA, 6.8, NA, 7.8, 6.9, 8.5, NA, 8.3, 8.5, 8.1, ~
## $ com_tot_11        <dbl> NA, 6.3, NA, 7.1, 6.2, 7.0, NA, 7.6, 7.6, 6.7, ~
## $ eng_tot_11        <dbl> NA, 6.7, NA, 7.2, 6.6, 7.7, NA, 8.1, 8.0, 7.5, ~
## $ aca_tot_11        <dbl> NA, 7.2, NA, 7.8, 7.0, 8.0, NA, 8.6, 8.7, 7.6, ~
```

You can find the cleaned dataset in `data/clean-data/school-data.csv`.

3 Data Analysis

I will divide this section in two parts: one for each question we have to address.

1. Do student, teacher and parent perceptions of NYC school quality appear to be related to demographic and academic success metrics?
2. Do students, teachers, and parents have similar perceptions of NYC school quality?

3.1 Question 1

For demographics metrics, in the dataset we have observations on the latitude, longitude and borough and race (*btw, this is an American thing... that's really racist. No wonder America is one of the most racist countries in the world!*). For our purposes the borough is enough, as the latitude and longitude provide overly detailed information on the position of the school. Here is some information.

##	Area	Median Household Income (USD)	Mean Household Income (USD)
## 1	Bronx	34156	46
## 2	Brooklyn	41406	298
## 3	Manhattan	64217	46
## 4	Queens	53171	298
## 5	Staten Islands	66985	121
##	Percentage in Poverty (%)		
## 1		27.1	
## 2		21.9	
## 3		17.6	
## 4		12.0	
## 5		9.8	

For academic metrics, in the dataset we have many data points on SAT results and class information. To properly address the question, we will consider as a metric the average SAT score. I also decide to keep other details like:

- **frl_percent**: percentage of a school's students eligible for receiving school lunch at a discount based on household income
- **ell_percent**: percentage of a school's students who are learning to speak English
- **sped_percent**: percentage of a school's students who receive specialized instruction to accommodate special needs such as learning or physical disabilities

They could provide more insights.

I decide to remove some other columns that might be useless (see code for more info).

I will also create new columns:

- **avg_p**, **avg_t** and **avg_s** to indicate the average score on the different questions type that each group answered to
- **avg_saf**, **avg_com**, **avg_eng** and **avg_aca** to indicate the average score on the average satisfaction on the different categories by all groups.

Our processed dataset for the question is now the following

```
glimpse(school_data_question)
```

```
