

Analyzing NYC School Data

May 25, 2018

0.0.1 Read in the data

```
In [1]: import pandas
import numpy
import re
import random
import matplotlib.pyplot as plt
import matplotlib.colors as colors
from mpl_toolkits.basemap import Basemap
%matplotlib inline

data_files = [
    "ap_2010.csv",
    "class_size.csv",
    "demographics.csv",
    "graduation.csv",
    "hs_directory.csv",
    "sat_results.csv"
]

data = {}

for f in data_files:
    d = pandas.read_csv("databank/{0}".format(f))
    data[f.replace(".csv", "")] = d
```

0.0.2 Read in the surveys

```
In [2]: all_survey = pandas.read_csv("databank/survey_all.txt", delimiter="\t", encoding='windows-1252')
d75_survey = pandas.read_csv("databank/survey_d75.txt", delimiter="\t", encoding='windows-1252')

# Combine two data frames by rows
survey = pandas.concat([all_survey, d75_survey], axis=0)

# Change the column head to align with other data frame
survey["DBN"] = survey["dbn"]

# Identify and make a feature list of our interest
```

```

survey_fields = [
    "DBN",
    "rr_s",
    "rr_t",
    "rr_p",
    "N_s",
    "N_t",
    "N_p",
    "saf_p_11",
    "com_p_11",
    "eng_p_11",
    "aca_p_11",
    "saf_t_11",
    "com_t_11",
    "eng_t_10",
    "aca_t_11",
    "saf_s_11",
    "com_s_11",
    "eng_s_11",
    "aca_s_11",
    "saf_tot_11",
    "com_tot_11",
    "eng_tot_11",
    "aca_tot_11",
]
survey = survey.reindex(survey_fields, axis=1)
data["survey"] = survey

# Print results for verification
print(data['survey'].head(5))
data['survey'].shape

```

	DBN	rr_s	rr_t	rr_p	N_s	N_t	N_p	saf_p_11	com_p_11	eng_p_11	\
0	01M015	NaN	88	60	NaN	22.0	90.0	8.5	7.6	7.5	
1	01M019	NaN	100	60	NaN	34.0	161.0	8.4	7.6	7.6	
2	01M020	NaN	88	73	NaN	42.0	367.0	8.9	8.3	8.3	
3	01M034	89.0	73	50	145.0	29.0	151.0	8.8	8.2	8.0	
4	01M063	NaN	100	60	NaN	23.0	90.0	8.7	7.9	8.1	

	...	eng_t_10	aca_t_11	saf_s_11	com_s_11	eng_s_11	aca_s_11	\
0	...	NaN	7.9	NaN	NaN	NaN	NaN	
1	...	NaN	9.1	NaN	NaN	NaN	NaN	
2	...	NaN	7.5	NaN	NaN	NaN	NaN	
3	...	NaN	7.8	6.2	5.9	6.5	7.4	
4	...	NaN	8.1	NaN	NaN	NaN	NaN	

	saf_tot_11	com_tot_11	eng_tot_11	aca_tot_11
0	8.0	7.7	7.5	7.9

1	8.5	8.1	8.2	8.4
2	8.2	7.3	7.5	8.0
3	7.3	6.7	7.1	7.9
4	8.5	7.6	7.9	8.0

[5 rows x 23 columns]

Out[2]: (1702, 23)

0.0.3 Add DBN columns

```
In [3]: # Change the column head to align with other data frame
data["hs_directory"]["DBN"] = data["hs_directory"]["dbn"]

# Set uniform field length to develop same size DBN value in the data frame
def pad_csd(num):
    string_representation = str(num)
    if len(string_representation) > 1:
        return string_representation
    else:
        return "0" + string_representation

# Call function to set same size of DBN prefix
data["class_size"]["padded_csd"] = data["class_size"]["CSD"].apply(pad_csd)

# Generate DBN field by combining two columns
data["class_size"]["DBN"] = data["class_size"]["padded_csd"] + data["class_size"]["SCH"]

# Print results for verification
data["class_size"]["DBN"].iloc[0:5]
```

```
Out[3]: 0    01M015
1    01M015
2    01M015
3    01M015
4    01M015
Name: DBN, dtype: object
```

0.0.4 Convert columns to numeric

```
In [4]: # List of useful columns from the sat_result data frame
cols = ['SAT Math Avg. Score', 'SAT Critical Reading Avg. Score', 'SAT Writing Avg. Score']

# Convert the string data into numeric form, transform errors into null
for c in cols:
    data["sat_results"][c] = pandas.to_numeric(data["sat_results"][c], errors="coerce")

# Combining three column values into one and store it into a new column
```

```
data['sat_results']['sat_score'] = data['sat_results'][cols[0]] + data['sat_results'][cols[1]]

# Display results for verification
data['sat_results']['sat_score'].iloc[0:5]
```

```
Out[4]: 0    1122.0
        1    1172.0
        2    1149.0
        3    1174.0
        4    1207.0
        Name: sat_score, dtype: float64
```

0.0.5 Extract Latitude and Longitude from the Data

```
In [5]: # Function to extract latitude from the given string
def find_lat(loc):
    coords = re.findall("\(.+, .+\)", loc)
    lat = coords[0].split(",")[0].replace("(", "")
    return lat

# Function to extract longitude from the given string
def find_lon(loc):
    coords = re.findall("\(.+, .+\)", loc)
    lon = coords[0].split(",")[1].replace(")", "").strip()
    return lon

# Extract latitude and longitude from the column at store them in new columns
data["hs_directory"]["lat"] = data["hs_directory"]["Location 1"].apply(find_lat)
data["hs_directory"]["lon"] = data["hs_directory"]["Location 1"].apply(find_lon)

# Convert the extracted latitude and longitude into numeric form, transform errors into NaN
data["hs_directory"]["lat"] = pandas.to_numeric(data["hs_directory"]["lat"], errors="coerce")
data["hs_directory"]["lon"] = pandas.to_numeric(data["hs_directory"]["lon"], errors="coerce")

# Print results for verification
data['hs_directory'].head(5)
```

```
Out[5]:
```

	dbn	school_name	boro	\
0	17K548	Brooklyn School for Music & Theatre	Brooklyn	
1	09X543	High School for Violin and Dance	Bronx	
2	09X327	Comprehensive Model School Project M.S. 327	Bronx	
3	02M280	Manhattan Early College School for Advertising	Manhattan	
4	28Q680	Queens Gateway to Health Sciences Secondary Sc...	Queens	

	building_code	phone_number	fax_number	grade_span_min	grade_span_max	\
0	K440	718-230-6250	718-230-6262	9	12	
1	X400	718-842-0687	718-589-9849	9	12	
2	X240	718-294-8111	718-294-8109	6	12	

```

3          M520  718-935-3477          NaN          9          10
4          Q695    718-969-3155  718-969-3552          6          12

expgrade_span_min  expgrade_span_max  ...  \
0          NaN          NaN  ...
1          NaN          NaN  ...
2          NaN          NaN  ...
3          9          14.0  ...
4          NaN          NaN  ...

          priority05  priority06  priority07  priority08  \
0          NaN          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN
2  Then to New York City residents          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN

priority09  priority10          Location 1  \
0          NaN          NaN  883 Classon Avenue\nBrooklyn, NY 11225\n(40.67...
1          NaN          NaN  1110 Boston Road\nBronx, NY 10456\n(40.8276026...
2          NaN          NaN  1501 Jerome Avenue\nBronx, NY 10452\n(40.84241...
3          NaN          NaN  411 Pearl Street\nNew York, NY 10038\n(40.7106...
4          NaN          NaN  160-20 Goethals Avenue\nJamaica, NY 11432\n(40...

      DBN      lat      lon
0  17K548  40.670299 -73.961648
1  09X543  40.827603 -73.904475
2  09X327  40.842414 -73.916162
3  02M280  40.710679 -74.000807
4  28Q680  40.718810 -73.806500

[5 rows x 61 columns]

```

0.0.6 Condense Datasets

Data frame 'class_size'

```

In [6]: class_size = data["class_size"]

# Segregate the data frame from high school students under general education category
class_size = class_size[class_size["GRADE "] == "09-12"]
class_size = class_size[class_size["PROGRAM TYPE"] == "GEN ED"]
print(class_size[["GRADE ", "PROGRAM TYPE"]].head(5))

# Consolidate the data frame for unique DBN field
class_size = class_size.groupby("DBN").agg('mean')

# Converting back DBN as index to column

```

```

class_size.reset_index(inplace=True)
data["class_size"] = class_size

# Print data frame for verification
data['class_size'].head(5)

```

```

GRADE  PROGRAM TYPE
225  09-12      GEN ED
226  09-12      GEN ED
227  09-12      GEN ED
228  09-12      GEN ED
229  09-12      GEN ED

```

```

Out[6]:      DBN  CSD  NUMBER OF STUDENTS / SEATS FILLED  NUMBER OF SECTIONS \
0  01M292    1                88.0000                4.000000
1  01M332    1                46.0000                2.000000
2  01M378    1                33.0000                1.000000
3  01M448    1               105.6875                4.750000
4  01M450    1                57.6000                2.733333

```

```

      AVERAGE CLASS SIZE  SIZE OF SMALLEST CLASS  SIZE OF LARGEST CLASS \
0                22.564286                18.50                26.571429
1                22.000000                21.00                23.500000
2                33.000000                33.00                33.000000
3                22.231250                18.25                27.062500
4                21.200000                19.40                22.866667

```

```

      SCHOOLWIDE PUPIL-TEACHER RATIO
0                                NaN
1                                NaN
2                                NaN
3                                NaN
4                                NaN

```

Data frame 'demographics'

```

In [7]: # Seggregating the dataframe 'demographics' based on the 'schoolyear' to extract unique
data["demographics"] = data["demographics"][data["demographics"]["schoolyear"] == 2011]

# Print for verification
data['demographics'].head(5)

```

```

Out[7]:      DBN      Name  schoolyear \
6  01M015  P.S. 015 ROBERTO CLEMENTE      20112012
13 01M019  P.S. 019 ASHER LEVY      20112012
20 01M020  PS 020 ANNA SILVER      20112012
27 01M034  PS 034 FRANKLIN D ROOSEVELT      20112012