## Rows: 478
## Columns: 35
## Rowwise:
## $ dbn      <chr> "01M292", "01M448", "01M450", "01M458", "01M509", "01M~
## $ school_name <chr> "HENRY STREET SCHOOL FOR INTERNATIONAL STUDIES", "UNIV~
## $ avg_sat_score <int> 1122, 1172, 1149, 1174, 1207, 1205, 1621, 1246, 1856, ~
## $ avg_class_size <int> 23, 22, 21, 23, 24, 23, 26, 22, 21, 16, 23, 15, 23, 21~
## $ frl_percent <dbl> 88.6, 71.8, 71.8, 72.8, 80.7, NA, 23.0, 69.8, 18.0, 66~
## $ ell_percent <dbl> 22.3, 21.1, 5.0, 4.0, 11.2, NA, 0.2, 3.2, 0.2, 8.0, 2.~
## $ sped_percent <dbl> 24.9, 21.8, 26.4, 8.9, 25.9, NA, 2.7, 6.9, 0.8, 32.2, ~
## $ asian_per <dbl> 14.0, 29.2, 9.7, 2.2, 9.3, NA, 27.8, 0.5, 15.1, 1.7, 3~
## $ black_per <dbl> 29.1, 22.6, 23.9, 34.4, 31.6, NA, 11.7, 45.4, 15.1, 32~
## $ hispanic_per <dbl> 53.8, 45.9, 55.4, 59.4, 56.9, NA, 14.2, 49.5, 18.2, 59~
## $ white_per <dbl> 1.7, 2.3, 10.4, 3.6, 1.6, NA, 44.9, 4.1, 49.8, 6.3, 4.~
## $ male_per <dbl> 61.4, 57.4, 54.7, 43.3, 46.3, NA, 49.2, 39.9, 31.3, 42~
## $ female_per <dbl> 38.6, 42.6, 45.3, 56.7, 53.7, NA, 50.8, 60.1, 68.7, 57~
## $ grads_percent <dbl> 55.1, 42.7, 77.8, NA, 56.0, 54.4, 100.0, 55.1, 96.4, 7~
## $ dropout_percent <dbl> 14.1, 16.1, 5.6, NA, 6.0, 18.1, 0.0, 6.7, 0.7, 4.0, 2.~
## $ boro      <chr> "Manhattan", "Manhattan", "Manhattan", NA, "Manhattan"~
## $ saf_p_11 <dbl> NA, 7.9, NA, 8.1, 7.7, 8.3, NA, 9.0, 8.8, 8.9, 7.6, 8.~
## $ com_p_11 <dbl> NA, 7.4, NA, 7.0, 7.4, 7.2, NA, 8.4, 8.2, 7.7, 7.0, 8.~
## $ eng_p_11 <dbl> NA, 7.2, NA, 6.7, 7.2, 7.4, NA, 8.1, 8.3, 7.9, 6.9, 7.~
## $ aca_p_11 <dbl> NA, 7.3, NA, 7.6, 7.3, 7.5, NA, 8.6, 9.1, 8.1, 7.6, 8.~
## $ saf_t_11 <dbl> NA, 6.6, NA, 8.5, 6.4, 9.1, NA, 7.6, 8.2, 8.1, 7.3, 8.~
## $ com_t_11 <dbl> NA, 5.8, NA, 8.2, 5.3, 7.3, NA, 7.5, 7.4, 6.1, 7.1, 7.~
## $ eng_t_11 <dbl> NA, 6.6, NA, 8.9, 6.1, 8.7, NA, 8.3, 7.5, 7.7, 7.8, 7.~
## $ aca_t_11 <dbl> NA, 7.3, NA, 8.9, 6.8, 9.1, NA, 8.7, 8.3, 7.2, 7.7, 8.~
## $ saf_s_11 <dbl> NA, 6.0, NA, 6.8, 6.4, 8.0, NA, 8.1, 8.3, 7.3, 6.2, 7.~
## $ com_s_11 <dbl> NA, 5.7, NA, 6.1, 5.9, 6.3, NA, 6.9, 7.3, 6.3, 5.7, 6.~
## $ eng_s_11 <dbl> NA, 6.3, NA, 6.1, 6.4, 7.0, NA, 7.9, 8.0, 7.0, 6.1, 7.~
## $ aca_s_11 <dbl> NA, 7.0, NA, 6.8, 7.0, 7.3, NA, 8.4, 8.9, 7.5, 7.2, 7.~
## $ avg_p <dbl> NA, 7.35, NA, 7.30, 7.35, 7.45, NA, 8.50, 8.55, 8.00, ~
## $ avg_t <dbl> NA, 6.60, NA, 8.70, 6.25, 8.90, NA, 7.95, 7.85, 7.45, ~
## $ avg_s <dbl> NA, 6.15, NA, 6.45, 6.40, 7.15, NA, 8.00, 8.15, 7.15, ~
## $ avg_saf <dbl> NA, 6.6, NA, 8.1, 6.4, 8.3, NA, 8.1, 8.3, 8.1, 7.3, 8.~
## $ avg_com <dbl> NA, 5.8, NA, 7.0, 5.9, 7.2, NA, 7.5, 7.4, 6.3, 7.0, 7.~
## $ avg_eng <dbl> NA, 6.6, NA, 6.7, 6.4, 7.4, NA, 8.1, 8.0, 7.7, 6.9, 7.~
## $ avg_aca <dbl> NA, 7.3, NA, 7.6, 7.0, 7.5, NA, 8.6, 8.9, 7.5, 7.6, 8.~
```

From here we proceed constructing the correlation matrix keeping only values with correlation $|r| \geq 0.2$.