```

	fl_percent	frl_percent	total_enrollment	prek	k	grade1	grade2	\
6	NaN	89.4	189	13	31	35	28	
13	NaN	61.5	328	32	46	52	54	
20	NaN	92.5	626	52	102	121	87	
27	NaN	99.7	401	14	34	38	36	
35	NaN	78.9	176	18	20	30	21	

	...	black_num	black_per	hispanic_num	hispanic_per	white_num	\
6	...	63	33.3	109	57.7	4	
13	...	81	24.7	158	48.2	28	
20	...	55	8.8	357	57.0	16	
27	...	90	22.4	275	68.6	8	
35	...	41	23.3	110	62.5	15	

	white_per	male_num	male_per	female_num	female_per
6	2.1	97.0	51.3	92.0	48.7
13	8.5	147.0	44.8	181.0	55.2
20	2.6	330.0	52.7	296.0	47.3
27	2.0	204.0	50.9	197.0	49.1
35	8.5	97.0	55.1	79.0	44.9

[5 rows x 38 columns]

Data frame 'graduation'

```
In [8]: # Seggregating the dataframe 'graduation' for features useful to get unique DBN
data["graduation"] = data["graduation"][data["graduation"]["Cohort"] == "2006"]
data["graduation"] = data["graduation"][data["graduation"]["Demographic"] == "Total Cohort"]

# Print for verification
data["graduation"].head(5)
```

```
Out [8]:
```

	Demographic	DBN	School Name	Cohort	\
3	Total Cohort	01M292	HENRY STREET SCHOOL FOR INTERNATIONAL	2006	
10	Total Cohort	01M448	UNIVERSITY NEIGHBORHOOD HIGH SCHOOL	2006	
17	Total Cohort	01M450	EAST SIDE COMMUNITY SCHOOL	2006	
24	Total Cohort	01M509	MARTA VALLE HIGH SCHOOL	2006	
31	Total Cohort	01M515	LOWER EAST SIDE PREPARATORY HIGH SCHO	2006	

	Total Cohort	Total Grads - n	Total Grads - % of cohort	Total Regents - n	\
3	78	43	55.1%	36	
10	124	53	42.7%	42	
17	90	70	77.8%	67	
24	84	47	56%	40	
31	193	105	54.4%	91	

	Total Regents - % of cohort	Total Regents - % of grads \
3	46.2%	83.7%
10	33.9%	79.2%
17	74.40000000000006%	95.7%
24	47.6%	85.1%
31	47.2%	86.7%

	...	Regents w/o Advanced - n \
3	...	36
10	...	34
17	...	67
24	...	23
31	...	22

	Regents w/o Advanced - % of cohort	Regents w/o Advanced - % of grads \
3	46.2%	83.7%
10	27.4%	64.2%
17	74.40000000000006%	95.7%
24	27.4%	48.9%
31	11.4%	21%

	Local - n	Local - % of cohort	Local - % of grads	Still Enrolled - n \
3	7	9%	16.3%	16
10	11	8.9%	20.8%	46
17	3	3.3%	4.3%	15
24	7	8.300000000000001%	14.9%	25
31	14	7.3%	13.3%	53

	Still Enrolled - % of cohort	Dropped Out - n	Dropped Out - % of cohort
3	20.5%	11	14.1%
10	37.1%	20	16.100000000000001%
17	16.7%	5	5.6%
24	29.8%	5	6%
31	27.5%	35	18.100000000000001%

[5 rows x 23 columns]

0.0.7 Convert AP scores to numeric

```
In [9]: # Convert 'ap_2010' data frame columns to numeric format, transform errors into null
cols = ['AP Test Takers ', 'Total Exams Taken', 'Number of Exams with scores 3 4 or 5']

for col in cols:
    data["ap_2010"][col] = pandas.to_numeric(data["ap_2010"][col], errors="coerce")

# Print for verification
print(data['ap_2010'].shape)
data["ap_2010"].head(5)
```


(258, 5)

```
Out [9]:
```

	DBN	SchoolName	AP Test Takers	\
0	01M448	UNIVERSITY NEIGHBORHOOD H.S.	39.0	
1	01M450	EAST SIDE COMMUNITY HS	19.0	
2	01M515	LOWER EASTSIDE PREP	24.0	
3	01M539	NEW EXPLORATIONS SCI,TECH,MATH	255.0	
4	02M296	High School of Hospitality Management	NaN	

	Total Exams Taken	Number of Exams with scores 3 4 or 5	
0	49.0	10.0	
1	21.0	NaN	
2	26.0	24.0	
3	377.0	191.0	
4	NaN	NaN	

0.0.8 Combine the Datasets

```
In [10]: combined = data["sat_results"]

combined = combined.merge(data["ap_2010"], on="DBN", how="left")
combined = combined.merge(data["graduation"], on="DBN", how="left")

# Print for verification
print(combined.shape)
combined.head(5)
```

(479, 33)

```
Out [10]:
```

	DBN	SCHOOL NAME	\
0	01M292	HENRY STREET SCHOOL FOR INTERNATIONAL STUDIES	
1	01M448	UNIVERSITY NEIGHBORHOOD HIGH SCHOOL	
2	01M450	EAST SIDE COMMUNITY SCHOOL	
3	01M458	FORSYTH SATELLITE ACADEMY	
4	01M509	MARTA VALLE HIGH SCHOOL	

	Num of SAT Test Takers	SAT Critical Reading Avg. Score	\
0	29	355.0	
1	91	383.0	
2	70	377.0	
3	7	414.0	
4	44	390.0	

	SAT Math Avg. Score	SAT Writing Avg. Score	sat_score	\
0	404.0	363.0	1122.0	
1	423.0	366.0	1172.0	
2	402.0	370.0	1149.0	

3	401.0	359.0	1174.0
4	433.0	384.0	1207.0

	SchoolName	AP Test Takers	Total Exams Taken \
0	NaN	NaN	NaN
1	UNIVERSITY NEIGHBORHOOD H.S.	39.0	49.0
2	EAST SIDE COMMUNITY HS	19.0	21.0
3	NaN	NaN	NaN
4	NaN	NaN	NaN

	...	Regents w/o Advanced - n \
0	...	36
1	...	34
2	...	67
3	...	NaN
4	...	23

	Regents w/o Advanced - % of cohort	Regents w/o Advanced - % of grads \
0	46.2%	83.7%
1	27.4%	64.2%
2	74.40000000000006%	95.7%
3	NaN	NaN
4	27.4%	48.9%

	Local - n	Local - % of cohort	Local - % of grads	Still Enrolled - n \
0	7	9%	16.3%	16
1	11	8.9%	20.8%	46
2	3	3.3%	4.3%	15
3	NaN	NaN	NaN	NaN
4	7	8.300000000000001%	14.9%	25

	Still Enrolled - % of cohort	Dropped Out - n	Dropped Out - % of cohort
0	20.5%	11	14.1%
1	37.1%	20	16.100000000000001%
2	16.7%	5	5.6%
3	NaN	NaN	NaN
4	29.8%	5	6%

[5 rows x 33 columns]

```
In [11]: to_merge = ["class_size", "demographics", "survey", "hs_directory"]
```

```
for m in to_merge:
    combined = combined.merge(data[m], on="DBN", how="inner")
```

```
# Print for verification
print(combined.shape)
combined.head(5)
```

(363, 159)

```
Out[11]:      DBN      SCHOOL NAME \
0  01M292      HENRY STREET SCHOOL FOR INTERNATIONAL STUDIES
1  01M448      UNIVERSITY NEIGHBORHOOD HIGH SCHOOL
2  01M450      EAST SIDE COMMUNITY SCHOOL
3  01M509      MARTA VALLE HIGH SCHOOL
4  01M539  NEW EXPLORATIONS INTO SCIENCE, TECHNOLOGY AND ...

      Num of SAT Test Takers  SAT Critical Reading Avg. Score \
0          29          355.0
1          91          383.0
2          70          377.0
3          44          390.0
4         159          522.0

      SAT Math Avg. Score  SAT Writing Avg. Score  sat_score \
0          404.0          363.0      1122.0
1          423.0          366.0      1172.0
2          402.0          370.0      1149.0
3          433.0          384.0      1207.0
4          574.0          525.0      1621.0

      SchoolName  AP Test Takers  Total Exams Taken \
0          NaN          NaN          NaN
1  UNIVERSITY NEIGHBORHOOD H.S.          39.0          49.0
2      EAST SIDE COMMUNITY HS          19.0          21.0
3          NaN          NaN          NaN
4  NEW EXPLORATIONS SCI,TECH,MATH          255.0          377.0

      ...      priority04 \
0  ...      Then to Manhattan students or residents
1  ...          NaN
2  ...          NaN
3  ...          NaN
4  ...          NaN

      priority05  priority06  priority07  priority08 \
0  Then to New York City residents          NaN          NaN          NaN
1          NaN          NaN          NaN          NaN
2          NaN          NaN          NaN          NaN
3          NaN          NaN          NaN          NaN
4          NaN          NaN          NaN          NaN

      priority09  priority10      Location 1 \
0          NaN          NaN  220 Henry Street\nNew York, NY 10002\n(40.7137...
1          NaN          NaN  200 Monroe Street\nNew York, NY 10002\n(40.712...
```

```

2      NaN      NaN  420 East 12 Street\nNew York, NY 10009\n(40.72...
3      NaN      NaN  145 Stanton Street\nNew York, NY 10002\n(40.72...
4      NaN      NaN  111 Columbia Street\nNew York, NY 10002\n(40.7...

```

```

      lat      lon
0  40.713764 -73.985260
1  40.712332 -73.984797
2  40.729783 -73.983041
3  40.720569 -73.985673
4  40.718725 -73.979426

```

```
[5 rows x 159 columns]
```

0.0.9 Fill Up Null Values

```

In [12]: # Fill up the null values with the column average value
combined = combined.fillna(combined.mean())
combined = combined.fillna(0)

# Check for null values
print("Null Values in Combined Data Frame =", combined.isnull().sum().sum())

```

```
Null Values in Combined Data Frame = 0
```

0.0.10 Add a School District Column for Mapping

```

In [13]: def get_first_two_chars(dbn):
          return dbn[0:2]

combined["school_dist"] = combined["DBN"].apply(get_first_two_chars)

# Print for verification
combined["school_dist"].head(5)

```

```

Out[13]: 0    01
         1    01
         2    01
         3    01
         4    01
         Name: school_dist, dtype: object

```

0.0.11 Find correlations

```

In [14]: correlations = combined.corr()
corr_satscore = correlations.corr()["sat_score"]
print(corr_satscore)

```

SAT Critical Reading Avg. Score	0.997433
SAT Math Avg. Score	0.992862
SAT Writing Avg. Score	0.997205
sat_score	1.000000
AP Test Takers	0.742299
Total Exams Taken	0.747097
Number of Exams with scores 3 4 or 5	0.751203
Total Cohort	0.469707
CSD	0.209195
NUMBER OF STUDENTS / SEATS FILLED	0.521990
NUMBER OF SECTIONS	0.497414
AVERAGE CLASS SIZE	0.580089
SIZE OF SMALLEST CLASS	0.547800
SIZE OF LARGEST CLASS	0.498482
SCHOOLWIDE PUPIL-TEACHER RATIO	NaN
schoolyear	NaN
fl_percent	NaN
frl_percent	-0.926402
total_enrollment	0.493900
ell_num	-0.032734
ell_percent	-0.588053
sped_num	0.202543
sped_percent	-0.719101
asian_num	0.652992
asian_per	0.831369
black_num	0.178459
black_per	-0.401030
hispanic_num	0.143639
hispanic_per	-0.639662
white_num	0.706445
	...
rr_p	-0.085942
N_s	0.551170
N_t	0.436806
N_p	0.628105
saf_p_11	-0.078582
com_p_11	-0.308995
eng_p_11	-0.173111
aca_p_11	-0.171177
saf_t_11	0.275014
com_t_11	0.034989
eng_t_10	NaN
aca_t_11	0.063366
saf_s_11	0.243283
com_s_11	0.083379
eng_s_11	0.134303
aca_s_11	0.216600
saf_tot_11	0.164197

```

com_tot_11                -0.068616
eng_tot_11                -0.026598
aca_tot_11                0.029286
grade_span_max            NaN
expgrade_span_max         NaN
zip                       0.002559
total_students            0.544247
number_programs           0.296832
priority08                NaN
priority09                NaN
priority10                NaN
lat                       -0.416402
lon                       -0.424829
Name: sat_score, Length: 67, dtype: float64

```

0.0.12 Plot Correlations

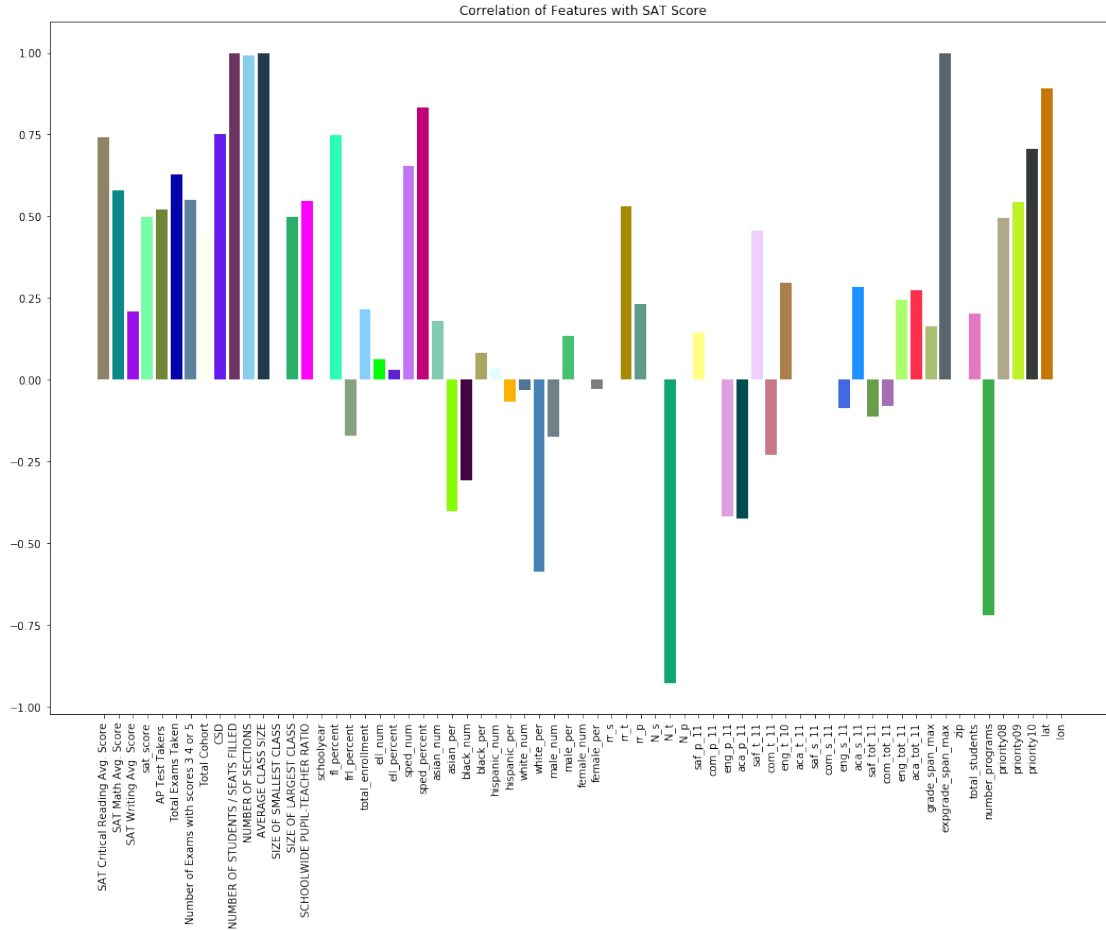
```

In [15]: # Preparing a list of colors from matplotlib
         colors_list = list(colors._colors_full_map.values())
         random.shuffle(colors_list, random.random)

         fig, ax = plt.subplots(figsize=(18, 12))
         ax.bar(corr_satscore.index, corr_satscore, align='center', color=colors_list)
         ax.set_xticklabels(corr_satscore.index, rotation=90)
         ax.set_title("Correlation of Features with SAT Score")

         plt.show()

```



We observe high correlations between SAT score and following factors:

- o Number of Students / Seats Filled
- o Average Class Size
- o The highest grade the school expects to serve eventually
- o Number of Teacher Respondents (-ve)
- o SAT Critical Reading Average Score
- o Free Lunch Percent
- o Number of distinct programs available at the school (-ve)

Its obvious to see how the class-size, number of students and the highest grade the school expects creates a competitive environment for the students to encourage them working hard to perform better in SAT.

The strong positive relationship of SAT Critical Reading Average Score with the SAT score shows the impact of effective reading skills on the overall SAT performance.

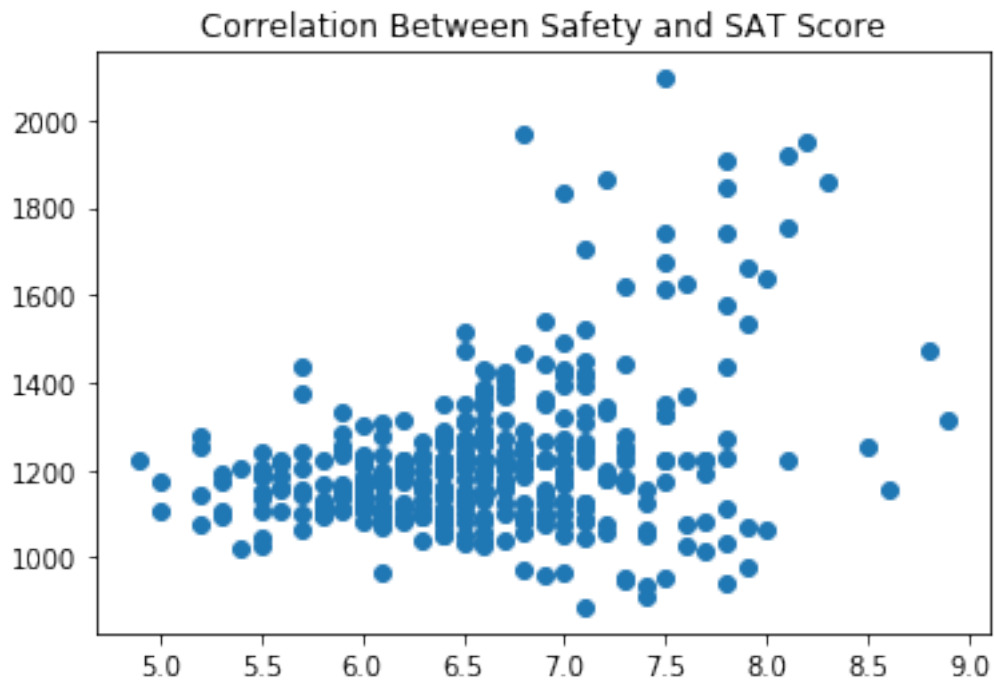
The positive correlation of Free Lunch with SAT score tells the success story of governments welfare program in the area of economically developing neighborhood and low-income immigrant regions.

It is interesting to note that higher the number of teachers participation in survey for expectation about students academia negatively influence the overall student performance in SAT.

The negative correlation of Number of distinct programs available at the school with SAT score goes in reverse parity with the positive correlation of class-size and number of students factors above as more program diversity tends to reduce the class-size an number of students per course.

0.0.13 Analyze Effect of Safety on SAT Score

```
In [16]: plt.scatter(combined['saf_s_11'], combined['sat_score'])  
plt.title("Correlation Between Safety and SAT Score")  
plt.show()
```



There appears to be a positive correlation between safety and SAT score though not so strong. There are some schools that have high safety standard and achieve high SAT score and some schools with low safety standard got low SAT score. Majority of the school from the sample falls between the safety score of 6.0 to 7.5 with an average SAT score below 1500.