```
cor_df
```

```
## # A tibble: 16 x 2
##   variable      avg_sat_score
##   <chr>          <dbl>
## 1 avg_sat_score      1
## 2 avg_class_size    0.395
## 3 frl_percent     -0.724
## 4 ell_percent     -0.392
```

```
## 5 sped_percent      -0.438
## 6 asian_per         0.567
## 7 black_per         -0.308
## 8 hispanic_per      -0.372
## 9 white_per         0.651
## 10 grads_percent    0.546
## 11 dropout_percent  -0.481
## 12 saf_t_11         0.309
## 13 saf_s_11         0.277
## 14 aca_s_11         0.293
## 15 avg_s            0.237
## 16 avg_saf          0.301
```

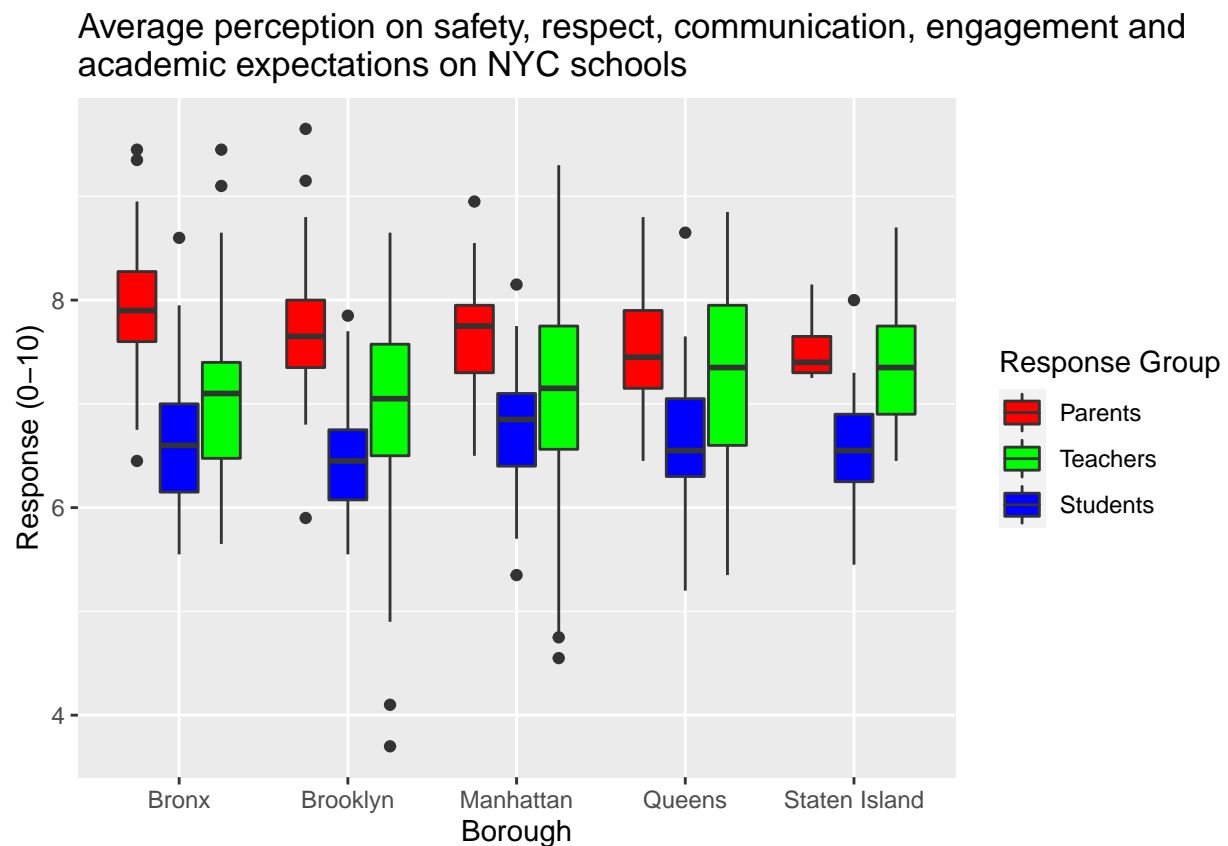
3.2 Question 2

Still using the previous dataset, we can plot some graphs to easily address this question.

NOTE You can visualize the graph also in the `output-graphics` folder.