0.0.14 Map Safety Score by Districts

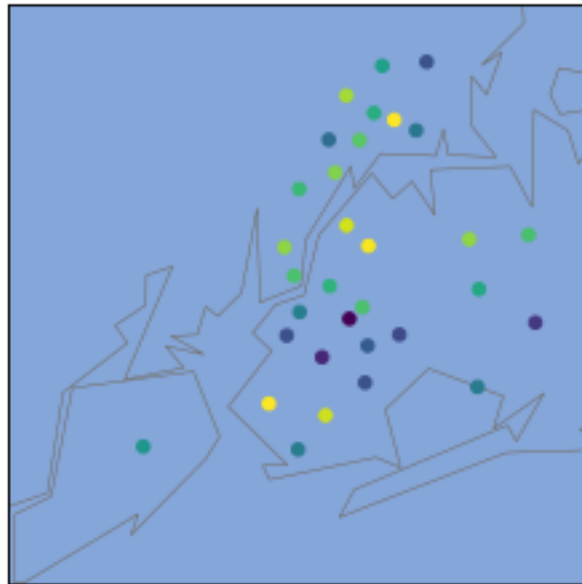
```
In [17]: m = Basemap(  
    projection='merc',  
    llcrnrlat=40.496044,  
    urcrnrlat=40.915256,  
    llcrnrlon=-74.255735,  
    urcrnrlon=-73.700272,  
    resolution='i'  
)  
  
m.drawmapboundary(fill_color='#85A6D9')  
m.drawcoastlines(color='#6D5F47', linewidth=.4)  
m.drawrivers(color='#6D5F47', linewidth=.4)
```



```
distr = combined.groupby("school_dist").mean()
distr.reset_index(inplace=True)

longitudes = (distr["lon"]).tolist()
latitudes = (distr["lat"]).tolist()
m.scatter(longitudes, latitudes, s=20, zorder=2, latlon=True, c=distr["saf_s_11"])
plt.show()
```

```
C:\Users\Yogi_Ashwast\Anaconda3\lib\site-packages\mpl_toolkits\basemap\__init__.py:1708: MatplotlibDeprecationWarning:
  limb = ax.axesPatch
C:\Users\Yogi_Ashwast\Anaconda3\lib\site-packages\mpl_toolkits\basemap\__init__.py:1711: MatplotlibDeprecationWarning:
  if limb is not ax.axesPatch:
```



Brooklyn seems to have better safety score compared to the same for the parts of Manhattan, Queens and Bronx region.

0.0.15 Evaluate Racial Performance in SAT

```
In [18]: # Listing the races of interest
races = ["white_per", "asian_per", "black_per", "hispanic_per"]
racial_per = combined[races]

# Extracting the coorelation value for the shortlisted races
value_ht = combined.corr()["sat_score"][races]

# Establish plot parameters
x_cor = [1,2,3,4]
```

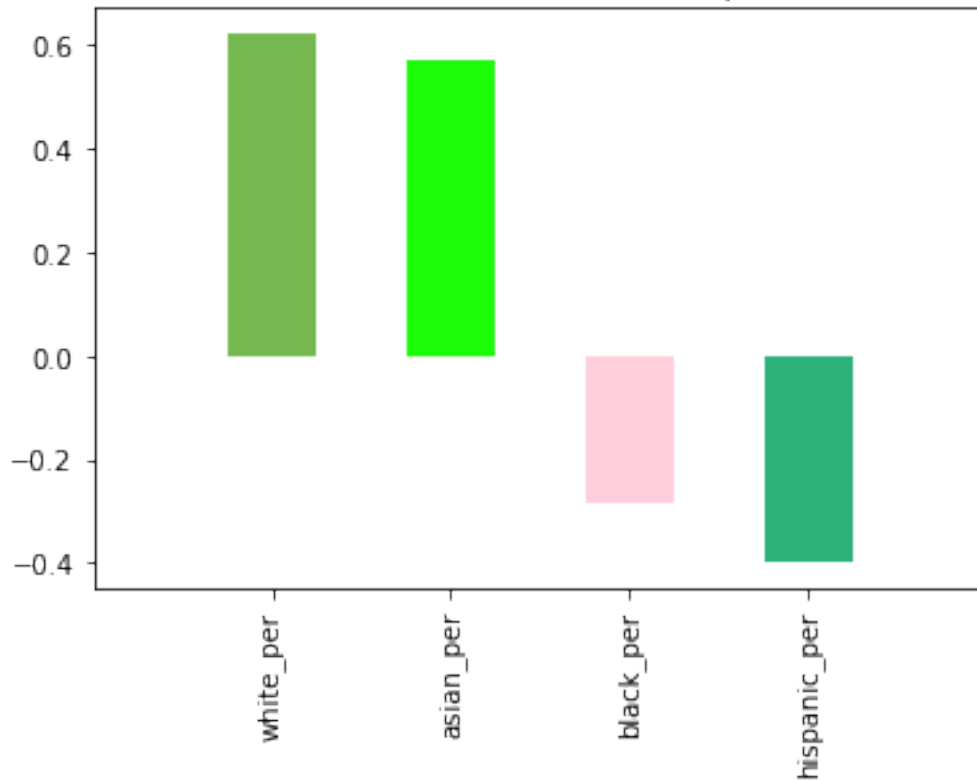
```

random.shuffle(colors_list, random.random)
plt.bar(x_cor, value_ht, width=0.5, align="center", tick_label=races, color=colors_list)
plt.xlim(0,5)
plt.xticks(rotation=90)
plt.title("Correlation of Whites, Asians, Blacks and Hispanics with SAT Score")

plt.show()

```

Correlation of Whites, Asians, Blacks and Hispanics with SAT Score



The whites and the Asians are found having strong positive correlation while the Blacks and the Hispanic are found having moderate negative correlation with the SAT score.

This is due to the fact that the Hispanic and the Blacks might be coming from the immigrant families. The socio-economic factors, family support and surrounding environment play significant role in overall performance of the students.

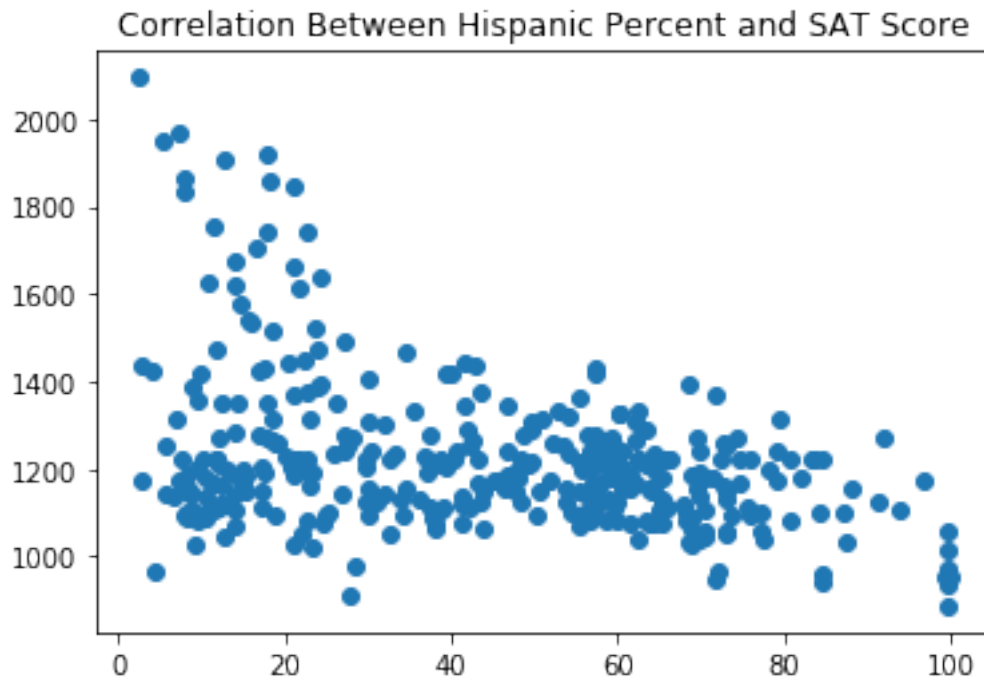
0.0.16 Plot Correlation Between Hispanic Proportion & SAT Score

```

In [19]: plt.scatter(combined['hispanic_per'], combined['sat_score'])
plt.title("Correlation Between Hispanic Percent and SAT Score")

plt.show()

```



There seems to be a moderately strong downward trend with the increase of Hispanic Population. Very small portion of population attains a SAT score of 1800 or more while majority falls under the score of 1500.

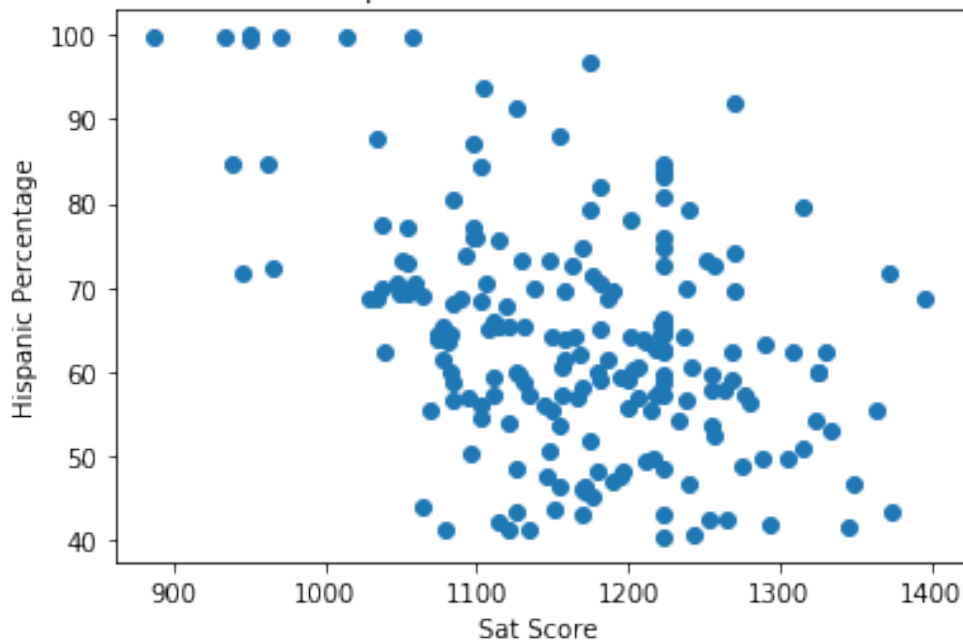
0.0.17 Dependency: Low Sat Score & Hispanic Percent

```
In [20]: low_sat_high_hisp = combined[combined["sat_score"] < 1400]
low_sat_high_hisp = low_sat_high_hisp[low_sat_high_hisp["hispanic_per"] > 40]
sat_sc = low_sat_high_hisp["sat_score"].values
hisp_per = low_sat_high_hisp["hispanic_per"].values

plt.scatter(sat_sc, hisp_per)
plt.xlabel("Sat Score")
plt.ylabel("Hispanic Percentage")
plt.title("Correlation Between Hispanic Percent (> 40%) and SAT Score (< 1400)")
print("Correlation Value =", low_sat_high_hisp.corr()["sat_score"]["hispanic_per"])
```

Correlation Value = -0.41737620009586124

Correlation Between Hispanic Percent (> 40%) and SAT Score (< 1400)



Majority of the schools with Hispanic population in the range of 40% - 80% get average SAT score of around 1150. The results become clearly evident when plotted with 40% or more Hispanic Proportion for SAT score of 1400 or less.

This is mainly due to the immigrant population along with the socio-economic and demographic factors.

0.0.18 List Schools with Hispanic More Than 95%

```
In [21]: hisp_per_95 = combined[combined["hispanic_per"] > 95]
         print(hisp_per_95["SCHOOL NAME"].unique())
```

```
['MANHATTAN BRIDGES HIGH SCHOOL'
 'WASHINGTON HEIGHTS EXPEDITIONARY LEARNING SCHOOL'
 'GREGORIO LUPERON HIGH SCHOOL FOR SCIENCE AND MATHEMATICS'
 'ACADEMY FOR LANGUAGE AND TECHNOLOGY'
 'INTERNATIONAL SCHOOL FOR LIBERAL ARTS'
 'PAN AMERICAN INTERNATIONAL HIGH SCHOOL AT MONROE'
 'MULTICULTURAL HIGH SCHOOL' 'PAN AMERICAN INTERNATIONAL HIGH SCHOOL']
```

0.0.19 List Schools with Hispanic Less Than 10%

```
In [22]: hisp_10_sat_1800 = combined[combined["hispanic_per"] < 10]
         hisp_10_sat_1800 = hisp_10_sat_1800[hisp_10_sat_1800["sat_score"] > 1800]
         print(hisp_10_sat_1800["SCHOOL NAME"].unique())
```

```
['STUYVESANT HIGH SCHOOL' 'BRONX HIGH SCHOOL OF SCIENCE'
 'BROOKLYN TECHNICAL HIGH SCHOOL'
 'QUEENS HIGH SCHOOL FOR THE SCIENCES AT YORK COLLEGE'
 'STATEN ISLAND TECHNICAL HIGH SCHOOL']
```

0.0.20 Enlist Schools in NYC with Low Total Enrollment and Low SAT Score

```
In [23]: # Find the school with low enrollment that get low SAT score
low_enrollment = combined[(combined['total_enrollment'] < 1000) & (combined['sat_score'] < 1000)]

# Remove rows with invalid school name
low_enrollment = low_enrollment[low_enrollment['School Name'] != 0]

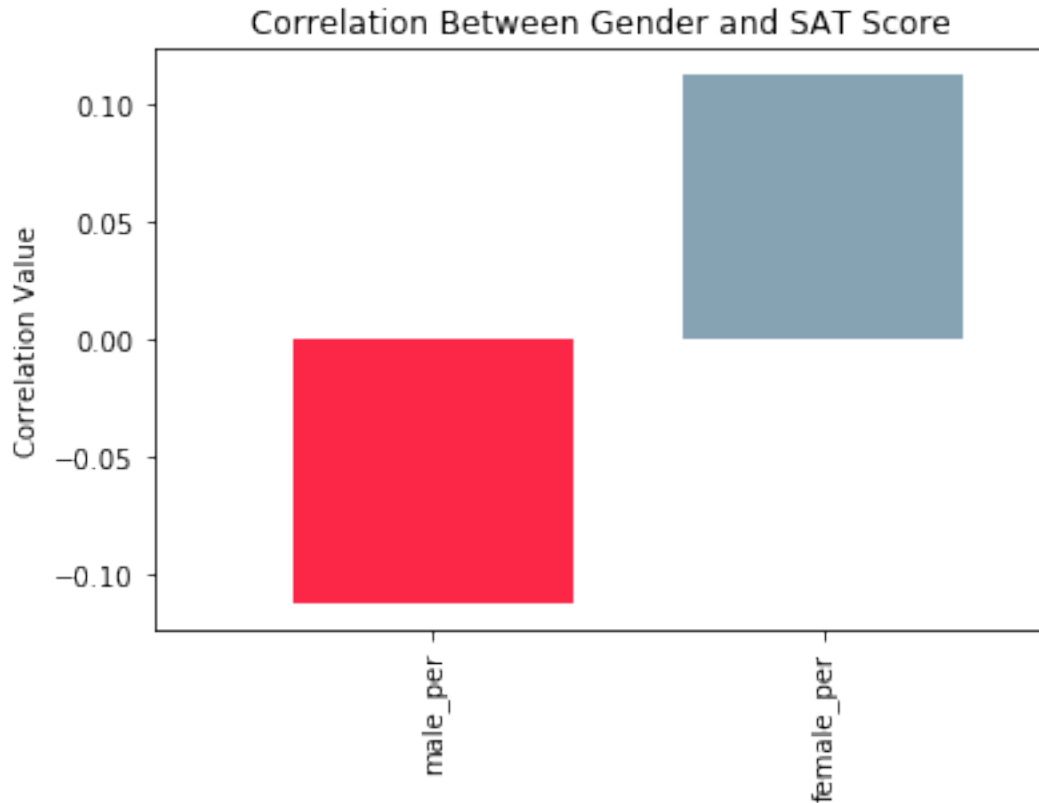
# Print for verification
low_enrollment['School Name']
```

```
Out[23]: 91      INTERNATIONAL COMMUNITY HIGH SCHOOL
126      BRONX INTERNATIONAL HIGH SCHOOL
139      KINGSBRIDGE INTERNATIONAL HIGH SCHOOL
141      INTERNATIONAL SCHOOL FOR LIBERAL ARTS
179      HIGH SCHOOL OF WORLD CULTURES
188      BROOKLYN INTERNATIONAL HIGH SCHOOL
225      INTERNATIONAL HIGH SCHOOL AT PROSPECT
237      IT TAKES A VILLAGE ACADEMY
253      MULTICULTURAL HIGH SCHOOL
286      PAN AMERICAN INTERNATIONAL HIGH SCHOOL
Name: School Name, dtype: object
```

0.0.21 Plot Correlation Between Sat Score & Gender

```
In [24]: gender = ["male_per", "female_per"]
cor_val = combined.corr()["sat_score"][gender]
x_val = [1, 1.0070]
random.shuffle(colors_list, random.random)

plt.bar(x_val, cor_val, 0.005, align='center', tick_label=gender, color=colors_list)
plt.xlim(0.995, 1.011)
plt.ylabel("Correlation Value")
plt.xticks(rotation=90)
plt.title("Correlation Between Gender and SAT Score")
plt.show()
```



Female show very weak positive and male show very weak negative correlation for SAT score. This shows the relative performance of female and male students – which is more or less the same.