This is the first graph:

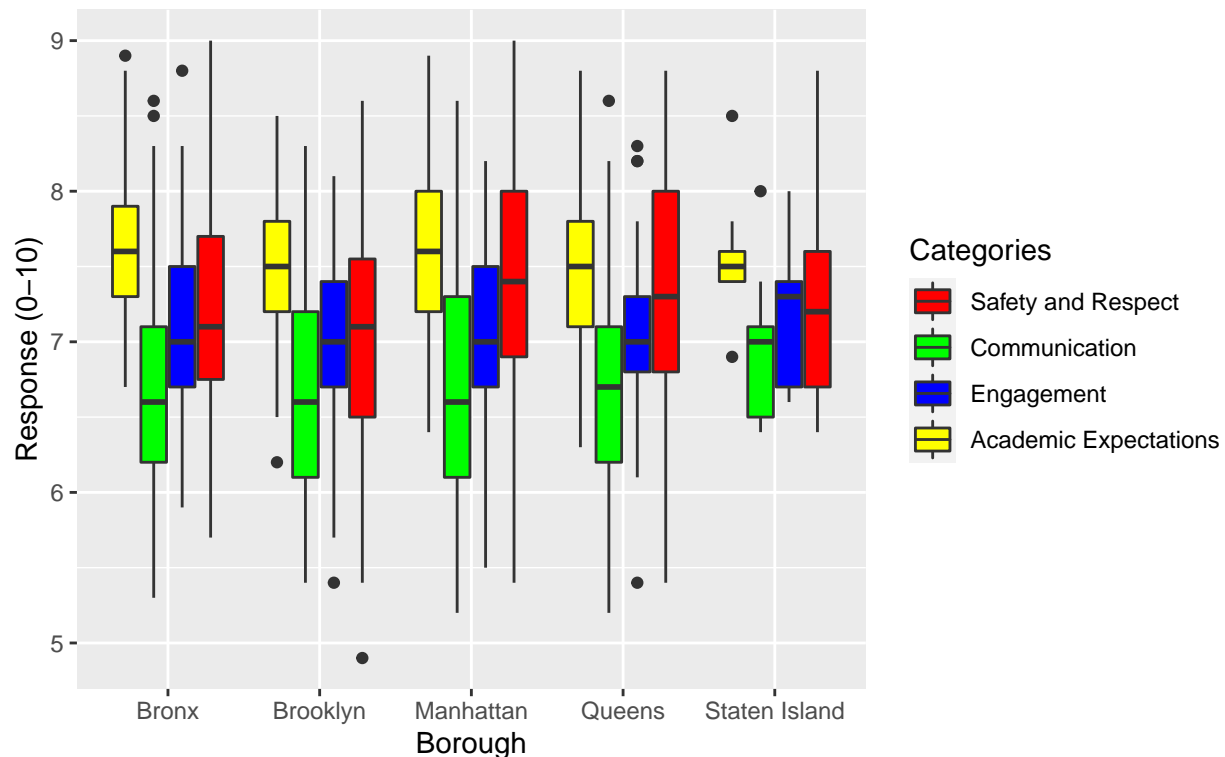
```
## Warning: Removed 238 rows containing non-finite values (stat_boxplot).
```



While this is the second graph:

```
## Warning: Removed 320 rows containing non-finite values (stat_boxplot).
```

Average perception by parents, teachers and students on different aspects of NYC schools



4 Findings

4.1 Question 1

4.2 Question 2

The answer to the question seems easy: no.

From Graph 1 we can notice that on average the perception on parent in all boroughs is higher than that of students and teachers. In addition there seems to be a recurring trend: as the borough's poverty decreases, the parent's satisfaction mean decreases, the teacher's increases and that of students remains pretty much constant. Other inferences could be drawn from Graph 1, but it's summer and really hot, so sorry for the inconvenience.

As far as Graph 2 goes, we seem to have a pretty common mean for academic expectations in all boroughs. And it is the highest. The safety and respect is the most fluctuating category.

Overall, in both graphs, the Staten Island is the less distributed borough in terms of scores. Most values are concentrated around the mean. Instead, for the other boroughs we have 50% of the data between ± 0.5 .

If you've been careful enough, I have never drawn any causal connection so far. I just stated facts. It's not my job to find causal connections between human perceptions and data. Sorry.

RIVEDI FINDINGS!!!