0.0.22 High SAT Score & High Female Percentage

```
In [25]: high_sat_n_fem = combined[combined["female_per"] > 50]
        high_sat_n_fem = high_sat_n_fem[high_sat_n_fem["sat_score"] > 1500]
        print("Schools with SAT > 1500 & Female > 50% =\n", high_sat_n_fem["SCHOOL NAME"].unique())

        # Plot the scatter diagram
        plt.scatter(combined["sat_score"], combined["female_per"])
        plt.xlabel("Sat Score")
        plt.ylabel("female_per")
        plt.title("Correlation Between Female Percent (> 50%) and SAT Score (> 1500)")

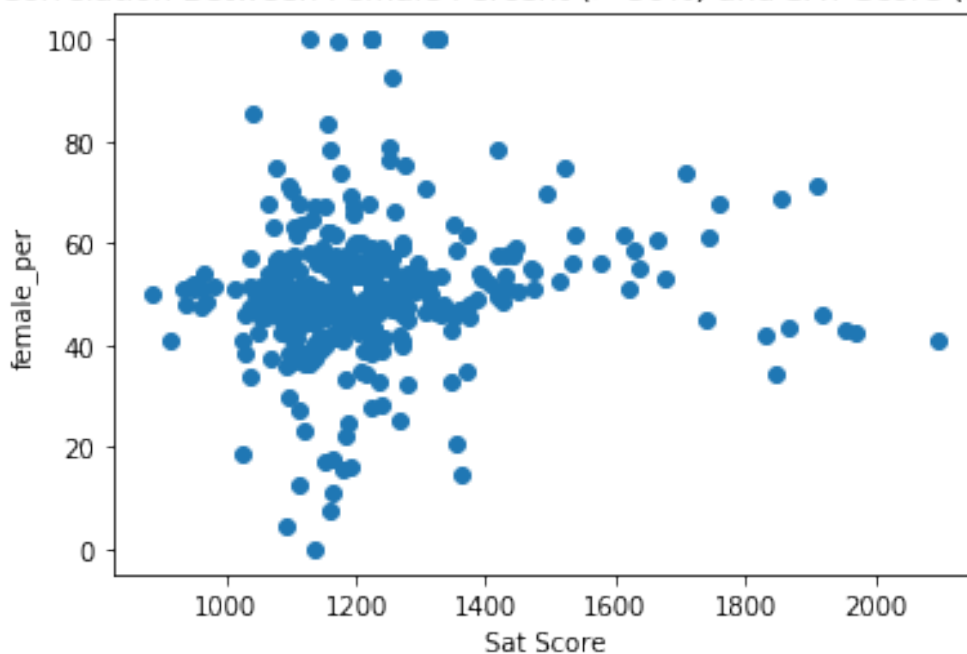
        print("\nCorrelation Value between SAT Score and Female Percentage =", high_sat_n_fem
```

```
Schools with SAT > 1500 & Female > 50% =
['NEW EXPLORATIONS INTO SCIENCE, TECHNOLOGY AND MATH HIGH SCHOOL'
'BARD HIGH SCHOOL EARLY COLLEGE'
'PROFESSIONAL PERFORMING ARTS HIGH SCHOOL'
'BARUCH COLLEGE CAMPUS HIGH SCHOOL']
```

```
'N.Y.C. LAB SCHOOL FOR COLLABORATIVE STUDIES'
'ELEANOR ROOSEVELT HIGH SCHOOL' 'MILLENNIUM HIGH SCHOOL'
'BEACON HIGH SCHOOL'
'FIORELLO H. LAGUARDIA HIGH SCHOOL OF MUSIC & ART AND PERFORMING ARTS'
'LEON M. GOLDSTEIN HIGH SCHOOL FOR THE SCIENCES'
'BARD HIGH SCHOOL EARLY COLLEGE II' 'TOWNSEND HARRIS HIGH SCHOOL'
'BENJAMIN N. CARDOZO HIGH SCHOOL' "SCHOLARS' ACADEMY"
'QUEENS GATEWAY TO HEALTH SCIENCES SECONDARY SCHOOL'
'BACCALAUREATE SCHOOL FOR GLOBAL EDUCATION']
```

Correlation Value between SAT Score and Female Percentage = 0.44951913501293517

Correlation Between Female Percent (> 50%) and SAT Score (> 1500)



There exists moderately positive correlation between the female proportion and SAT score. While tested for pool of students having more than 50% female proportion and SAT score of greater than 1500, it is observed that around 40% - 65% of the total students attain SAT score in the range of 1000 – 1350.

0.0.23 SAT Score > 1700 & Female Percentage > 60

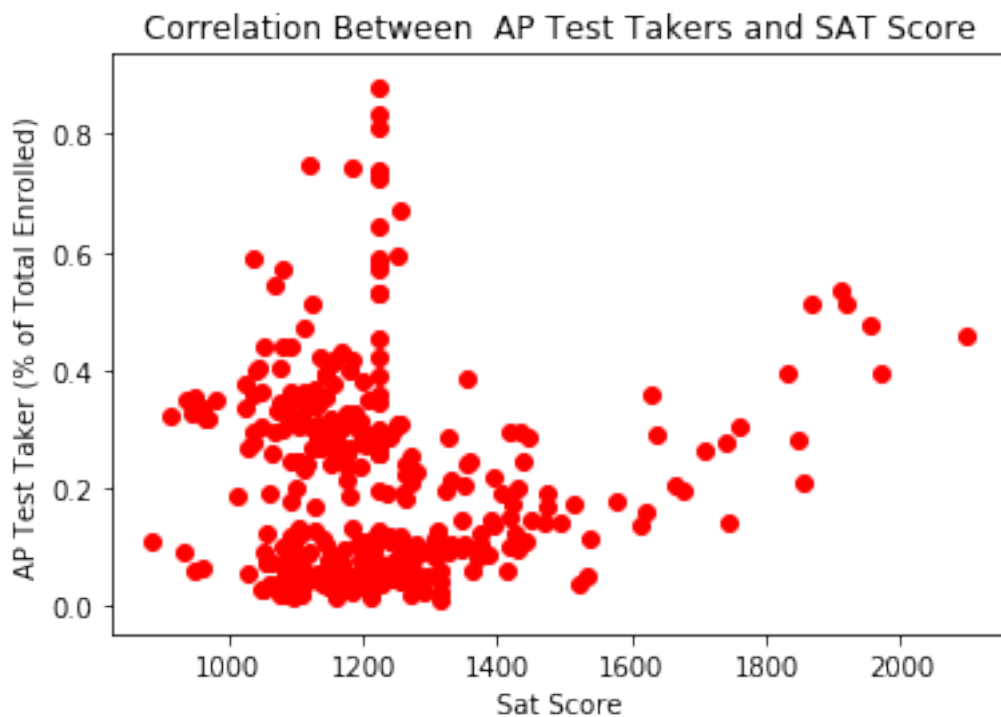
```
In [26]: fem_60_sat_1700 = combined[(combined["sat_score"] > 1700) & (combined["female_per"] > 60)]
print("Schools with SAT > 1700 & Female > 60% =\n", fem_60_sat_1700["SCHOOL_NAME"].unique())
```

```
Schools with SAT > 1700 & Female > 60% =
['BARD HIGH SCHOOL EARLY COLLEGE' 'ELEANOR ROOSEVELT HIGH SCHOOL'
'BEACON HIGH SCHOOL']
```

```
'FIORELLO H. LAGUARDIA HIGH SCHOOL OF MUSIC & ART AND PERFORMING ARTS'  
'TOWNSEND HARRIS HIGH SCHOOL']
```

0.0.24 Relationship Between AP Test Takers & SAT Score

```
In [27]: combined["ap_per"] = combined["AP Test Takers "] / combined["total_enrollment"]  
plt.scatter(combined["sat_score"], combined["ap_per"], color='r')  
plt.xlabel("Sat Score")  
plt.ylabel("AP Test Taker (% of Total Enrolled)")  
plt.title("Correlation Between AP Test Takers and SAT Score")  
plt.show()  
  
print("Corrleation value between SAT Score & Percent of AP Test Takers =", combined.c
```



```
Corrleation value between SAT Score & Percent of AP Test Takers = 0.05717081390766967
```

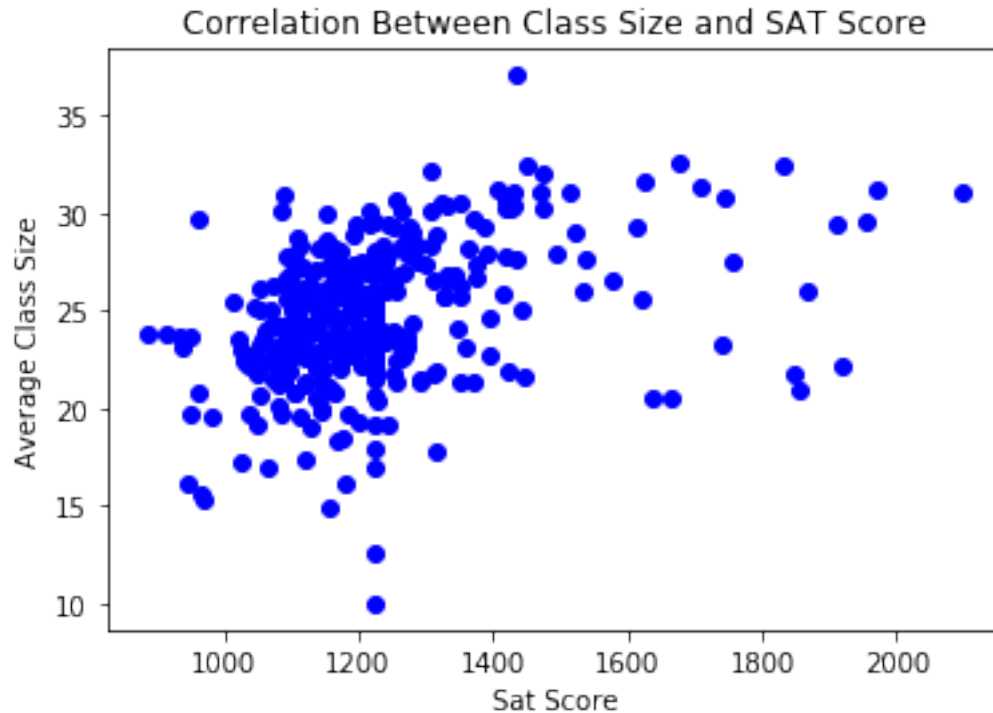
No correlation is found between the AP Test Takers and the SAT score. In fact, up to 40% of the total enrollment who took AP Test scored less than 1400 in SAT. There are few percent of students who took AP Test and secured SAT score of 1800 – 2000.

The data about students' performance in AP Test Vs. SAT could give us more insight to further comment about the AP Test results predictive relevance for SAT score.

0.0.25 Relationship Between Class Size & SAT Score

```
In [28]: plt.scatter(combined["sat_score"], combined["AVERAGE CLASS SIZE"], color='b')
plt.xlabel("Sat Score")
plt.ylabel("Average Class Size")
plt.title("Correlation Between Class Size and SAT Score")
plt.show()

print("Corrleation value between SAT Score & Average Class Size =", combined.corr()["sat_score", "AVERAGE CLASS SIZE"])
```



Corrleation value between SAT Score & Average Class Size = 0.3810143308095523

Moderately strong positive correlation has been observed between the class size and SAT score. Students' SAT score slowly improves as the class size increases from 20 to 30 students. Majority of the students score between 1000 – 1400 irrespective of class size. However, there are few exceptional cases where the students score beyond 1800.

This clearly shows that performance of students in SAT is strongly impacted by his/her class size, higher student-teacher ratio and consequently the dense social environment -which collectively proves to be encouraging for the students.

0.0.26 Correlation Between Different in Parent, Teacher and Student Responses to Surveys with SAT Score

Listing and Cleaning Data

```
In [29]: # short listing the relevant columns
surv_col = ['aca_p_11', 'aca_t_11', 'aca_s_11', 'sat_score']
response = combined[surv_col]

# Cleaning the data with null values
response = response.dropna(axis=0, how='any')

# Making sure no null is left
response.isnull().sum().sum()
```

Out[29]: 0

Develop Survey Response Difference Data

```
In [30]: # Developing the survey difference response data
response['aca_p_s'] = (response['aca_p_11'] - response['aca_s_11']).abs()
response['aca_p_t'] = (response['aca_p_11'] - response['aca_t_11']).abs()
response['aca_t_s'] = (response['aca_t_11'] - response['aca_s_11']).abs()

# Plot survey response difference
resp_cols = ['aca_p_s', 'aca_p_t', 'aca_t_s']

# Print for verification
print(response[resp_cols].head())
```

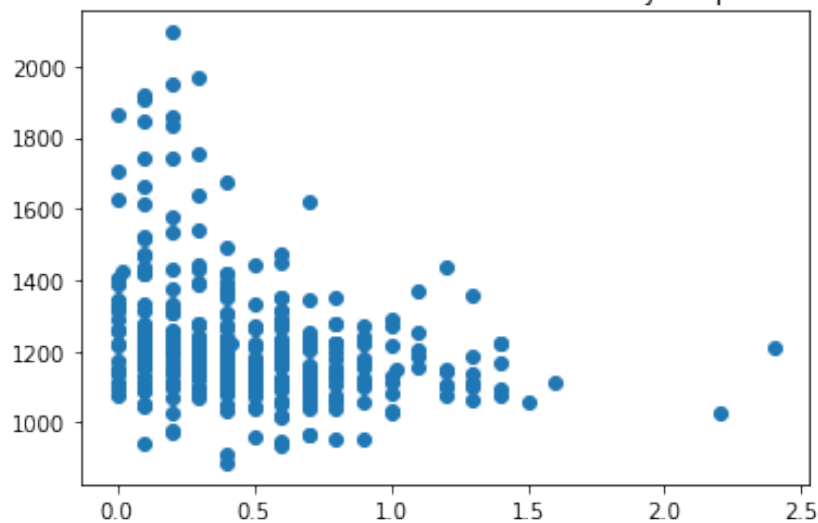
	aca_p_s	aca_p_t	aca_t_s
0	0.900000	1.1	0.200000
1	0.300000	0.0	0.300000
2	1.018611	0.4	1.418611
3	0.300000	0.5	0.200000
4	0.700000	1.1	0.400000

Correlation Between Parent-Student Survey Difference Response & SAT Score

```
In [31]: pss_cor0 = response.corr()[resp_cols[0]]["sat_score"]
print("\nCorrelation between Parent-Student Survey Response & SAT Score =",
      pss_cor0)
plt.scatter(response[resp_cols[0]], response["sat_score"])
plt.title("Correlation for Difference between Parent-Student Survey \
Response and SAT Score")
plt.show()
```

Correlation between Parent-Student Survey Response & SAT Score = -0.2892526616448787

Correlation for Difference between Parent-Student Survey Response and SAT Score



It appears that there is a moderately strong negative correlation between the difference in Parent-Student Survey Response and SAT Score. Hence, more similarity of parents and student's opinion about the latter's academic expectation, better would it be reflected in to the higher SAT score. In other words, more the disparity between parents and student's responses for students' academic expectation score, lower would be the SAT score.

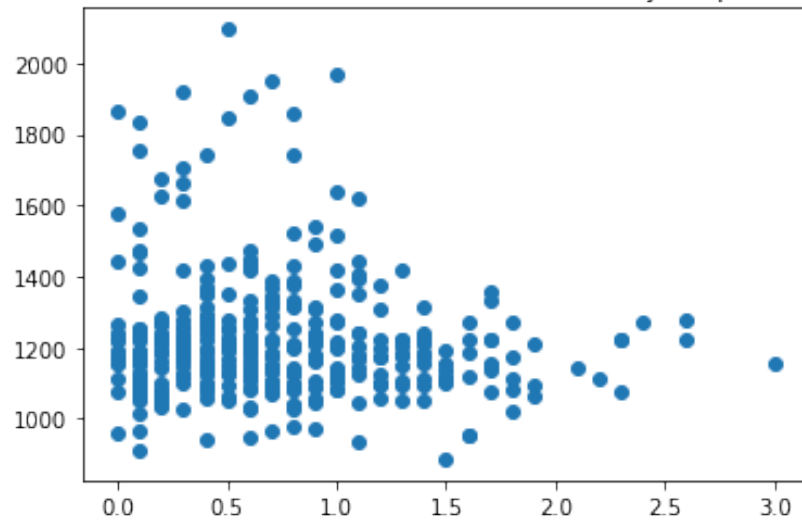
This clearly indicates that parental involvement in student's education results into a better SAT performance and vice versa.

Correlation Between Parent-Teacher Survey Difference Response & SAT Score

```
In [32]: pss_cor1 = response.corr()[resp_cols[1]]["sat_score"]
         print("\nCorrelation between Parent-Teacher Survey Response & SAT Score =",
               pss_cor1)
         plt.scatter(response[resp_cols[1]], response["sat_score"])
         plt.title("Correlation for Difference between Parent-Teacher Survey \
Response and SAT Score")
         plt.show()
```

Correlation between Parent-Teacher Survey Response & SAT Score = -0.11002982952218382

Correlation for Difference between Parent-Teacher Survey Response and SAT Score



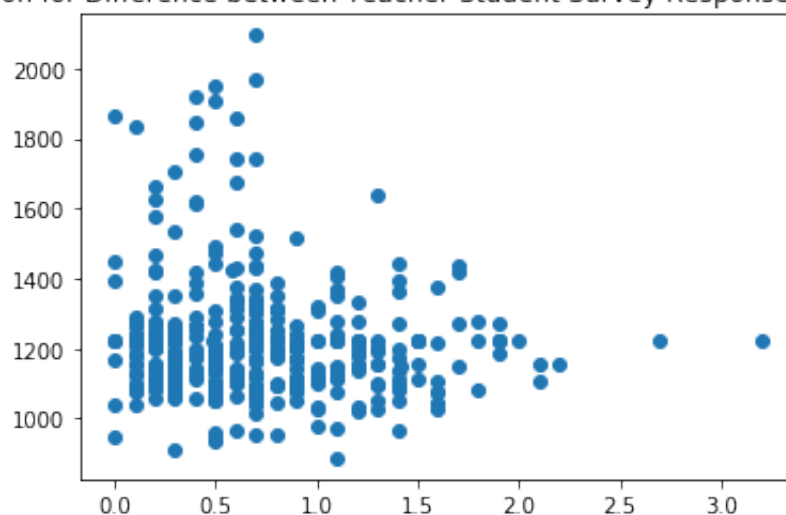
There exists weak negative relationship between the difference in parents and teachers' survey response and SAT score. This indicates that difference of opinion between the parents and the teachers over the expectation of student's academia has moderately reverse impact over student's performance in SAT. In other words, less the differences between the parental and teacher's opinion about student's academic expectation, moderately better would be student's performance in SAT.

Correlation Between Teacher-Student Survey Difference Response & SAT Score

```
In [33]: pss_cor2 = response.corr()[resp_cols[2]]["sat_score"]
print("\nCorrelation between Teacher-Student Survey Response & SAT Score =",
      pss_cor2)
plt.scatter(response[resp_cols[2]], response["sat_score"])
plt.title("Correlation for Difference between Teacher-Student Survey \
Response and SAT Score")
plt.show()
```

Correlation between Teacher-Student Survey Response & SAT Score = -0.09657508196544748

Correlation for Difference between Teacher-Student Survey Response and SAT Score



No correlation is found between the difference in teachers' and students' survey response and SAT score. This indicates that difference of opinion between the teachers and students over the academic expectation for the students have no impact over student's performance in SAT.

0.0.27 Find out neighborhoods with Best Schools

Determine Top 10 Best School in NYC Based On SAT Score

In [34]: *# Find the top 10 school based on the SAT score*

```
good_schools = combined[combined['sat_score'] > 1750]
good_schools = good_schools.groupby('DBN').agg('max').sort_values(by='sat_score', ascending=False)
good_schools[['boro', 'sat_score', 'SCHOOL NAME', 'CSD', 'zip']].head(10)
```

Out [34]:

	boro	sat_score	\
DBN			
02M475	Manhattan	2096.0	
10X445	Bronx	1969.0	
31R605	Staten Island	1953.0	
10X696	Bronx	1920.0	
25Q525	Queens	1910.0	
28Q687	Queens	1868.0	
01M696	Manhattan	1856.0	
05M692	Manhattan	1847.0	
13K430	Brooklyn	1833.0	
02M416	Manhattan	1758.0	

	SCHOOL NAME	CSD	zip
DBN			
02M475	STUYVESANT HIGH SCHOOL	2	10282
10X445	BRONX HIGH SCHOOL OF SCIENCE	10	10468

31R605	STATEN ISLAND TECHNICAL HIGH SCHOOL	31	10306
10X696	HIGH SCHOOL OF AMERICAN STUDIES AT LEHMAN COLLEGE	10	10468
25Q525	TOWNSEND HARRIS HIGH SCHOOL	25	11367
28Q687	QUEENS HIGH SCHOOL FOR THE SCIENCES AT YORK CO...	28	11433
01M696	BARD HIGH SCHOOL EARLY COLLEGE	1	10002
05M692	HIGH SCHOOL FOR MATHEMATICS, SCIENCE AND ENGIN...	5	10031
13K430	BROOKLYN TECHNICAL HIGH SCHOOL	13	11217
02M416	ELEANOR ROOSEVELT HIGH SCHOOL	2	10021

Gathering NYC Property Value Information

```
In [35]: cols = ['Borough', 'CD', 'SchoolDist', 'ZipCode', 'BldgClass', 'price_sf', 'Address',
brk_data = pandas.read_csv(r"databank/nyc_property/BK2017V11.csv", usecols = cols)
brx_data = pandas.read_csv(r"databank/nyc_property/BX2017V11.csv", usecols = cols)
mnh_data = pandas.read_csv(r"databank/nyc_property/MN2017V11.csv", usecols = cols)
qns_data = pandas.read_csv(r"databank/nyc_property/QN2017V11.csv", usecols = cols)
snr_data = pandas.read_csv(r"databank/nyc_property/SI2017V11.csv", usecols = cols)
prop_val = pandas.concat([brk_data, brx_data, mnh_data, qns_data, snr_data], axis=0)

# Print for verification
print(prop_val.shape)
prop_val.head(10)
```

(53340, 8)

```
Out [35]:
```

	Borough	CD	SchoolDist	ZipCode	Address	BldgClass	\
0	BK	309	17.0	11213.0	400 UTICA AVENUE	02	
1	BK	303	13.0	11205.0	117 SANDFORD STREET	G9	
2	BK	301	14.0	11222.0	239 INDIA STREET	02	
3	BK	315	21.0	11229.0	1819 EAST 13 STREET	D7	
4	BK	313	21.0	11224.0	3740 OCEANIC AVENUE	M9	
5	BK	318	22.0	11210.0	1805 FLATBUSH AVENUE	K4	
6	BK	307	15.0	11215.0	511 7 AVENUE	W1	
7	BK	301	14.0	11249.0	58 NORTH 8 STREET	O5	
8	BK	303	14.0	11205.0	38 SKILLMAN STREET	R4	
9	BK	312	21.0	11230.0	1613 MC DONALD AVENUE	E1	

	OwnerName	price_sf
0	VIS BAN REALTY CORP	50.000000
1	117 SANFORD LLC	50.000000
2	INDIA STREET CORP.	50.000000
3	AMK II REALTY LLC	50.000000
4	KOZNITZ CONGREGATION	50.000000
5	MERVEILLE, GLADYS	50.000000
6	DCAS/DEPARTMENT OF ED	50.003959
7	101 KENT ASSOCIATES I	50.008548
8	NaN	50.015724
9	CB REALTY COMPANY LLC	50.019231

0.0.28 Finding Top 10 Cost Effective Properties for NYC School Neighborhood (2 Deals/School)

Define functions to segregate residential class

In [36]: *# Filter data frame for select residential building class*

```
def usage(char):
    usg = ['A', 'B', 'C', 'D', 'R']
    if char in usg:
        return 1
    else:
        return 0
```

Define Function to Extract Neighborhood Details

In [37]: *# Define function to extract the neighborhood details*

```
def find_property(data, df):
    sch_dst = data[0]
    zip_code = data[1]
    df = df[(df['ZipCode'] == zip_code) & (df['SchoolDist'] == sch_dst)]

    count = 0
    j = 0
    k = 0
    m = df.shape[0]
    inp_vals = [(0 * 5) for i in range(2)]

    if (m == 0):
        inp_vals[j][k] = data[3]
        inp_vals[j][k+1] = "No Resi. Property Found"
        inp_vals[j][k+2] = "N/A"
        inp_vals[j][k+3] = "N/A"
        inp_vals[j][k+4] = data[2]
        j += 1
        k = 0

    elif (m == 1):
        i = 0
        inp_vals[j][k] = data[3]
        inp_vals[j][k+1] = df['Address'].iloc[i]
        inp_vals[j][k+2] = df['OwnerName'].iloc[i]
        inp_vals[j][k+3] = df['price_sf'].iloc[i]
        inp_vals[j][k+4] = data[2]
        j += 1
        k = 0

    else:
        for i in range(m):
            if (count < 2):
```

```

inp_vals[j][k] = data[3]
inp_vals[j][k+1] = df['Address'].iloc[i]
inp_vals[j][k+2] = df['OwnerName'].iloc[i]
inp_vals[j][k+3] = df['price_sf'].iloc[i]
inp_vals[j][k+4] = data[2]
j += 1
k = 0
count += 1
elif (count >= 2):
    break
return inp_vals

```

Top 10 Cost Effective Neighborhood Properties in NYC for Best Schools (2 choices / school)

```

In [38]: # Set up the data frame per ascending property prices, building class and location zip
sorted_property = prop_val.sort_values(by=['price_sf', 'BldgClass', 'ZipCode'])
sorted_property['ZipCode'] = pandas.to_numeric(sorted_property['ZipCode'], errors = 'coerce')

# Segregate data based on the building class for residential properties
sorted_property['Usage'] = sorted_property['BldgClass'].str[:1].apply(usage)
sorted_property = sorted_property[sorted_property['Usage'] == 1]

# Removing null values from the data frame
sorted_property = sorted_property.dropna()

# Extracting Top 10 Best Neighborhood Data
neighbor = [[([0]*5) for i in range(20)]
            for j in range(10)]:
    first_row, second_row = find_property(good_schools[['CSD', 'zip', 'SCHOOL NAME', 'PRICE', 'BldgClass', 'ZipCode']])
    for k in range(5):
        neighbor[j][k] = first_row[k]
        neighbor[j+1][k] = second_row[k]
    j += 2

# Set up neighbor data frame for output
cols = ['Borough', 'Property Address', 'Owner', 'Price/Sq Ft', 'Neighborhood School']
great_deal = pandas.DataFrame(columns=cols)

# Feed the final output in the data frame
for i in range(len(neighbor)):
    great_deal[cols[0]] = ([x[0] for x in neighbor[i]])
    great_deal[cols[1]] = ([x[1] for x in neighbor[i]])
    great_deal[cols[2]] = ([x[2] for x in neighbor[i]])
    great_deal[cols[3]] = ([x[3] for x in neighbor[i]])
    great_deal[cols[4]] = ([x[4] for x in neighbor[i]])

# Removing data with missing values and resetting the index

```



```

great_deal = great_deal[great_deal['Borough'] != 0]
great_deal.reset_index(inplace=True, drop=True)

# Print the final results results
print("\nList of Least Expensive Neighborhood With Great Schools: \n")
great_deal

```

List of Least Expensive Neighborhood With Great Schools:

```

Out[38]:

```

	Borough	Property Address	Owner	Price/Sq Ft	\
0	Manhattan	201 WARREN STREET	TRIBECA NORTH END LLC	112.479	
1	Manhattan	399 CHAMBERS STREET	TRIBECA POINTE LLC	114.277	
2	Bronx	2450 DAVIDSON AVENUE	2460 DAVIDSON REALTY	51.4895	
3	Bronx	2776 SEDGWICK AVENUE	TINEO, JOSE RAMON	51.8865	
4	Staten Island	10 PEEL PLACE	ANN SOLAZZO	24.215	
5	Staten Island	41 PETER AVENUE	SCAROLA, GREGG M	24.2163	
6	Bronx	2450 DAVIDSON AVENUE	2460 DAVIDSON REALTY	51.4895	
7	Bronx	2776 SEDGWICK AVENUE	TINEO, JOSE RAMON	51.8865	
8	Queens	152-11 UNION TURNPIKE	ST. JOHN'S UNIVERSITY	50.8769	
9	Queens	154-27 64 AVENUE	WISCHHUSEN RICHARD	66.6693	
10	Queens	162-25 112 ROAD	CALVARY GRANDPARENT R	59.1462	
11	Manhattan	85 STANTON STREET	85 OWNERS CORP	97.2278	
12	Manhattan	138 LUDLOW STREET	TRIPUKA REALTY CORP	97.401	
13	Manhattan	No Resi. Property Found	N/A	N/A	
14	Brooklyn	220 LINCOLN PLACE	220 LINCOLN LLC	50.0592	
15	Brooklyn	233 BERKELEY PLACE	233 BERKELEY PLACE LL	50.2336	
16	Manhattan	230 EAST 71 STREET	230 OWNERS CORP	97.0392	
17	Manhattan	305 EAST 75 STREET	GRUMA REALTY CORP	97.0882	

	Neighborhood School
0	STUYVESANT HIGH SCHOOL
1	STUYVESANT HIGH SCHOOL
2	BRONX HIGH SCHOOL OF SCIENCE
3	BRONX HIGH SCHOOL OF SCIENCE
4	STATEN ISLAND TECHNICAL HIGH SCHOOL
5	STATEN ISLAND TECHNICAL HIGH SCHOOL
6	HIGH SCHOOL OF AMERICAN STUDIES AT LEHMAN COLLEGE
7	HIGH SCHOOL OF AMERICAN STUDIES AT LEHMAN COLLEGE
8	TOWNSEND HARRIS HIGH SCHOOL
9	TOWNSEND HARRIS HIGH SCHOOL
10	QUEENS HIGH SCHOOL FOR THE SCIENCES AT YORK CO...
11	BARD HIGH SCHOOL EARLY COLLEGE
12	BARD HIGH SCHOOL EARLY COLLEGE
13	HIGH SCHOOL FOR MATHEMATICS, SCIENCE AND ENGIN...
14	BROOKLYN TECHNICAL HIGH SCHOOL

15
16
17

BROOKLYN TECHNICAL HIGH SCHOOL
ELEANOR ROOSEVELT HIGH SCHOOL
ELEANOR ROOSEVELT HIGH SCHOOL

0.0.29 Conclusion

We are able to know various critical factors that do/do not affect students performance in SAT examination. Based on this info, we can verify and validate how fare the current SAT system is for the diverse demographics like NYC. In case we found any flaws in the SAT system for unfair testing performances, we can get better idea about the causes to focus on and fix the system.

We understand the impact of various demographic, socio-economic, and current credit and grading system related factors over the performance of students in SAT examination. This helps us to determine and verify how this test maintains balance amongst these factors for overall fairness of test within the widely diverse community.

We are able to determine top 10 best schools based on their average SAT score.

We shortlist the least expensive but situated with the top 10 best school neighborhood regions.

We could identify the regions of NYC neighborhood where schools do not perform well and understand whether or not there exists any ethnic diversity [to consider] for policy improvement.

We learn the impact of similarity and disparity of students/teachers/parents opinion towards students academia over the SAT performance. This highlights the roles and responsibilities of various players of the game and its relative significance for the final outcome.

Based on the correlations and its severity on students SAT score, we can mention that SAT is reasonably fair for the diverse NYC demographics.